Service Intelligence Week 3.

[Service Quality Representation]

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2022. 9. 14

Further Discussion on

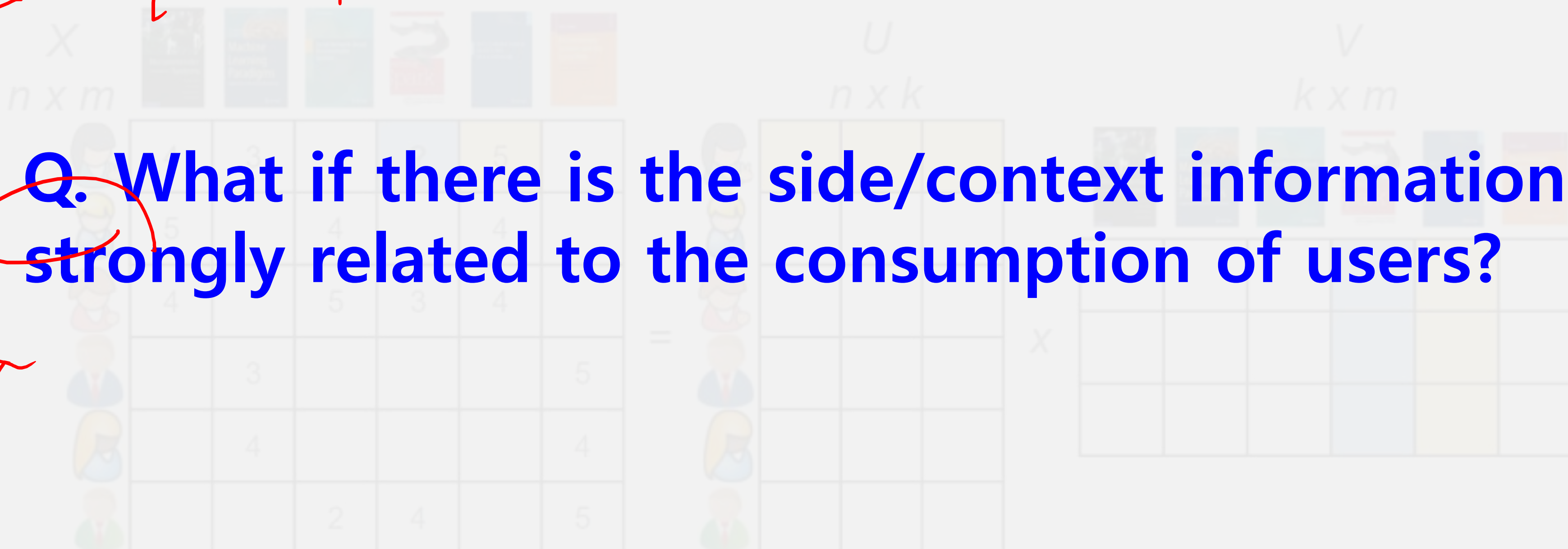
Recommender Systems for Services

Use of the Bag-of-Words-Form Transactions Matrix

Approaches of Recommender Systems

author year publisher type

A B C



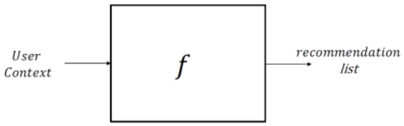
Q. What if there is the side/context information strongly related to the consumption of users?

gender age type

Approaches of Recommender Systems: A Data Perspective

- Recommender systems use analytic techniques to compute the value that a user will purchase one of the items; the techniques vary according to the purposes and data

$$y = f(x)$$



	Feature 1	Feature 2	Feature 3	…	Feature m-1	Feature m
Transaction 1	…	…	…	…	…	…
Transaction 2	…	…	…	…	…	…
Transaction 3	…	…	…	…	…	…
…	…	…	…	…	…	…
…	…	…	…	…	…	…
…	…	…	…	…	…	…
…	…	…	…	…	…	…
…	…	…	…	…	…	…
Transaction n-1	…	…	…	…	…	…
Transaction n	…	…	…	…	…	…

Approaches of Recommender Systems: A Data Perspective

- Recommender systems use analytic techniques to compute the value that a user will purchase one of the items; the techniques vary according to the purposes and data

Matrix Factorization Training Data

	i_1	i_2	i_3
u_1	2	4	
u_2		1	
u_3	3		5

vs.

Factorization Machine Training Data

	u_1	u_2	u_3	i_1	i_2	i_3	a_1	a_2	y
x_1	1	0	0	1	0	0	2.0	0.0	2
x_2	1	0	0	0	1	0	1.5	0.5	4
x_3	0	1	0	0	1	0	0.0	1.0	1
x_4	0	0	1	1	0	0	0.3	0.7	3
x_5	0	0	1	0	0	1	3.2	1.7	5

Users (u_1–u_3) | Items (i_1–i_3) | Auxiliary Features (a_1, a_2) | Observed Ratings (y)

Image reference: https://towardsdatascience.com/factorization-machines-for-item-recommendation-with-implicit-feedback-data-5655a7c749db

Factorization Machine

TI NH SW

	User A	User B	User C	User …	Movie TI	Movie NH	Movie SW	Movie ST	Movie …	Other Movies rated TI	Other Movies rated NH	Other Movies rated SW	Other Movies rated ST	Other Movies rated …	Time	Last Movie rated TI	Last Movie rated NH	Last Movie rated SW	Last Movie rated ST	Last Movie rated …	Target y	
$x^{(1)}$	1	0	0	...	1	0	0	0	...	0.3	0.3	0.3	0	...	13	0	0	0	0	...	5	$y^{(1)}$
$x^{(2)}$	1	0	0	...	0	1	0	0	...	0.3	0.3	0.3	0	...	14	1	0	0	0	...	3	$y^{(2)}$
$x^{(3)}$	1	0	0	...	0	0	1	0	...	0.3	0.3	0.3	0	...	16	0	1	0	0	...	1	$y^{(2)}$
$x^{(4)}$	0	1	0	...	0	0	1	0	...	0	0	0.5	0.5	...	5	0	0	0	0	...	4	$y^{(3)}$
$x^{(5)}$	0	1	0	...	0	0	0	1	...	0	0	0.5	0.5	...	8	0	0	1	0	...	5	$y^{(4)}$
$x^{(6)}$	0	0	1	...	1	0	0	0	...	0.5	0	0.5	0	...	9	0	0	0	0	...	1	$y^{(5)}$
$x^{(7)}$	0	0	1	...	0	0	1	0	...	0.5	0	0.5	0	...	12	1	0	0	0	...	5	$y^{(6)}$

Feature vector x — Target y

$$\hat{y}(\mathbf{x}) := w_0 + \sum_{i=1}^{n} w_i x_i + \sum_{i=1}^{n}\sum_{j=i+1}^{n} w_{ij} x_i x_j$$

$$\hat{y}(\mathbf{x}) := w_0 + \sum_{i=1}^{n} w_i\, x_i + \sum_{i=1}^{n}\sum_{j=i+1}^{n} \langle \mathbf{v}_i, \mathbf{v}_j \rangle\, x_i\, x_j \qquad (1)$$

where the model parameters that have to be estimated are:

$$w_0 \in \mathbb{R}, \quad \mathbf{w} \in \mathbb{R}^n, \quad \mathbf{V} \in \mathbb{R}^{n \times k} \qquad (2)$$

And $\langle \cdot, \cdot \rangle$ is the dot product of two vectors of size k:

$$\langle \mathbf{v}_i, \mathbf{v}_j \rangle := \sum_{f=1}^{k} v_{i,f} \cdot v_{j,f} \qquad (3)$$

A row $\mathbf{v}_i$ within $\mathbf{V}$ describes the i-th variable with k factors. $k \in \mathbb{N}_0^+$ is a hyperparameter that defines the dimensionality of the factorization.

symmetric

positive semidefinite

If Y is **symmetric**, then it is diagonalizable, its eigenvalues are real, and its eigenvectors are orthogonal. Hence, Y has an eigendecomposition $Y = Q\Lambda Q^\top$, where the columns of Q are the eigenvectors of Y and the diagonal entries of diagonal matrix Λ are the eigenvalues of Y.

If Y is also **positive semidefinite**, then all its eigenvalues are nonnegative, which means that we can take their square roots. Hence,

$$Y = Q\Lambda Q^\top = Q\Lambda^{\frac{1}{2}}\Lambda^{\frac{1}{2}}Q^\top = \underbrace{\left(Q\Lambda^{\frac{1}{2}}\right)}_{=:V^\top}\left(Q\Lambda^{\frac{1}{2}}\right)^\top = V^\top V$$

Note that the rows of V are the eigenvectors of Y multiplied by the square roots of the (nonnegative) eigenvalues of Y.

Reference: https://www.jefkine.com/recsys/2017/03/27/factorization-machines/
https://ieeexplore.ieee.org/abstract/document/5694074?casa_token=CV0m3FJ7U3UAAAAA:1rubmy3hLA6hvfRzAxZV4ykDx4kufMqEsGPX69_eJckG3BP05EJCh7DEkUcSmGQzc6JhEf37dX4
https://math.stackexchange.com/questions/1801403/decomposition-of-a-positive-semidefinite-matrix

① computation efficiency

② estimation

Factorization Machine

$O(n^2)$

	User A	B	C	...	Movie TI	NH	SW	ST	...	Other Movies rated TI	NH	SW	ST	...	Time	Last Movie rated TI	NH	SW	ST	...	Target y	
$x^{(1)}$	1	0	0	...	1	0	0	0	...	0.3	0.3	0.3	0	...	13	0	0	0	0	...	5	$y^{(1)}$
$x^{(2)}$	1	0	0	...	0	1	0	0	...	0.3	0.3	0.3	0	...	14	1	0	0	0	...	3	$y^{(2)}$
$x^{(3)}$	1	0	0	...	0	0	1	0	...	0.3	0.3	0.3	0	...	16	0	1	0	0	...	1	$y^{(2)}$
$x^{(4)}$	0	1	0	...	0	0	1	0	...	0	0	0.5	0.5	...	5	0	0	0	0	...	4	$y^{(3)}$
$x^{(5)}$	0	1	0	...	0	0	0	1	...	0	0	0.5	0.5	...	8	0	0	1	0	...	5	$y^{(4)}$
$x^{(6)}$	0	0	1	...	1	0	0	0	...	0.5	0	0.5	0	...	9	0	0	0	0	...	1	$y^{(5)}$
$x^{(7)}$	0	0	1	...	0	0	1	0	...	0.5	0	0.5	0	...	12	1	0	0	0	...	5	$y^{(6)}$

Feature vector **x**

$$\sum_{i=1}^{n}\sum_{j=i+1}^{n}\langle \mathbf{v}_i,\mathbf{v}_j\rangle x_i x_j$$
$$=\frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}\langle \mathbf{v}_i,\mathbf{v}_j\rangle x_i x_j-\frac{1}{2}\sum_{i=1}^{n}\langle \mathbf{v}_i,\mathbf{v}_i\rangle x_i x_i$$
$$=\frac{1}{2}\left(\sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{f=1}^{k}v_{i,f}\,v_{j,f}\,x_i x_j-\sum_{i=1}^{n}\sum_{f=1}^{k}v_{i,f}\,v_{i,f}\,x_i x_i\right)$$
$$=\frac{1}{2}\sum_{f=1}^{k}\left(\left(\sum_{i=1}^{n}v_{i,f}\,x_i\right)\left(\sum_{j=1}^{n}v_{j,f}\,x_j\right)-\sum_{i=1}^{n}v_{i,f}^2\,x_i^2\right)$$
$$=\frac{1}{2}\sum_{f=1}^{k}\left(\left(\sum_{i=1}^{n}v_{i,f}\,x_i\right)^2-\sum_{i=1}^{n}v_{i,f}^2\,x_i^2\right)$$

$O(kn)$

$$\hat{y}(\mathbf{x}) := w_0+\sum_{i=1}^{n}w_i\,x_i+\sum_{i=1}^{n}\sum_{j=i+1}^{n}\langle \mathbf{v}_i,\mathbf{v}_j\rangle x_i x_j \qquad (1)$$

where the model parameters that have to be estimated are:

$$w_0\in\mathbb{R},\quad \mathbf{w}\in\mathbb{R}^n,\quad \mathbf{V}\in\mathbb{R}^{n\times k} \qquad (2)$$

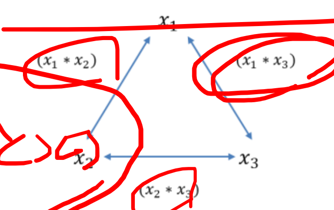
And $\langle\cdot,\cdot\rangle$ is the dot product of two vectors of size k:

$$\langle \mathbf{v}_i,\mathbf{v}_j\rangle := \sum_{f=1}^{k}v_{i,f}\cdot v_{j,f} \qquad (3)$$

A row $\mathbf{v}_i$ within $\mathbf{V}$ describes the i-th variable with k factors. $k\in\mathbb{N}_0^+$ is a hyperparameter that defines the dimensionality of the factorization.

$$\hat{y}(\mathbf{x}) := w_0+\sum_{i=1}^{n}w_i\,x_i+\frac{1}{2}\sum_{f=1}^{k}\left(\left(\sum_{i=1}^{n}v_{i,f}\,x_i\right)^2-\sum_{i=1}^{n}v_{i,f}^2\,x_i^2\right)$$

$$\frac{\partial}{\partial\theta}\hat{y}(\mathbf{x})=\begin{cases}1, & \text{if } \theta \text{ is } w_0\\ x_i, & \text{if } \theta \text{ is } w_i\\ x_i\sum_{j=1}^{n}v_{j,f}x_j-v_{i,f}x_i^2, & \text{if } \theta \text{ is } v_{i,f}\end{cases}$$



Reference: https://www.jefkine.com/recsys/2017/03/27/factorization-machines/
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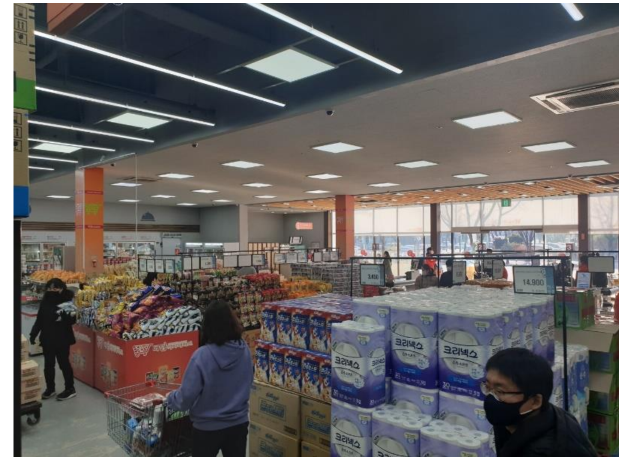
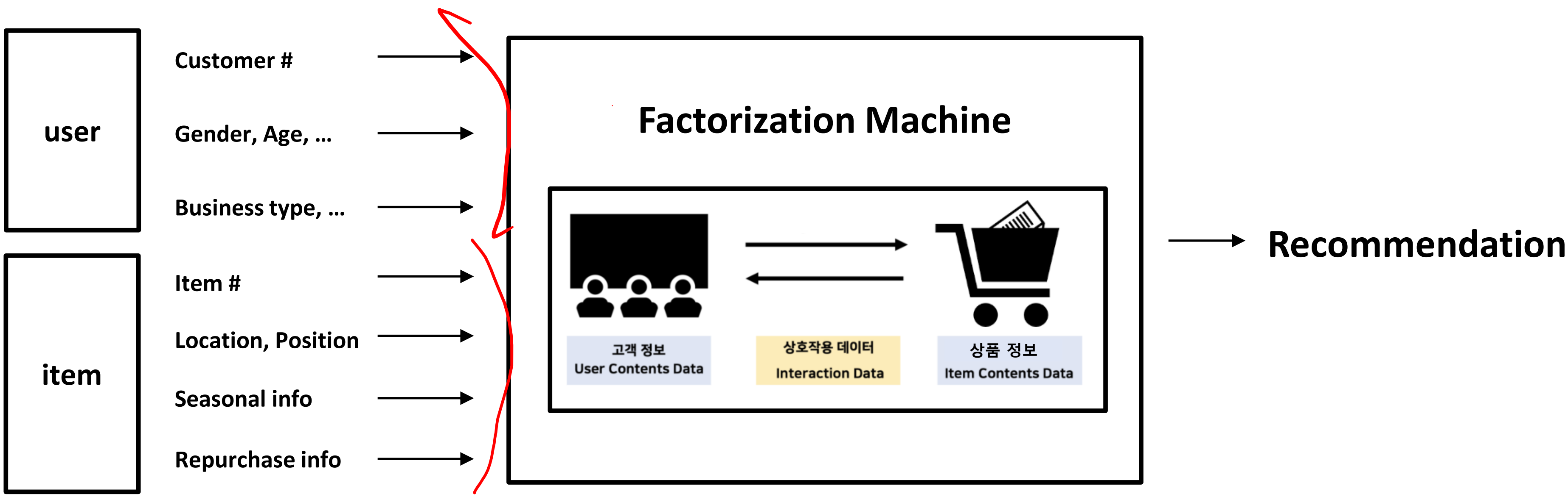
https://math.stackexchange.com/questions/1801403/decomposition-of-a-positive-semidefinite-matrix

Factorization Machine for Offline Contexts





Assignment 2 (by 9.16 11:59 pm)

- There are two types of practice demonstrated by TAs. One approach is to use the user-item matrix and the other is to use the transaction-feature matrix. By yourself, (1) identify several (i.e., top k) recommendations using one of the two approaches with the given datasets. Of course you can try both.
- (2) Then, evaluate and interpret the recommendation outcomes quantitatively (e.g., calculate the recall, calculate the similarities between the recommended items) and qualitatively (e.g., interpret the factorization outcome, identify the characteristics of the top k recommended items). Do it all by yourself, and describe the analysis/interpretation process and outcome in detail.
- (3) Assume you need to use your recommender system for real-world service (i.e., streaming service or hypermarket service). How can you improve your recommender system to be used for the service effectively? For example, what kinds of data should you use further? How would you design a method for using/learning the data? Think beyond these examples in your own creative, unique way!
- (4) You must have your own interested or favorite service WITHOUT a recommender system (i.e., it should be different with the intelligent services discussed in the class). Discuss the requirements of original recommender system development for the service. Describe the requirements in detail.
- (5) If you would conduct a study on the recommender system development for the service, how would you conduct the research 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). To facilitate your thinking, you may want to identify and review a recommender system paper related to the service you are interested or concerned.
- Upload your code and a several paragraph essay on the tasks (1)~(5) in the Blackboard.

Matrix Factorization Practice

Demonstrated by TA Seo

Factorization Machine Practice

Demonstrated by TA Shin

Assignment 2 (by 9.16 11:59 pm)

- There are two types of practice demonstrated by TAs. One approach is to use the user-item matrix and the other is to use the transaction-feature matrix. By yourself, (1) identify several (i.e., top k) recommendations using one of the two approaches with the given datasets. Of course you can try both.
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- (3) Assume you need to use your recommender system for real-world service (i.e., streaming service or hypermarket service). How can you improve your recommender system to be used for the service effectively? For example, what kinds of data should you use further? How would you design a method for using/learning the data? Think beyond these examples in your own creative, unique way!
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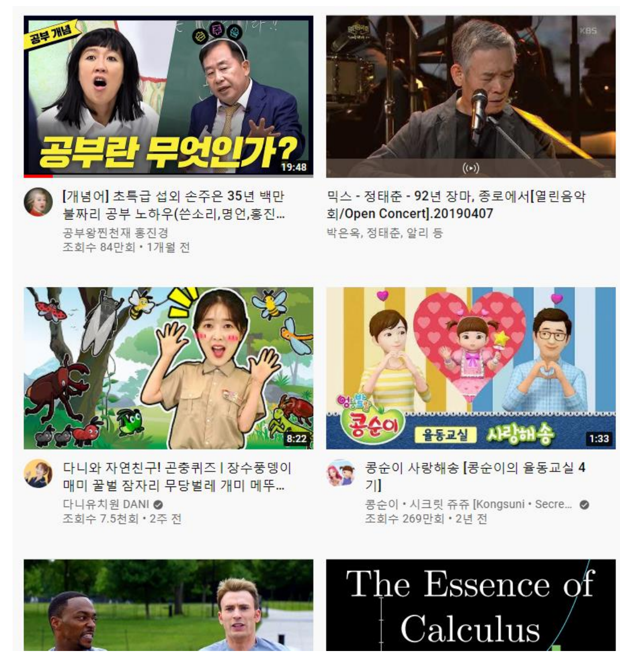
Concluding Remarks

Approaches of Recommender Systems: A Categorization

- Recommender systems use analytic techniques to compute the value that a user would purchase one of the items; the techniques vary according to the purposes and data
  - Content-based filtering
  - Collaborative filtering

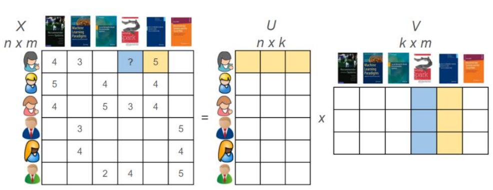


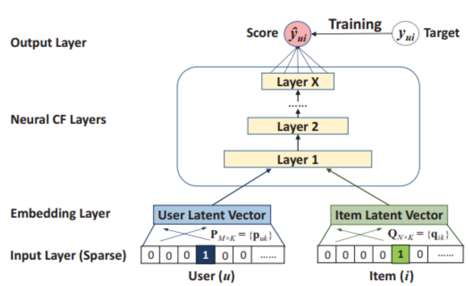
Approaches of Recommender Systems: Our Focus

- Recommender systems use analytic techniques to compute the value that a user would purchase one of the items; the techniques vary according to the purposes and data

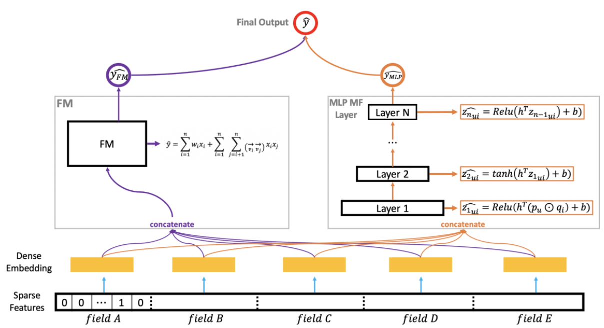
	Item 1	Item 2	Item 3	…	Item m-1	Item m
User 1	…	…	…	…	…	…
User 2	…	…	…	…	…	…
User 3	…	…	…	…	…	…
…	…	…	…	…	…	…
…	…	…	…	…	…	…
…	…	…	…	…	…	…
…	…	…	…	…	…	…
…	…	…	…	…	…	…
User n-1	…	…	…	…	…	…
User n	…	…	…	…	…	…

	Feature 1	Feature 2	Feature 3	…	Feature m-1	Feature m
Transaction 1	…	…	…	…	…	…
Transaction 2	…	…	…	…	…	…
Transaction 3	…	…	…	…	…	…
…	…	…	…	…	…	…
…	…	…	…	…	…	…
…	…	…	…	…	…	…
…	…	…	…	…	…	…
…	…	…	…	…	…	…
Transaction n-1	…	…	…	…	…	…
Transaction n	…	…	…	…	…	…



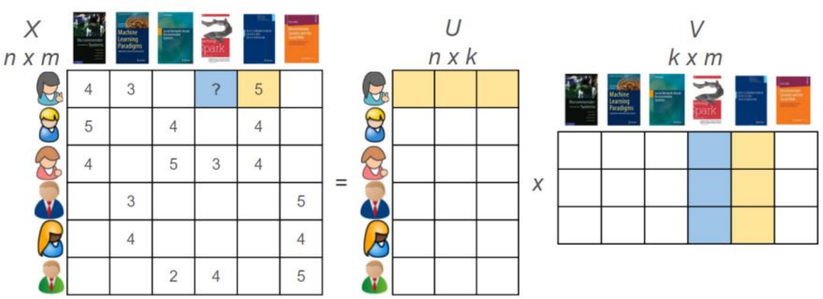


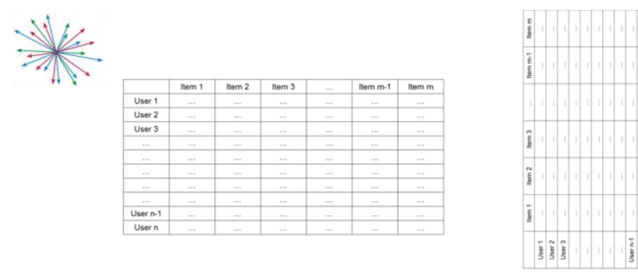
$$\hat{y}(\mathbf{x}) := w_0 + \sum_{i=1}^{n} w_i\, x_i + \sum_{i=1}^{n} \sum_{j=i+1}^{n} \langle \mathbf{v}_i, \mathbf{v}_j \rangle\, x_i\, x_j$$



Approaches of Collaborative Filtering: Emergence of Deep Learning

- Recommender systems use analytic techniques to compute the value that a user would purchase one of the items; the techniques vary according to the purposes and data
  - Collaborative filtering
    - Uses an information filtering technique based on the user's previous evaluation of items or history of previous purchases





- Euclidean distance
- Cosine similarity
- Jaccard coefficient
- Pearson correlation coefficient
- …

$$\mathrm{Sim}(u_a, u_b) = \frac{\sum_{i=1}^{i'} (r_{u_a,i})(r_{u_b,i})}{\sqrt{\sum_{i=1}^{n} (r_{u_a,i})}\sqrt{\sum_{i=1}^{n} (r_{u_b,i})}}$$

$$\mathrm{Sim}(u_a, u_b) = \frac{|I_{u_a}|\cap|I_{u_b}|}{|I_{u_a}|\cup|I_{u_b}|}$$

$$\mathrm{Sim}(u_a, u_b) = \frac{\sum_{i=1}^{i'} (r_{u_a,i} - r_{\overline{u_a}})(r_{u_b,i} - r_{\overline{u_b}})}{\sqrt{\sum_{i=1}^{i'} (r_{u_a,i} - r_{\overline{u_a}})^2} \cdot \sqrt{\sum_{i=1}^{i'} (r_{\overline{u_b,i}} - r_{\overline{u_b}})^2}}$$

Approaches of Collaborative Filtering: Emergence of Deep Learning

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

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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

*NExT research is supported by the National Research Foundation, Prime Minister's Office, Singapore under its IRC@SG Funding Initiative.

WWW 2017, April 3–7, 2017, Perth, Australia.
ACM 978-1-4503-4913-0/17/04.
http://dx.doi.org/10.1145/3038912.3052569

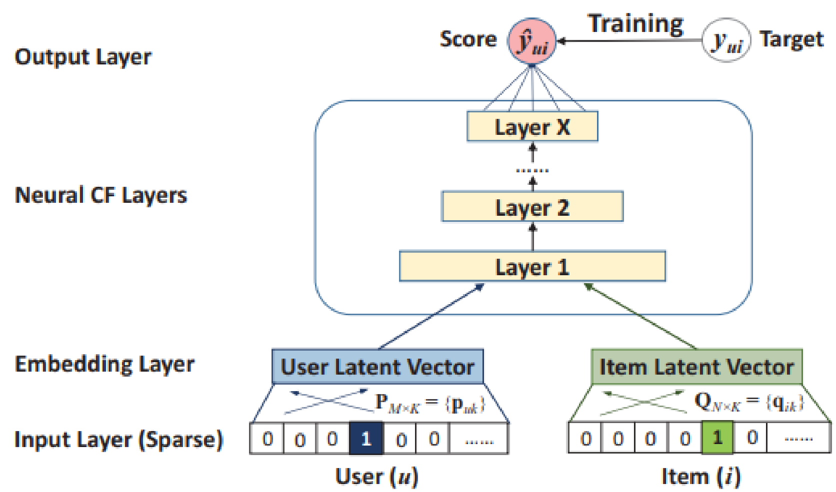
1. INTRODUCTION

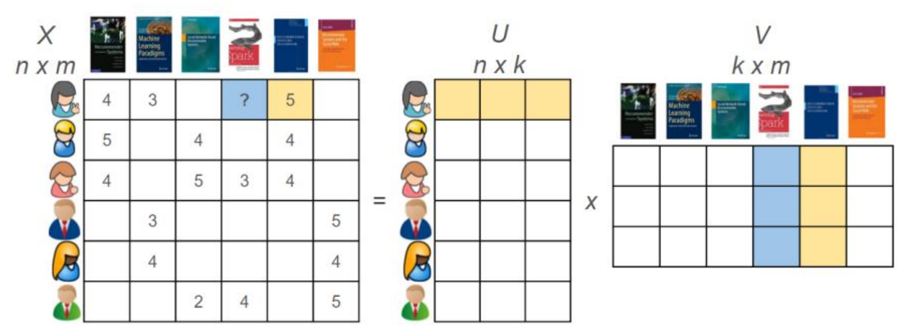
In the era of information explosion, recommender systems play a pivotal role in alleviating information overload, having been widely adopted by many online services, including E-commerce, online news and social media sites. The key to a personalized recommender system is in modelling users' preference 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





Approaches of Content-based Filtering: Emergence of Deep Learning

- Recommender systems use analytic techniques to compute the value that a user would purchase one of the items; the techniques vary according to the purposes and data
  - Content-based filtering
    - Analyzes a set of documents (of the items in question) rated by an individual user and uses the contents of the items, as well as the provided ratings, to infer a user profile that can be used to recommend additional items of interest

	Feature 1	Feature 2	Feature 3	…	Feature m-1	Feature m
Item 1	…	…	…	…	…	…
Item 2	…	…	…	…	…	…
Item 3	…	…	…	…	…	…
…	…	…	…	…	…	…
…	…	…	…	…	…	…
…	…	…	…	…	…	…
…	…	…	…	…	…	…
…	…	…	…	…	…	…
Item n-1	…	…	…	…	…	…
Item n	…	…	…	…	…	…

Approaches of Collaborative Filtering: Emergence of Deep Learning

- Deep-learning-based representation/embedding complements the traditional approaches

ITEM2VEC: NEURAL ITEM EMBEDDING FOR COLLABORATIVE FILTERING

*Oren Barkan^* and Noam Koenigstein**

^Tel Aviv University
*Microsoft

ABSTRACT

Many Collaborative Filtering (CF) algorithms are item-based in the sense that they analyze item-item relations in order to produce item similarities. Recently, several works in the field of Natural Language Processing (NLP) suggested to learn a latent representation of words using neural embedding algorithms. Among them, the Skip-gram with Negative Sampling (SGNS), also known as word2vec, was shown to provide state-of-the-art results on various linguistics tasks. In this paper, we show that item-based CF can be cast in the same framework of neural word embedding. Inspired by SGNS, we describe a method we name item2vec for item-based CF that produces embedding for items in a latent space. The method is capable of inferring item-item relations even when user information is not available. We present experimental results that demonstrate the effectiveness of the item2vec method and show it is competitive with SVD.

Index terms – skip-gram, word2vec, neural word embedding, collaborative filtering, item similarity, recommender systems, market basket analysis, item-item collaborative filtering, item recommendations.

People also like

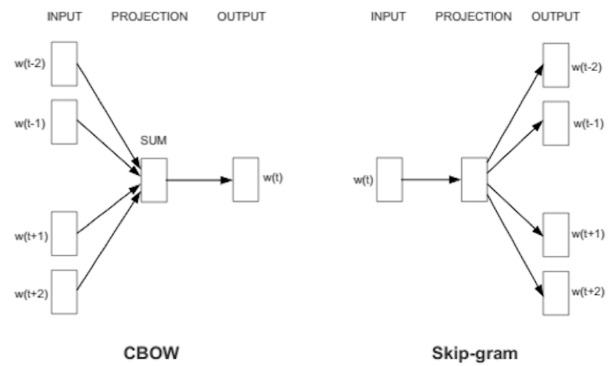
Fig. 1. Recommendations in Windows 10 Store based on similar items to Need For Speed.

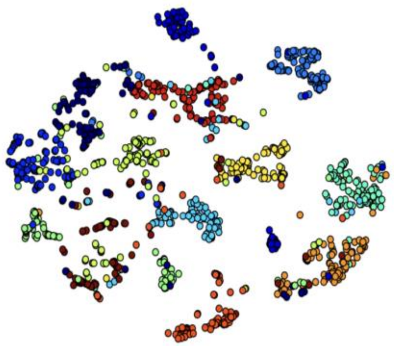
1. INTRODUCTION AND RELATED WORK

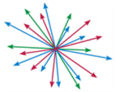
Computing item similarities is a key building block in modern recommender systems. While many recommendation algorithms are focused on learning a low dimensional embedding of users and items simultaneously [1, 2, 3], computing item similarities is an end in itself. Item similarities are extensively used by online retailers for many different recommendation tasks. This paper deals with the overlooked task of learning item similarities by embedding items in a low dimensional space.

Item-based similarities are used by online retailers for recommendations based on a single item. For example, in the Windows 10 App Store, the details page of each app or game includes a list of other similar apps titled "People also like". This list can be extended to a full page recommendation list of items similar to the original app as shown in Fig. 1. Similar recommendation lists which are based merely on similarities to a single item exist in most online stores e.g., Amazon, Netflix, Google Play, iTunes store and many others.

The single item recommendations are different than the more "traditional" user-to-item recommendations because they are usually shown in the context of an explicit user interest in a specific item and in the context of an explicit user intent to purchase. Therefore, single item recommendations based on item similarities often have higher Click-Through Rates (CTR) than user-to-item recommendations and consequently responsible for a larger share of sales or revenue.







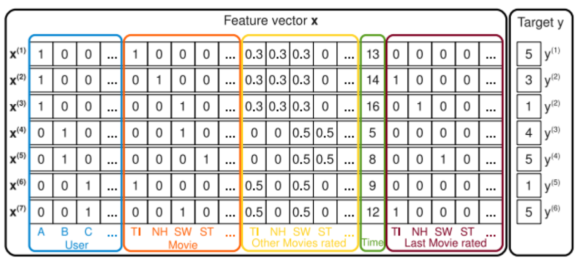
	Item 1	Item 2	Item 3	…	Item m-1	Item m
User 1	…	…	…	…	…	…
User 2	…	…	…	…	…	…
User 3	…	…	…	…	…	…
…	…	…	…	…	…	…
…	…	…	…	…	…	…
…	…	…	…	…	…	…
…	…	…	…	…	…	…
…	…	…	…	…	…	…
User n-1	…	…	…	…	…	…
User n	…	…	…	…	…	…

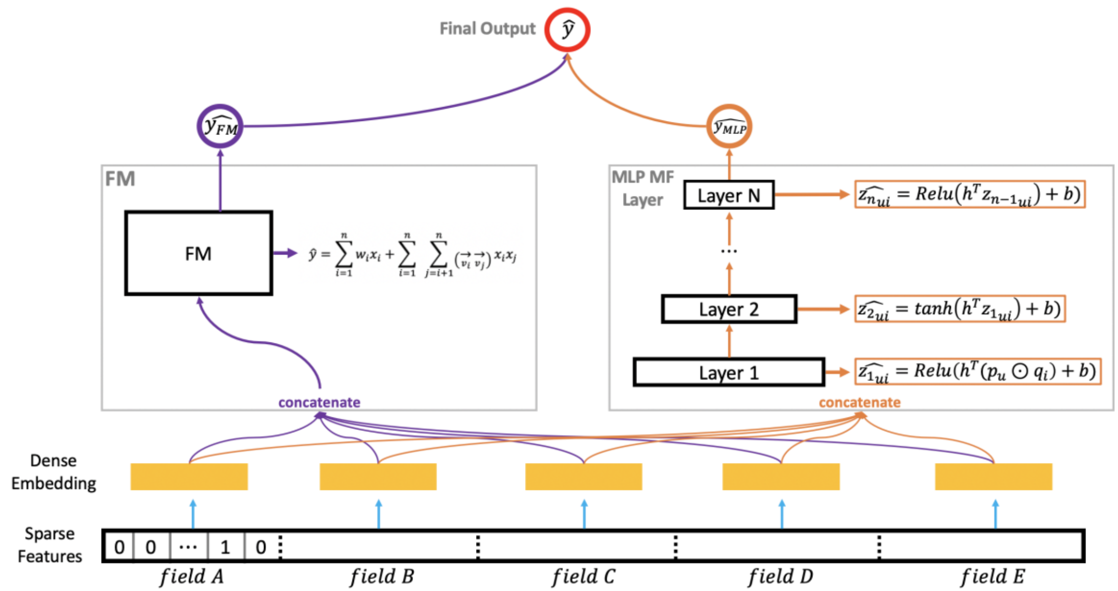
- Euclidean distance
- Cosine similarity
- Jaccard coefficient
- Pearson correlation coefficient
- …

Approaches of Collaborative Filtering: Emergence of Deep Learning

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

- Deep-learning-based representation/embedding complements the traditional approaches





Assignment 2 (by 9.16 11:59 pm)

- There are two types of practice demonstrated by TAs. One approach is to use the user-item matrix and the other is to use the transaction-feature matrix. By yourself, (1) identify several (i.e., top k) recommendations using one of the two approaches with the given datasets. Of course you can try both.
- (2) Then, evaluate and interpret the recommendation outcomes quantitatively (e.g., calculate the recall, calculate the similarities between the recommended items) and qualitatively (e.g., interpret the factorization outcome, identify the characteristics of the top k recommended items). Do it all by yourself, and describe the analysis/interpretation process and outcome in detail.
- (3) Assume you need to use your recommender system for real-world service (i.e., streaming service or hypermarket service). How can you improve your recommender system to be used for the service effectively? For example, what kinds of data should you use further? How would you design a method for using/learning the data? Think beyond these examples in your own creative, unique way!
- (4) You must have your own interested or favorite service WITHOUT a recommender system (i.e., it should be different with the intelligent services discussed in the class). Discuss the requirements of original recommender system development for the service. Describe the requirements in detail.
- (5) If you would conduct a study on the recommender system development for the service, how would you conduct the research 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). To facilitate your thinking, you may want to identify and review a recommender system paper related to the service you are interested or concerned.
- Upload your code and a several paragraph essay on the tasks (1)~(5) in the Blackboard.

Further Discussion Points

- Relation and gap between the recommender system and service quality
- Considerations of recommender system development for real-world services:

  (1) data, (2) model, (3) service speed, (4) service UI, (5) model and service evaluation …
- Beyond the user-item matrix
  - Consideration of the side information (details of items and user contexts) is also necessary
  - What other variabilities of the customer's contexts should be considered in recommendation?
- Objectives of recommendation from the customer vs. operations perspectives
- Dealing with the customer's cognitive processes unknown
- Knowledge discovery (customer understanding) for recommender system development
  - Performance of model + Explainability of model + Interpretability of result
- Ethics around the recommender systems

Service Intelligence Week 3.

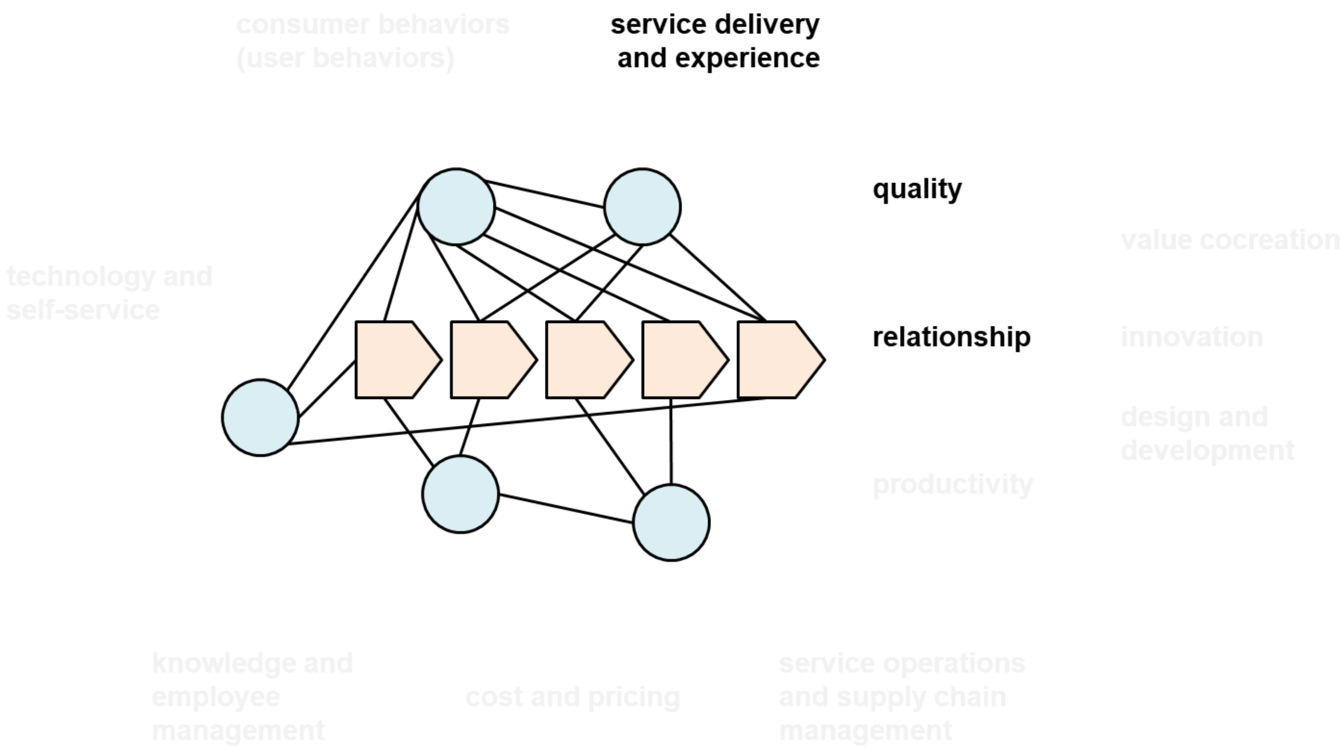
[Service Quality Representation]

Chiehyeon Lim

2022. 9. 14

Questions and Learning Objectives

- How can we “explicitly” evaluate and improve the “implicit” quality of services?
- How can we use data and learning intelligence for service quality representation?



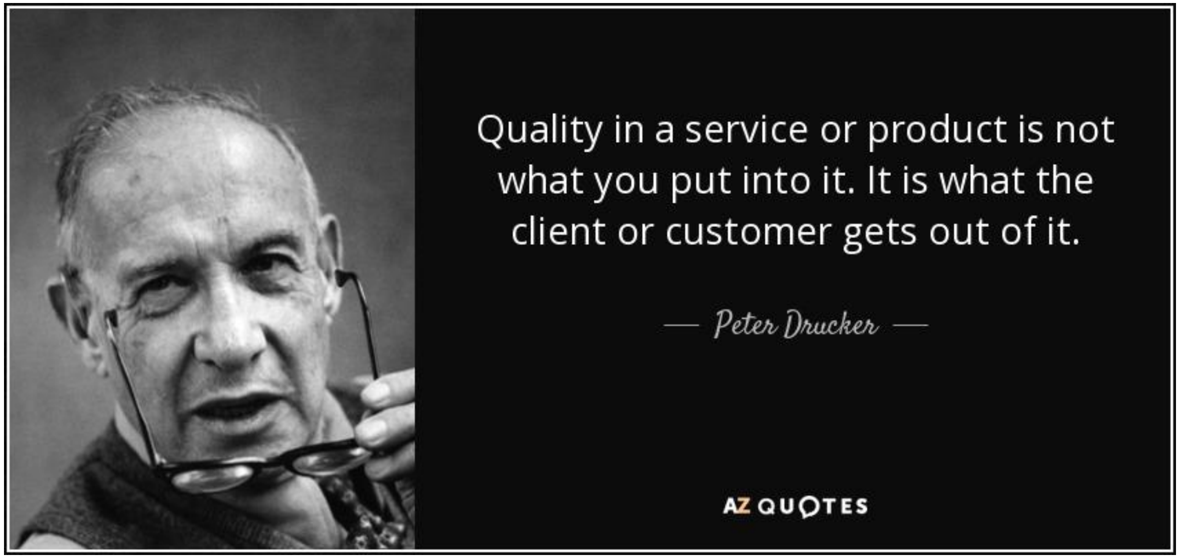
Quality

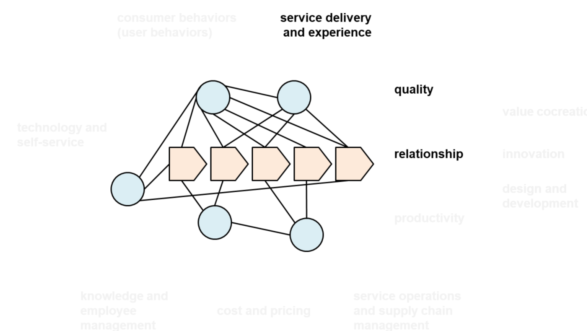
- Definition of quality
  - “The totality of characteristics of an entity that bears on its ability to satisfy stated and *implied* needs.” (ISO, 1994)

- Importance of quality

Service Quality

- A perspective of quality



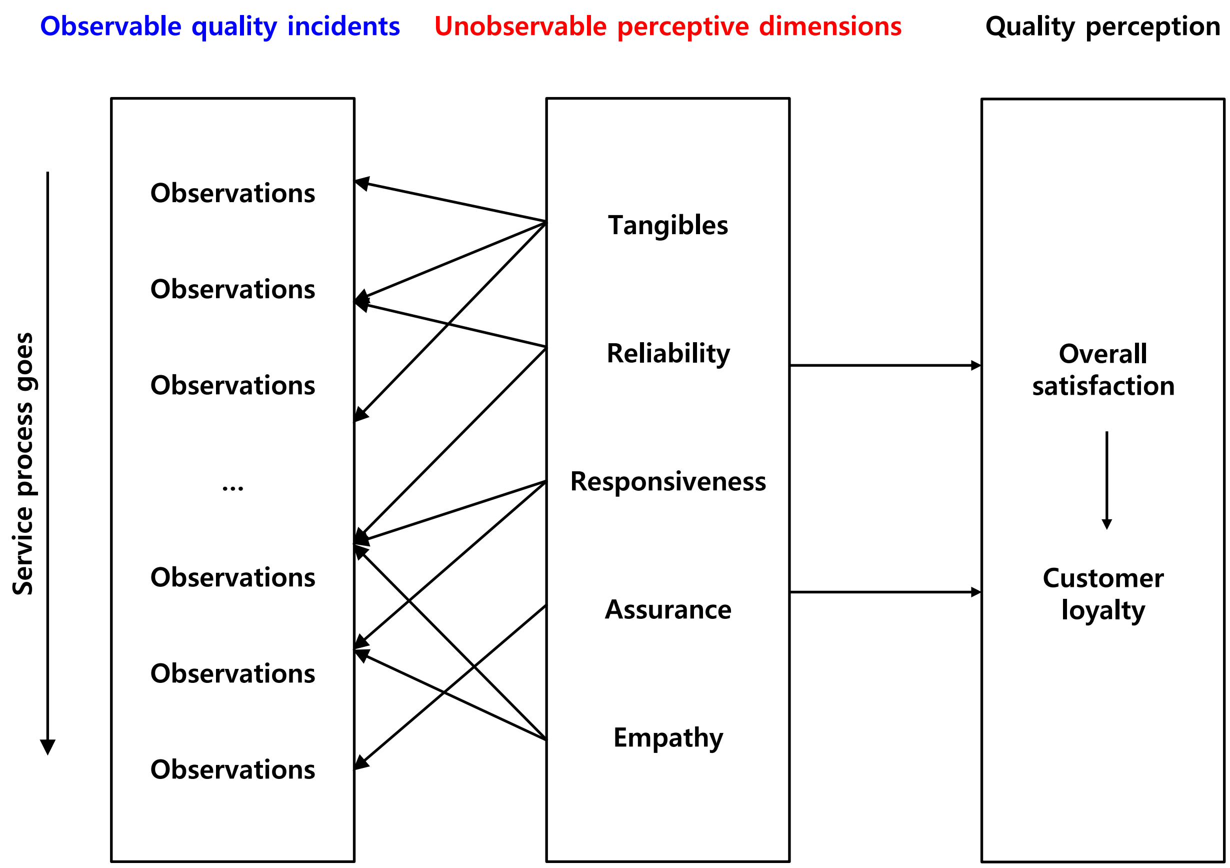


- A definition of service quality
  - "The totality of characteristics of a service that bears on its ability to satisfy stated and *implied* needs of customers."

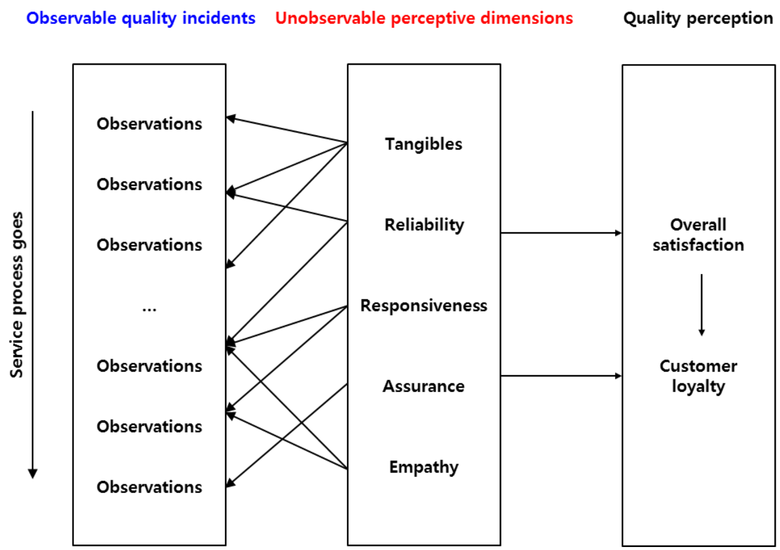
Service Quality Evaluation: Education Service Example

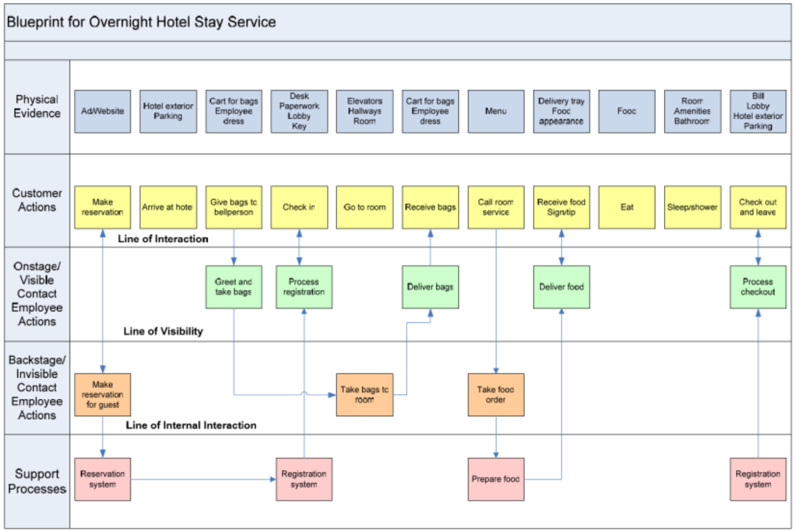
Observable quality incidents **Unobservable perceptive dimensions** **Quality perception**

Illustration of Service Quality Evaluation



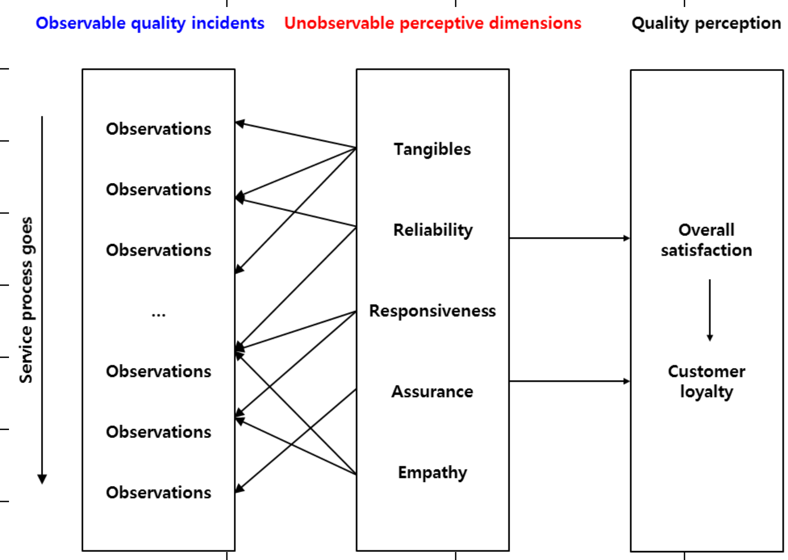
Service Quality Evaluation: Hotel Service Example





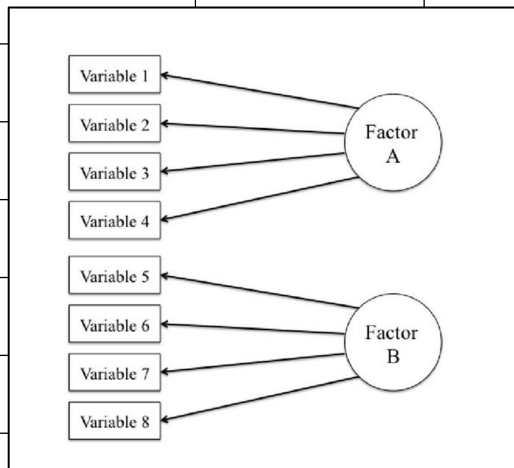
Service Quality “Representation”

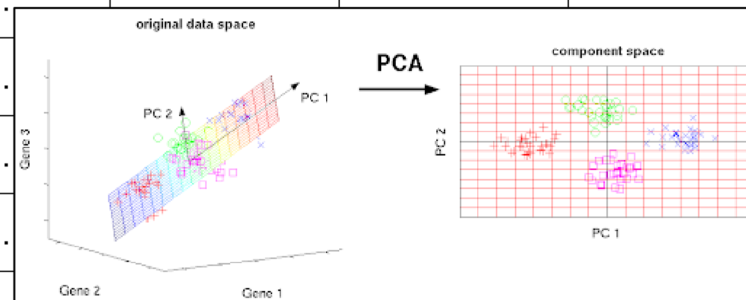
	Feature 1	Feature 2	Feature 3	…	Feature m-1	Feature m
Customer 1	…	…	…	…	…	…
Customer 2	…	…	…	…	…	…
Customer 3	…				..	…
…	…				..	…
…	…				..	…
…	…				..	…
…	…				..	…
…	…				..	…
…	…				..	…
…	…				..	…
Customer n-1	…	…	…	…	…	…
Customer n	…	…	…	…	…	…

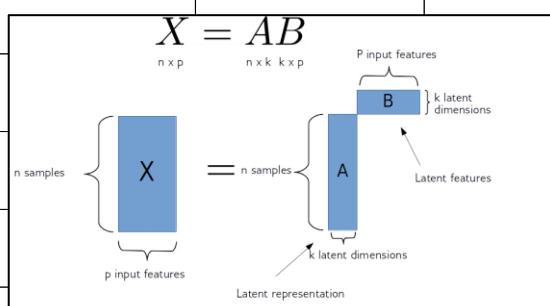


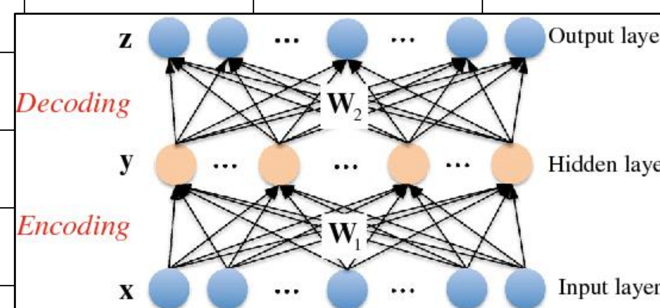
Service Quality "Representation"

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







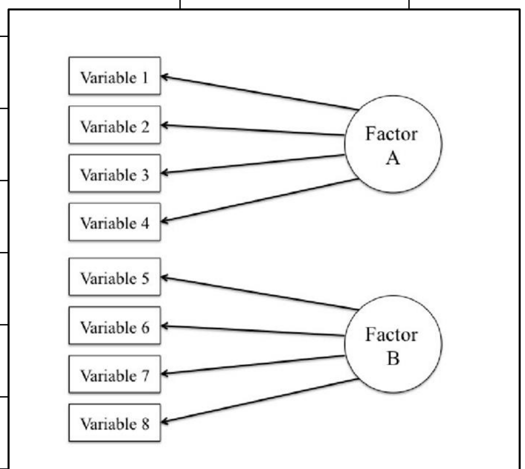


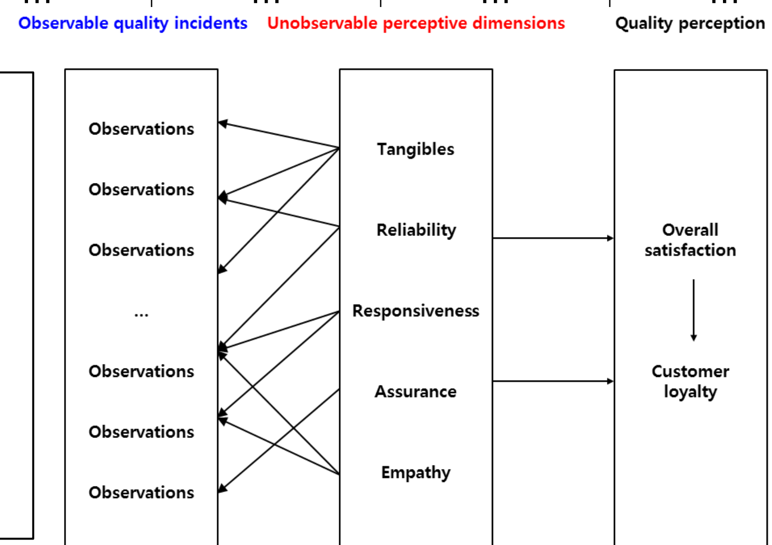
For Your Comprehension: A First Study on Service Quality Representation

SERVQUAL: A Multiple-Item Scale for Measuring Service Quality (PZB, 1988)

SERVQUAL: A Multiple-Item Scale for Measuring Service Quality

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





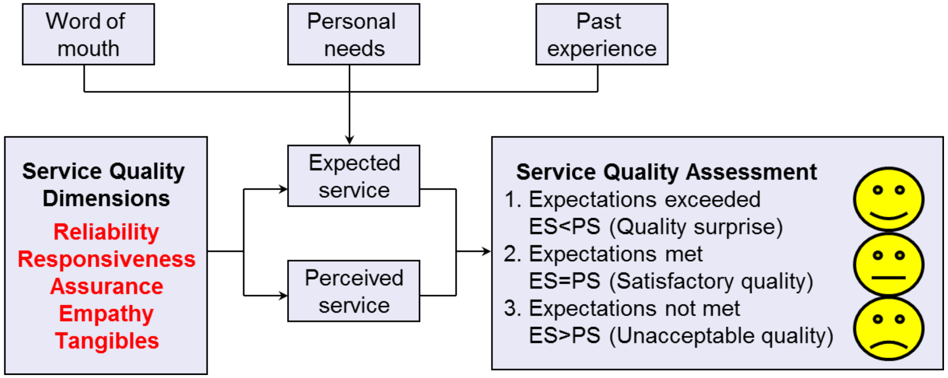
A Perspective on the Service Quality Evaluation

- Traditional challenge in service businesses: Absence of **object measures of service quality**
- The most appropriate approach would be to measure consumer's perception of quality:

  "Service quality, as **perceived** by consumers, stems from a **comparison of what they feel service firms should offer** with their **perception of the performance of firms** providing the service"

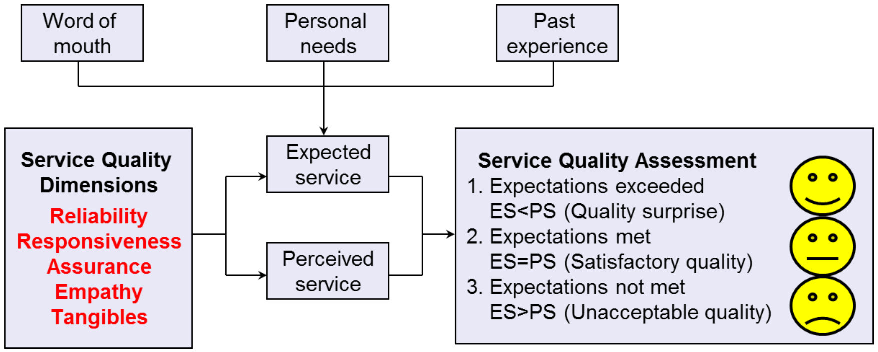
  (Parasuraman et al., 1985)
- **The gap** between customers' **perception** of service performance and their **expectation**

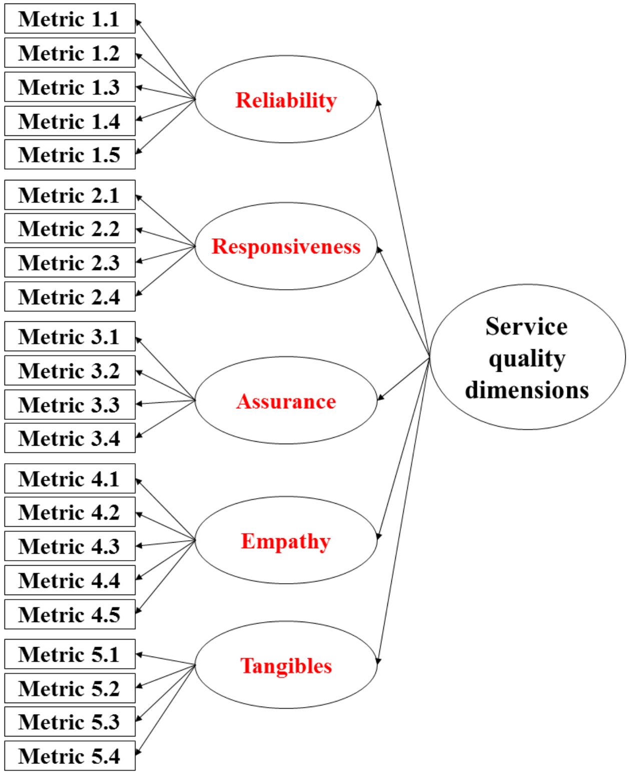
"Quality = Perception – Expectation"



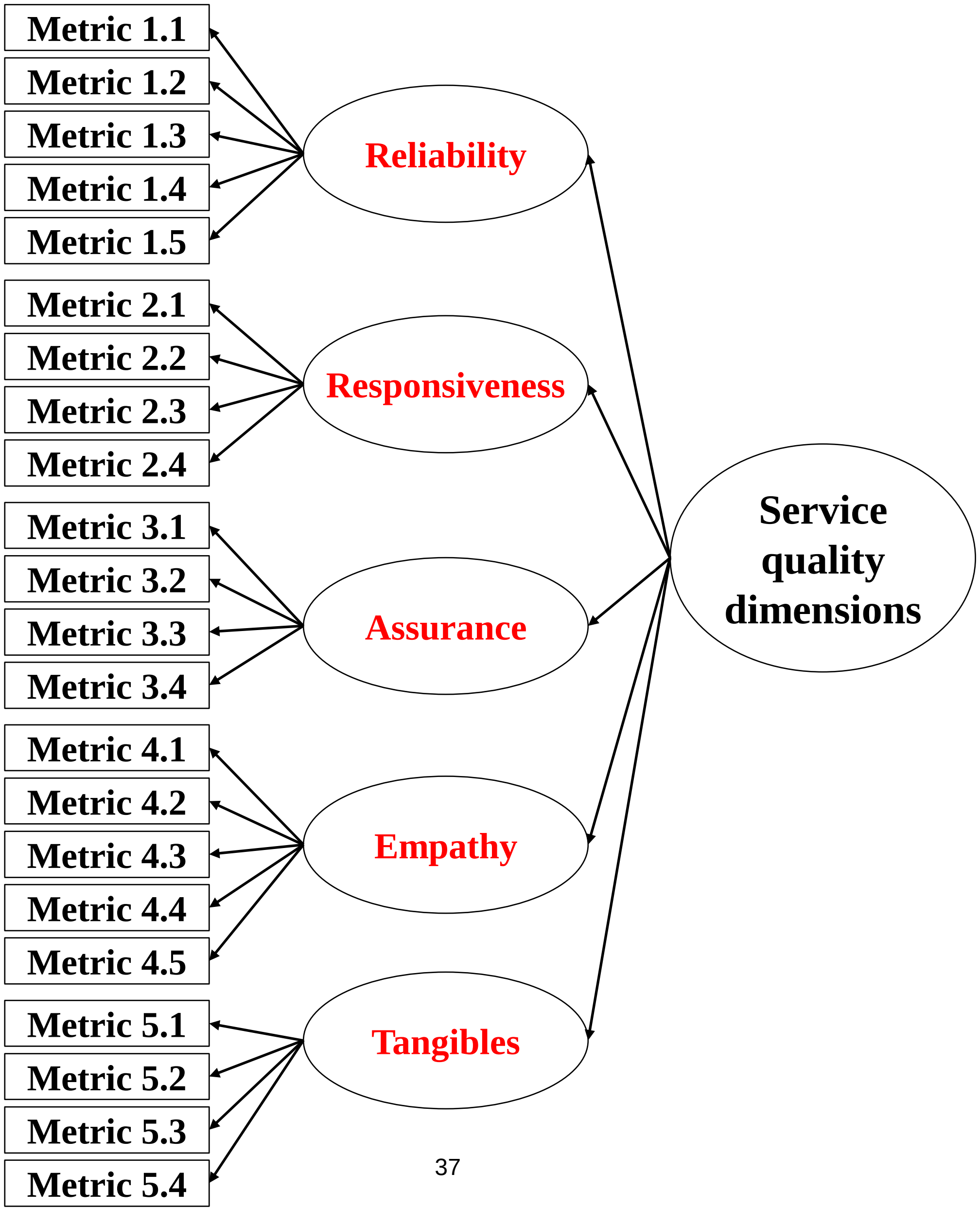
SERVQUAL: A Multiple-Item Scale for Measuring Service Quality

- Definition of service quality
  - “The totality of characteristics of a service that bears on its ability to satisfy stated and *implied* needs of customers.”



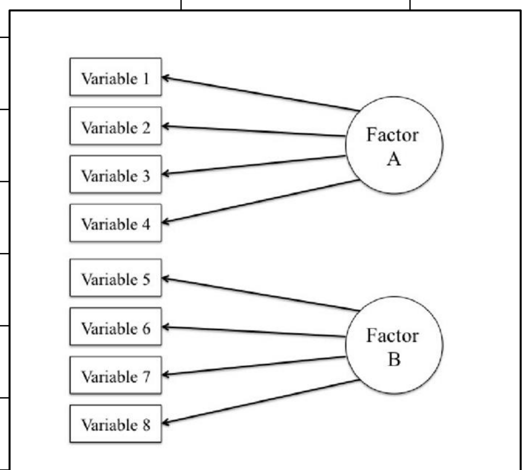


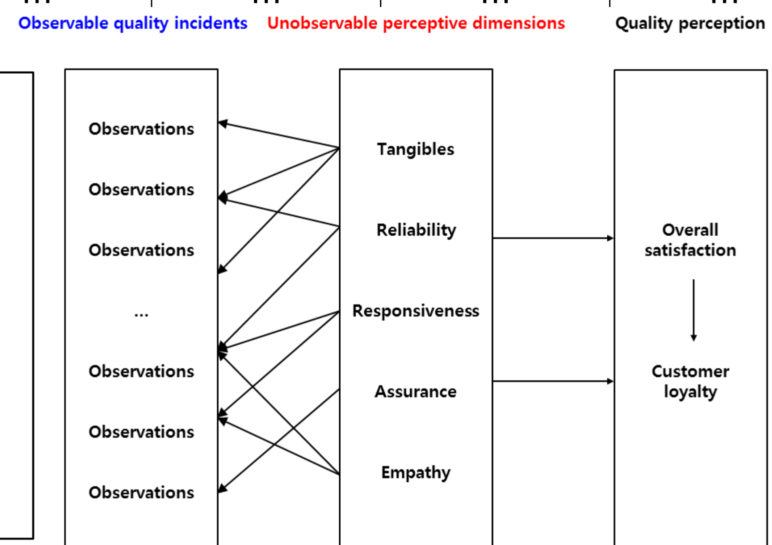
SERVQUAL: A Multiple-Item Scale for Measuring Service Quality



SERVQUAL: A Multiple-Item Scale for Measuring Service Quality

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



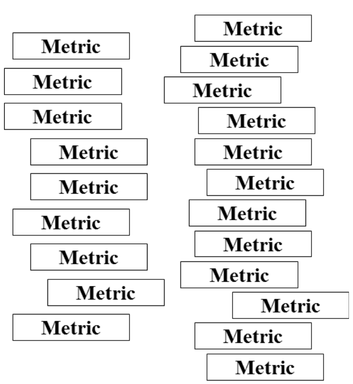


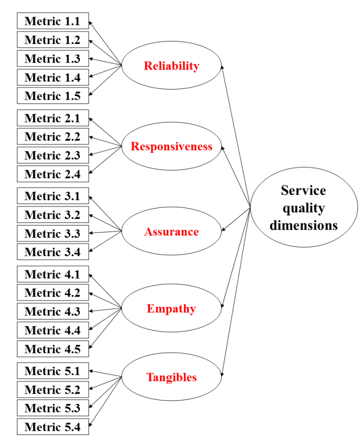
Data Collection and Purification (1st & 2nd stages)

1st stage | **2nd stage**

10 dimensions A set of 97 items	→	10 dimensions A set of 54 items	→	7 dimensions A set of 34 items	→	5 dimensions A set of 22 items

tangibles
reliability
responsiveness
communication
credibility
security
competence
courtesy
understanding the customer
access





tangibles
reliability*
responsiveness*
assurance
empathy

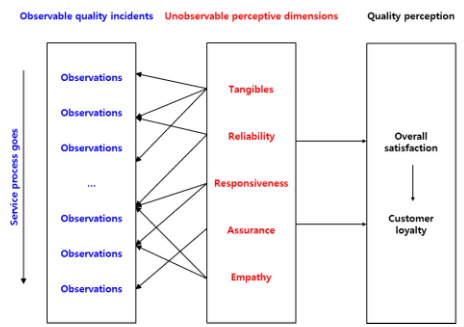
1st Data Collection

10 dimensions A set of 97 items	→	10 dimensions A set of 54 items	→	7 dimensions A set of 34 items	→	5 dimensions A set of 22 items

- 200 adult respondents in shopping mall
  - Used the services of the firm within the past three months

- Five different service categories
  - Appliance repair and maintenance
  - retail banking
  - long-distance telephone
  - securities brokerage
  - credit card

tangibles
reliability
responsiveness
communication
credibility
security
competence
courtesy
understanding the customer
access



1st Purification with the Reliability Analysis

- Coefficient alpha

10 dimensions A set of 97 items → 10 dimensions A set of 54 items → 7 dimensions A set of 34 items → 5 dimensions A set of 22 items

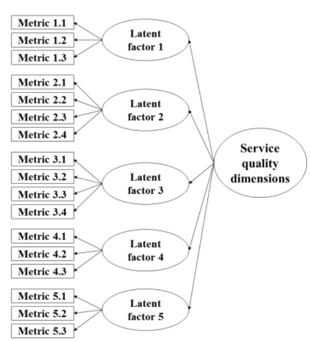
.55 ~ .78

.72 ~ .83

- tangibles
- reliability
- responsiveness
- communication
- credibility
- security
- competence
- courtesy
- understanding the customer
- access

Coefficient alpha (Cronbach's alpha) analysis

- Estimate of reliability and an indicator of internal consistency
- Deletion of certain items based on the corrected item-to-total correlations
- .55 ~ .78 → .72 ~.83 across 10 dimensions
- > .70 reliable variance



$$\rho_T = \frac{k^2 \overline{\sigma_{ij}}}{\sigma_X^2}$$

k = number of items

σ_{ij} = covariance between Xi and Xj

σ_X^2 = item variances and inter-item covariances

1^{st} Purification with the 1^{st} Factor Analysis

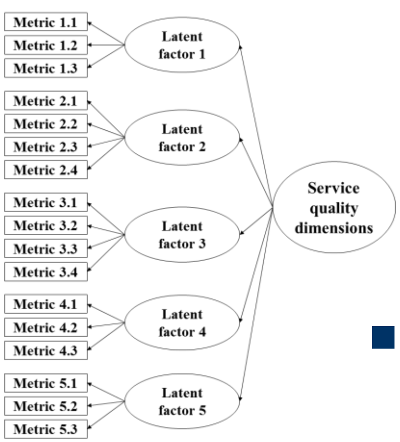
-Factor analysis
-Factor loading matrix

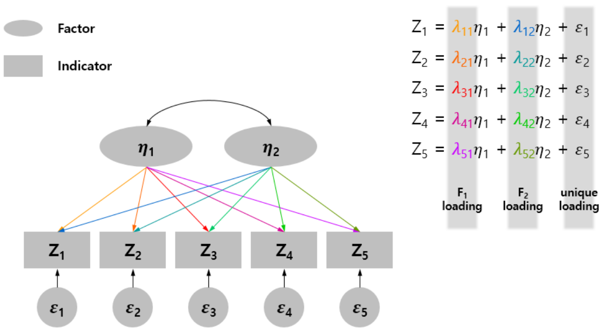
10 dimensions
A set of 97 items

10 dimensions
A set of 54 items

7 dimensions
A set of 34 items

5 dimensions
A set of 22 items

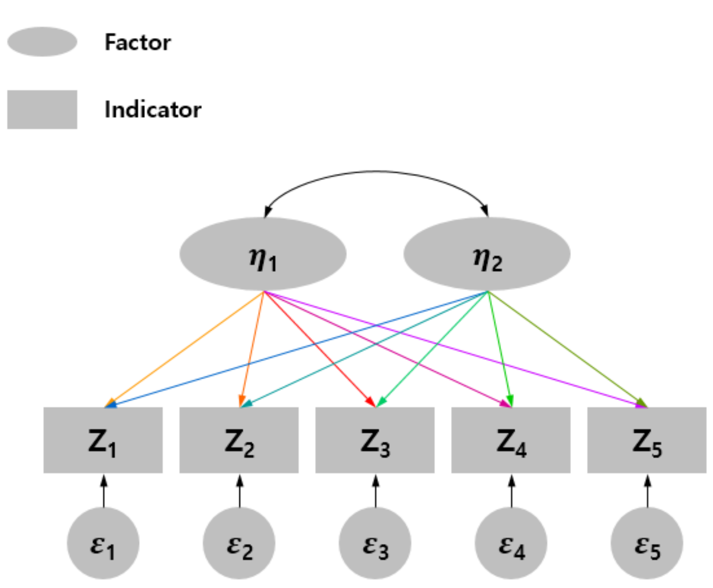




- Factor analysis
  - Analyze interrelations among the dimensions and facilitate easy interpretation
  - 10 factors were assumed in this study initially
- Factor loading matrix interpretation
  - Items with high loadings on more than one factor → removed or integrated
  - Relatively meaningless factors → removed

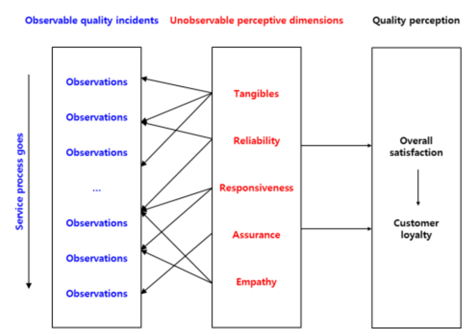
Factor Analysis

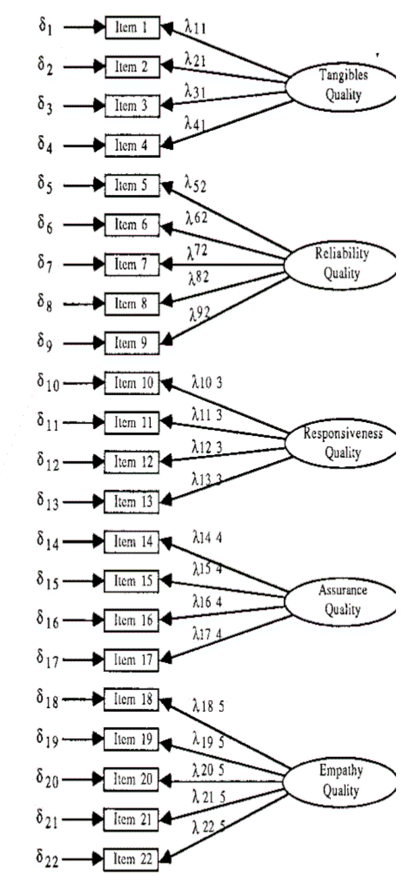
- Statistical method to analyze observable variables in understanding a specific topic
- To identify the underling constructs (i.e., to represent latent variables)



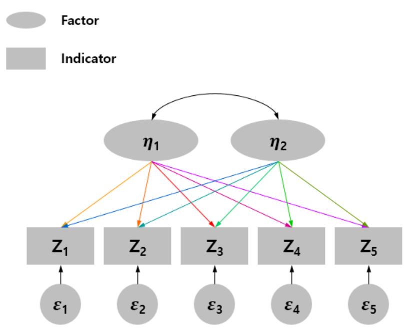
$$Z_1 = \lambda_{11}\eta_1 + \lambda_{12}\eta_2 + \varepsilon_1$$
$$Z_2 = \lambda_{21}\eta_1 + \lambda_{22}\eta_2 + \varepsilon_2$$
$$Z_3 = \lambda_{31}\eta_1 + \lambda_{32}\eta_2 + \varepsilon_3$$
$$Z_4 = \lambda_{41}\eta_1 + \lambda_{42}\eta_2 + \varepsilon_4$$
$$Z_5 = \lambda_{51}\eta_1 + \lambda_{52}\eta_2 + \varepsilon_5$$

F_1 loading | F_2 loading | unique loading





Factor Analysis



$$Z_1 = \lambda_{11}\eta_1 + \lambda_{12}\eta_2 + \varepsilon_1$$
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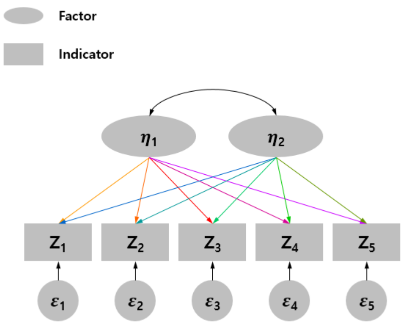
$$Z_5 = \lambda_{51}\eta_1 + \lambda_{52}\eta_2 + \varepsilon_5$$

F_1 loading | F_2 loading | unique loading

$$\Sigma = \Lambda\Phi\Lambda' + \Psi$$

Factor Analysis

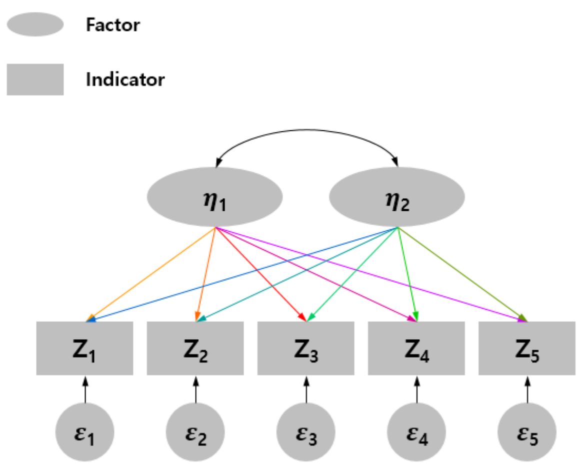


$$
\begin{array}{lllll}
Z_1 & = \lambda_{11}\eta_1 & + \lambda_{12}\eta_2 & + \varepsilon_1 \\
Z_2 & = \lambda_{21}\eta_1 & + \lambda_{22}\eta_2 & + \varepsilon_2 \\
Z_3 & = \lambda_{31}\eta_1 & + \lambda_{32}\eta_2 & + \varepsilon_3 \\
Z_4 & = \lambda_{41}\eta_1 & + \lambda_{42}\eta_2 & + \varepsilon_4 \\
Z_5 & = \lambda_{51}\eta_1 & + \lambda_{52}\eta_2 & + \varepsilon_5 \\
 & \text{F_1 loading} & \text{F_2 loading} & \text{unique loading}
\end{array}
$$

$$R = \Lambda\Phi\Lambda' + \Psi$$

Factor Analysis

- Statistical method to analyze observable variables in understanding a specific topic
- To identify the underling constructs (i.e., to represent latent variables)



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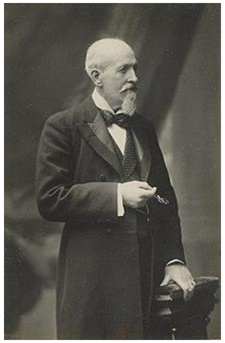
F_1 loading | F_2 loading | unique loading



"GENERAL INTELLIGENCE," OBJECTIVELY DETERMINED AND MEASURED.

By C. SPEARMAN.

TABLE OF CONTENTS.

Discussion

- Think about
  - Fundamental reasons to use the latent factors rather than the observed variables
  - Directions from the factors to the observed variables
  - Implications of the unique loadings about the reliability of observations (i.e., raw data collection)
  - Factor Analysis vs. Principal Component Analysis
  - Use of covariance matrix vs. Use of correlation matrix
  - Estimation of the parameters depending upon the model assumptions
  - Pros and Cons coming from the ambiguity of factor rotations (i.e., $R = \Lambda\Lambda' + \Psi = (\Lambda M)(\Lambda M)' + \Psi$)
  - Validation of the factor analysis outcomes (i.e., Validity of the identified factors)
  - …

2nd Data Collection

10 dimensions
A set of 97 items

→

10 dimensions
A set of 54 items

→

7 dimensions
A set of 34 items

→

5 dimensions
A set of 22 items

- 200 adult respondents in shopping mall
  - Used the services of the firm within the past three months

- Four different service categories
  - Appliance repair and maintenance
  - Retail banking
  - Long-distance telephone
  - Credit card

2nd Data Collection

-Factor analysis
-Factor loading matrix

10 dimensions A set of 97 items → 10 dimensions A set of 54 items → 7 dimensions A set of 34 items →

Dimension	Label
Tangibles	D1
Reliability	D2
Responsiveness	D3
Communication Credibility Security Competence Courtesy	D4 D5
Understanding/ Knowing Customers	D6
Access	D7

- Two differences emerged
  - (1) Corrected item-to-total correlations for several items were lower and the alpha for the dimensions were lower (items making up the dimensions D4 and D7)
  - (2) Factor-loading matrices showed much greater overlap between dimensions D4 and D5, between dimensions D6 and D7
- Further purification of 34-item scale was necessary

2nd Purification after the 2nd Factor Analysis

10 dimensions
A set of 97 items
→
10 dimensions
A set of 54 items
→
7 dimensions
A set of 34 items
→
5 dimensions
A set of 22 items

- 2nd stage of purifications
  - Items with low item-to-total correlations were deleted
  - As suggested by the second factor analysis, the items remaining in D4&D5 and D6&D7 were combined to form two separate dimensions
- This procedure resulted in SERVQUAL with 22 items spread among five dimensions

5 Dimensions and 22 Items of SERVQUAL

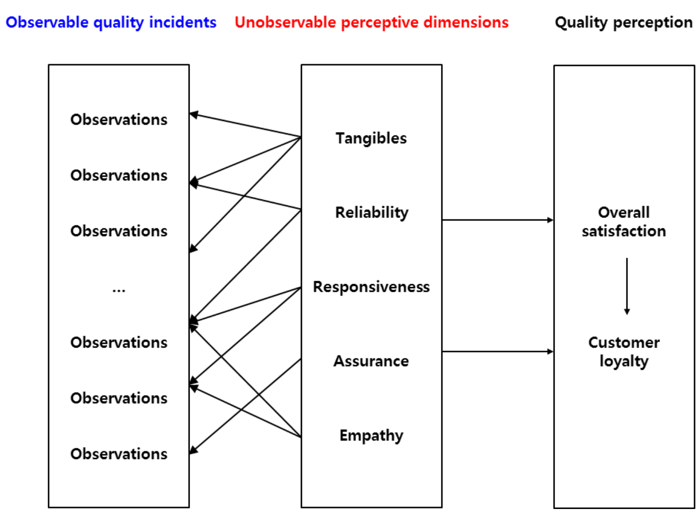
Dimension	Label	Number of Items	Reliability Coefficients (Alphas)	Items	Factor Loadings of Items on Dimensions to Which They Belong*
Tangibles	F1	4	.72	Q1	69
				Q2	68
				Q3	64
				Q4	51
Reliability	F2	5	.83	Q5	75
				Q6	63
				Q7	71
				Q8	75
				Q9	50
Responsiveness	F3	4	.82	Q10	51
				Q11	77
				Q12	66
				Q13	86
Assurance	F4	4	.81	Q14	38
				Q15	72
				Q16	80
				Q17	45
Empathy	F5	5	.86	Q18	78
				Q19	81
				Q20	59
				Q21	71
				Q22	68

	FACTOR LOADINGS																				
	Bank					Credit Card Co.					Repair & Maintenance Co.					L-D Telephone Co.					
Items	F1	F2	F3	F4	F5	F1	F2	F3	F4	F5	F1	F2	F3	F4	F5	F1	F2	F3	F4	F5	
Q1	34	28	—	—	—	36	—	35	—	—	34	—	—	—	—	42	—	—	—	—	
Q2	64	—	—	—	—	70	—	—	—	—	70	—	—	—	—	72	—	—	—	—	
Q3	39	—	—	28	—	52	—	—	—	—	53	—	—	—	—	51	—	—	—	—	
Q4	28	—	—	28	—	52	—	—	—	—	65	—	—	—	—	59	—	—	30	—	
Q5	—	72	—	—	—	—	54	—	—	—	—	73	—	—	—	—	52	—	—	—	
Q6	—	63	—	—	—	—	43	27	—	—	—	51	—	—	—	—	40	—	—	—	
Q7	—	71	—	—	—	—	87	—	—	—	—	84	—	—	—	—	79	—	—	—	
Q8	—	80	—	—	—	—	83	—	—	—	—	88	—	—	—	—	59	—	—	—	
Q9	—	39	—	—	—	—	49	—	—	—	—	29	—	30	—	—	54	—	—	—	
Q10	—	—	37	—	—	—	—	43	—	26	—	—	56	—	—	—	—	39	—	—	
Q11	—	—	55	—	—	—	—	48	—	—	—	—	52	—	—	—	—	43	—	—	
Q12	—	—	62	—	—	—	—	54	—	—	—	—	74	—	—	—	—	92	—	—	
Q13	—	—	69	—	—	—	—	33	—	—	—	—	71	—	—	—	—	53	—	—	
Q14	—	—	—	68	—	—	—	—	65	—	—	—	—	86	—	—	—	—	69	—	
Q15	—	—	—	84	—	—	—	—	76	—	—	—	—	89	—	—	—	—	81	—	
Q16	—	—	—	72	—	—	—	—	73	—	—	—	—	65	—	—	—	—	61	—	
Q17	—	—	—	64	—	—	—	—	61	—	—	—	—	64	—	—	—	—	66	—	
Q18	—	—	—	—	37	—	—	—	—	64	—	—	—	—	42	—	—	—	—	59	
Q19	—	—	—	—	48	—	—	—	—	72	—	—	—	—	61	—	—	—	—	79	
Q20	—	—	—	—	41	—	—	—	—	63	—	28	34	—	46	—	—	—	—	55	
Q21	—	—	—	—	33	—	—	—	—	59	—	—	—	—	32	—	—	—	—	36	
Q22	—	—	—	—	68	—	—	—	—	64	—	—	—	—	61	—	—	—	—	59	

* All numbers in the table are magnitudes of the factor loadings multiplied by 100. Loadings that are .25 or less are not shown. The percentage of variance extracted by the five factors in the bank, credit card, repair and maintenance, and long-distance telephone samples were 56.0%, 57.5%, 61.6%, and 56.2%, respectively.

5 Dimensions and 22 Items of SERVQUAL

- Relative importance of the five dimensions in validation
  - 1st : **Reliability**
  - 2nd : **Assurance**
  - 5th **: Empathy** (the least important)



Relative Importance of the Five Dimensions in Predicting Overall Quality

Dimension	Standardized Slope Coefficient	Significance Level of Slope[a]	Adusted R^2
Bank			
Tangibles	.13	.07	.28 ($p < .00$)
Reliability	.39	.00	
Responsiveness	.07	.35	
Assurance	.13	.09	
Empathy	.01	.89	
Credit Card Co.			
Tangibles	.07	.26	.27 ($p < .00$)
Reliability	.33	.00	
Responsiveness	.12	.11	
Assurance	.17	.02	
Empathy	.04	.58	
Repair & Maintenance Co.			
Tangibles	.04	.48	.52 ($p < .00$)
Reliability	.54	.00	
Responsiveness	.11	.09	
Assurance	.16	.02	
Empathy	.01	.81	
L-D Telephone Co.			
Tangibles	.08	.17	.37 ($p < .00$)
Reliability	.45	.00	
Responsiveness	.12	.09	
Assurance	.15	.03	
Empathy	.02	.78	

[a] Significance levels are for two-tailed tests.

5 Dimensions and 22 Items of SERVQUAL

▪ Dimensions of Service Quality

Reliability	The ability to <u>perform the promised service</u> both dependably and accurately
Responsiveness	
Assurance	
Empathy	
Tangibles	

- The firm meets their promised time-frames for response
- The firm is sympathetic and reassuring, when the customer has problems
- They are dependable
- They provide their services at the times promised
- They keep accurate records

5 Dimensions and 22 Items of SERVQUAL

- **Dimensions of Service Quality**

Reliability

Responsiveness

Assurance

Empathy

Tangibles

The willingness to help customers and to provide prompt service

- Employees tell customers exactly when the service will be performed,
- It is reasonable to expect prompt service from employees
- Employees are always willing to help customers
- Employees respond promptly to customer requests

5 Dimensions and 22 Items of SERVQUAL

▪ Dimensions of Service Quality

- Reliability
- Responsiveness
- **Assurance**
- Empathy
- Tangibles

The knowledge and courtesy of employees as well as their ability to convey trust and confidence

- Employees are trustworthy
- Customers feel safe when transacting with employees
- Employees are polite
- Employees get adequate support from the firm to do their job well

5 Dimensions and 22 Items of SERVQUAL

▪ Dimensions of Service Quality

Reliability

Responsiveness

Assurance

Empathy

Tangibles

The provision of caring, individualized attention to customers

- Firms give each customer individualized attention
- Employees give each customer individualized attention
- Employees fully understand the needs of the customer
- Employees have the best interests of the customer at heart
- Firms operate at hours convenient to all customers

5 Dimensions and 22 Items of SERVQUAL

- **Dimensions of Service Quality**

Reliability

Responsiveness

Assurance

Empathy

Tangibles

The appearance of physical facilities, equipment, personnel, and communication materials

- Up-to-date equipment
- Physical facilities are visually appealing
- Employees well-dressed/neat
- Appearance of the physical facilities are consistent with the type of service industry

Validation of the Quality Dimensions

Construct Validity

1 Convergent Validity

The extent to which a set of the items assumed to represent a dimension does in fact converge on the same dimension

2 Discriminant Validity

The extents to which measures of theoretically unrelated dimension do not correlate with one another

3 Predictive Validity

(Nomological Validity)

The extents to which the score of one dimension is empirically related to the scores of other conceptually related constructs

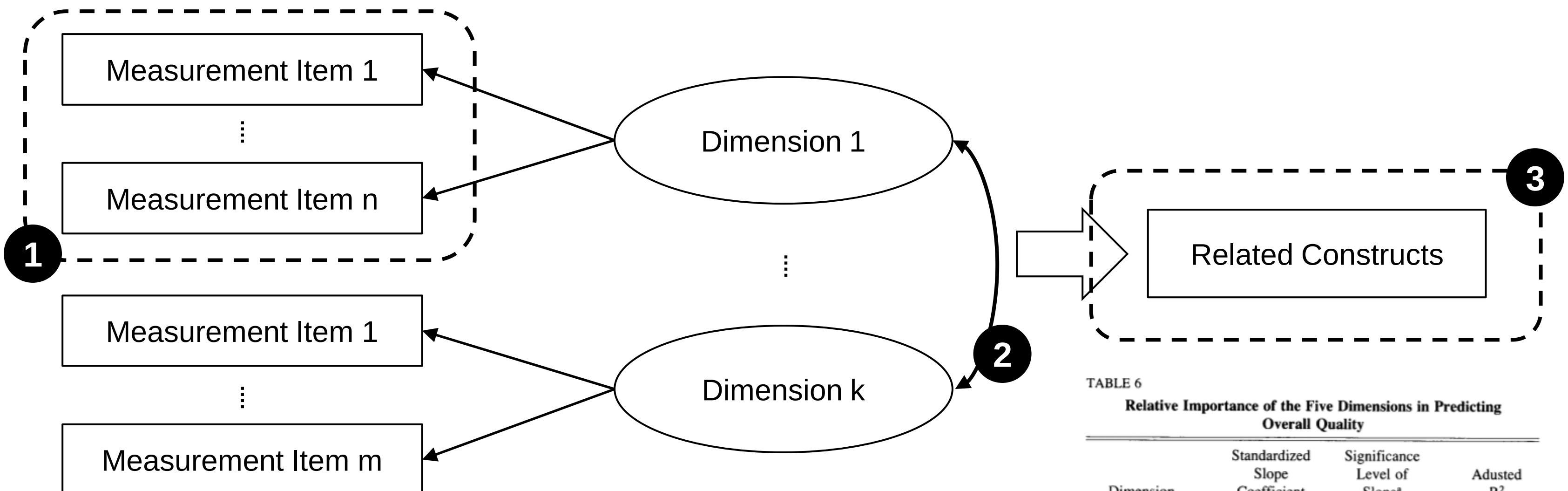


TABLE 6

Relative Importance of the Five Dimensions in Predicting Overall Quality

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Bank			
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Reliability	.39	.00	
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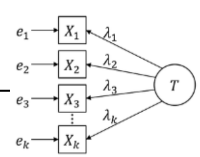
Assurance	.13	.09	
Empathy	.01	.89	



$$\frac{(\sum \lambda_i{}^2)}{(\sum \lambda_i{}^2) + (\sum_i var\,(\varepsilon_i))}$$

Reference: Peter (1981)

Service Quality Standards Vary and Change

Does SERVQUAL Work Well for Every Service?

▪ Dimensions of Service Quality

Reliability

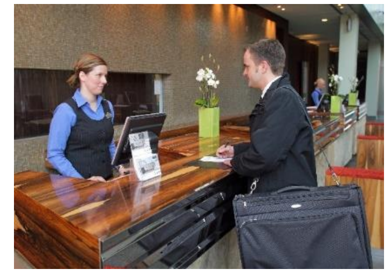
Responsiveness

Assurance

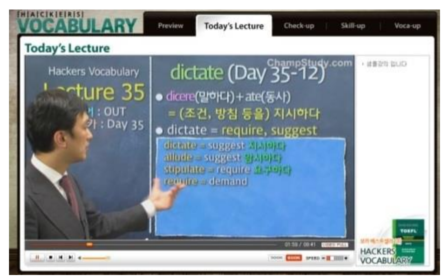
Empathy

Tangibles

Restaurant Service



Restaurant Service



E-learning Service

Car Sharing Service

?

Quality Dimensions Change

Service quality in general

- Reliability
- Assurance
- Tangible
- Empathy
- Responsiveness

Electronic service (e-service) quality

- Reliability
- Usability
- Information content
- Web design
- Responsiveness
- Security

Mobile service (m-service) quality

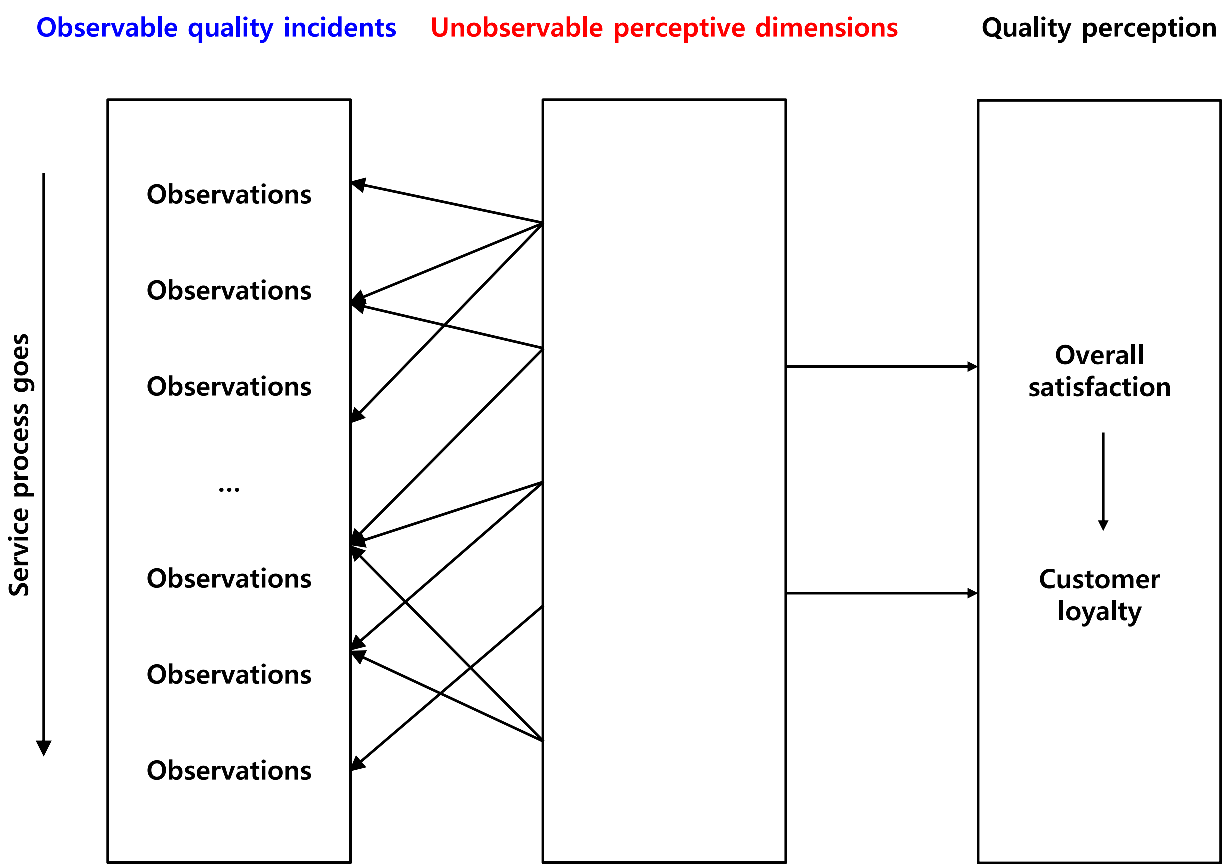
- Reliability
- Usability
- Content
- Interaction
- Interface
- Security
- Connection
- Contextual

+ Machine-to-Human Interactions
+ Virtual Environment
– Human-to-Human Interactions
– Real Environment

+ Diversity of Context
+ Mobile Connection
+ Small Device Interactions
– Desktop Interactions

Sourse: Development of Scales to Measure Quality of Mobile Location-Based Services (Heo, 2016)

Quality of AI-based Services? (Assignment 3)

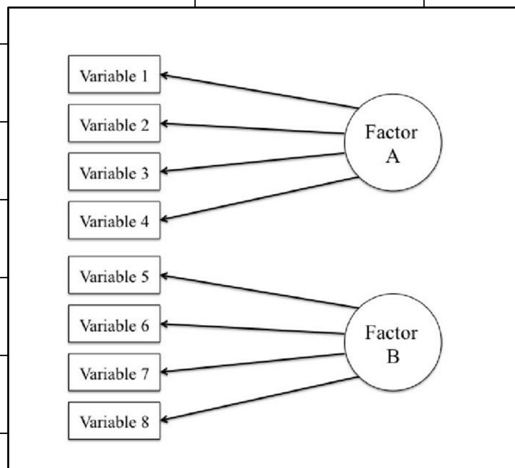


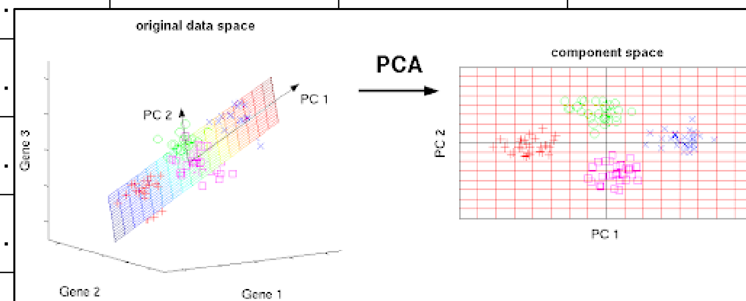
Practice and Assignment

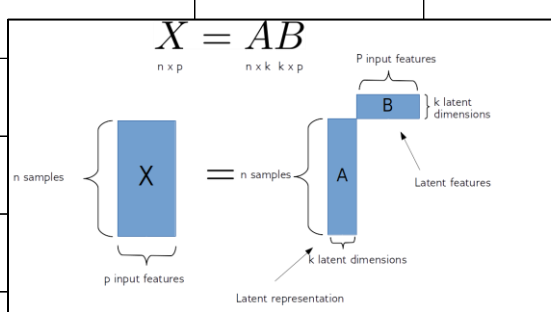
Several Methods Are Available for the Representation

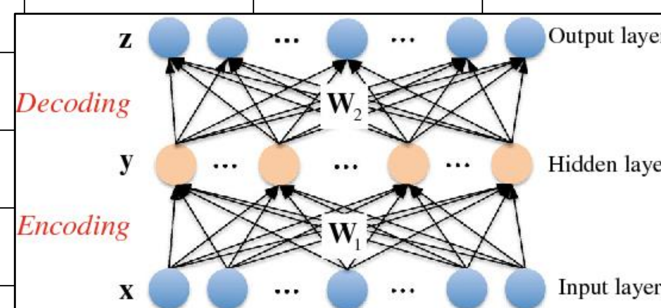
- What other methods are available these days?

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









Practice Demonstrated by TA (Hyunwoo Seo)

In [2]:
```
!pip install factor-analyzer
```

```
Defaulting to user installation because normal site-packages is not writeable
Requirement already satisfied: factor-analyzer in /home/ta57xr/.local/lib/python3.8/site-packages (0.3.2)
Requirement already satisfied: numpy in /opt/anaconda3/lib/python3.8/site-packages (from factor-analyzer) (1.19.2)
Requirement already satisfied: scipy in /opt/anaconda3/lib/python3.8/site-packages (from factor-analyzer) (1.5.2)
Requirement already satisfied: scikit-learn in /opt/anaconda3/lib/python3.8/site-packages (from factor-analyzer) (0.23.2)
Requirement already satisfied: pandas in /opt/anaconda3/lib/python3.8/site-packages (from factor-analyzer) (1.2.0)
Requirement already satisfied: python-dateutil>=2.7.3 in /opt/anaconda3/lib/python3.8/site-packages (from pandas->factor-analyzer) (2.8.1)
Requirement already satisfied: pytz>=2017.3 in /opt/anaconda3/lib/python3.8/site-packages (from pandas->factor-analyzer) (2020.5)
Requirement already satisfied: six>=1.5 in /opt/anaconda3/lib/python3.8/site-packages (from python-dateutil>=2.7.3->pandas->factor-analyzer) (1.15.0)
Requirement already satisfied: joblib>=0.11 in /opt/anaconda3/lib/python3.8/site-packages (from scikit-learn->factor-analyzer) (1.0.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in /opt/anaconda3/lib/python3.8/site-packages (from scikit-learn->factor-analyzer) (2.1.0)
```

In [50]:
```
import numpy as np
import pandas as pd
from factor_analyzer import FactorAnalyzer
import matplotlib.pyplot as plt
import seaborn as sns

import random
seed = 0
np.random.seed(seed)
random.seed(seed)
```

Survey data on Onecare service quality

- The survey response data comes from the service quality survey that measures mental health care service to university students, called onecare service.
- They are collected from the students who used the service for a period of time.
- Based on existing studies, the survey consists of a total of 21 survey questions (features) and 191 responses (samples) collected on a likert scale from 1 to 7.

In [71]:
```
from sklearn.decomposition import NMF
```

In [112]:
```
# There are several methods to determine the number of components in NMF, but the most commonly used one is based on expert knowledge.
n_components = 4
max_iter = 5000
solver = 'cd'
init = 'nndsvda'
nmf = NMF(n_components=n_components, solver=solver, random_state=seed, max_iter=max_iter)
nmf.fit(data)
```

Out[112]:
```
NMF(max_iter=5000, n_components=4, random_state=0)
```

In [113]:
```
W = nmf.fit_transform(data)
H = nmf.components_
```

In [114]:
```
W.shape, H.shape
```

Out[114]:
```
((191, 4), (4, 21))
```

In [115]:
```
pd.DataFrame(H.T, index=data.columns, columns=['factor_{}'.format(i+1) for i in range(n_components)])
```

Out[115]:

	factor_1	factor_2	factor_3	factor_4
C1	2.602854	1.532453	2.956408	1.536123
C2	1.751155	2.458214	2.680014	1.225691

In [20]:
```
# rotation of loading matrix for interpretation
rotation = 'varimax'
fa = FactorAnalyzer(n_factors=n_factors, rotation=rotation)
fa.fit(data)
pd.DataFrame(fa.loadings_, index=data.columns, columns=['factor_{}'
```

Out[20]:

	factor_1	factor_2	factor_3	factor_4
C1	0.556864	0.424503	0.131646	-0.207354
C2	0.443397	0.558572	0.205606	-0.067859
C3	0.364477	0.609672	0.282022	-0.155859
E1	0.488824	0.385487	0.200505	0.327874
E2	0.419344	0.293987	0.151642	0.206786
E3	0.530113	0.259336	0.147030	0.435455
P1	0.209006	0.261902	0.856052	0.073274
P2	0.178822	0.244810	0.882046	0.048451
R1	0.540055	0.425143	-0.005615	-0.119930
R2	0.408139	0.380469	0.093014	-0.111780
U1	0.116235	0.682331	0.255107	0.203066
U2	0.288420	0.482988	0.129406	0.231443
U3	0.599849	0.221959	0.110381	0.128002
U4	0.086847	0.788175	0.122433	0.130111
CI1	0.695351	0.050667	0.167367	0.150193
CI2	0.670945	0.300767	0.087668	0.142217
CI3	0.834818	0.070130	0.194153	0.210391
SA1	0.752563	0.301313	0.090846	0.078963
SA2	0.815798	0.239667	0.088588	0.038922
SA3	0.759715	0.195785	0.189685	-0.064918

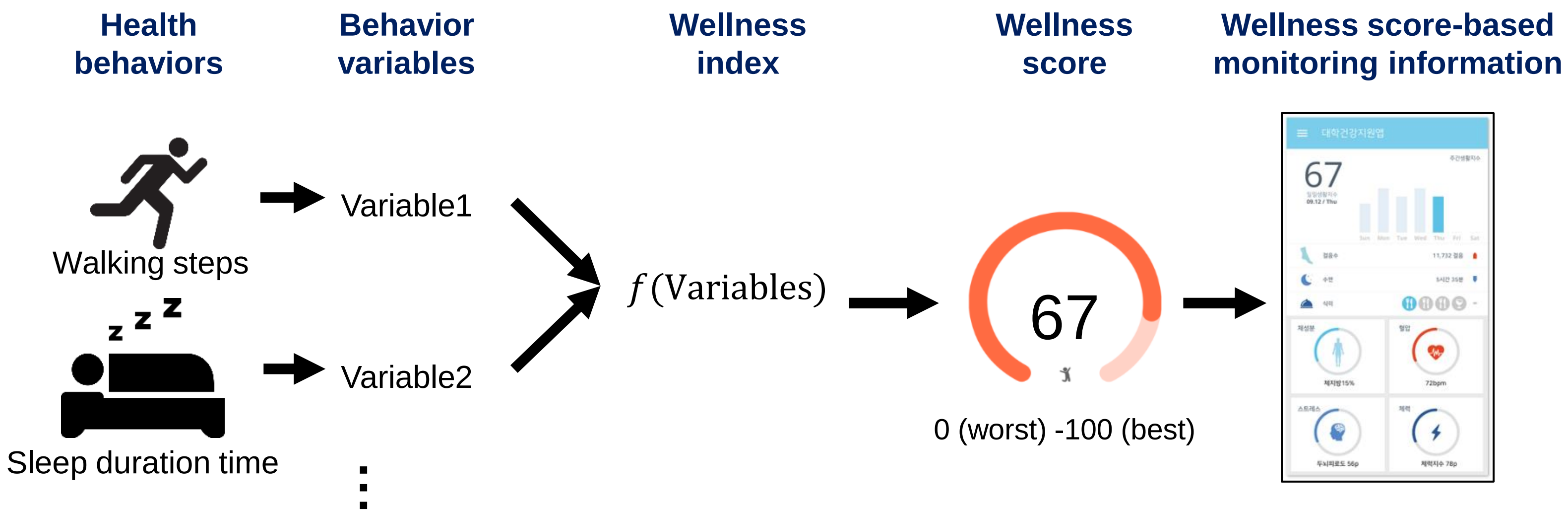
Assignment 3 (by 09.23 11:59 pm)

- Read Article 3. Summarize the article (one paragraph) with your own comments to the article (one paragraph) (i.e., two paragraphs in total).
- By yourself, complete the identification of the latent factors indicating the quality of the Onecare mobile healthcare service based on the practice demonstrated by the TA. Use the user-question matrix data provided. Do it all by yourself, and describe the identification process and outcome in detail. Interpret the outcome (i.e., interpret the quality dimensions you identified).
- Discuss the “quality representation and measurement of service systems from a customer/user perspective” (focus on the service system you are interested or concerned). What other data and learning methods can be used for the identification of the latent factors indicating the quality of a service? Describe your thoughts/ideas on learning service quality dimensions with data about customer perception, behaviors, etc., in detail.
- What dimensions do you think we should consider for the evaluation of quality of AI-based services? i.e., As a user/customer of AI services (as an undergraduate student researcher), what are the requirements of AI service you think important? And why do you think so? Describe the rationale or reasons for your suggestion.
- Furthermore, assume that you actually need to represent and evaluate the quality of an AI-based service in your company or institute. How would you develop a quality representation and measurement method for the service? What AI-based service are you going to focus on? What kinds of data and methods are you going to collect, analyze, and learn? Describe your research plan in detail. If possible, visualize your research framework clearly (e.g., draw image, mathematical model).
- Upload your code and a several paragraph essay in the Blackboard.

Read Article 3: Onecare Service Overview

- Necessity of wellness management support for college students
  - Wellness means lifestyle to maintain good mental and physical health (Myers et al. 2000)
  - Many students have unhealthy activity, sleep, and diet behaviors (Small et al. 2012)
  - Students need overall support to manage various behaviors

- Concept of Onecare



Source: Kim, K., Kim, K., Lim, C., and Heo, J., "Development of a Lifelogs-based Daily Wellness Score to Advance a Smart Wellness Service," *Service Science*, Vol. 10, No. 4, 408–422, 2018.

Read Article 3: Onecare Service Overview

Onecare pilot run

191 college students → Use Onecare over 3 weeks → **Respond to a survey** → 191 survey responses

Quality dimensions of mHealth services

Content quality	Quality of provided service content (Stoyanov et al. 2015)
Engagement	Ability to increase user engagement with a service (Platt et al. 2016)
Privacy	Ability to protect the privacy of users (Akter et al. 2013)
Reliability	Ability to perform the promised service dependably and accurately (Akter et al. 2013)
Usability	Ease of service use (Zapata et al. 2015)
Continuance Intention (CI)	User intention to continuously use (Limayem et al. 2007)

Source: Kim, K., Kim, K., Lee, D., and Kim, M., "Identification of Critical Quality Dimensions for mHealth Services: A Case Study of Onecare Service," International Journal of Information Management, Vol. 46, 187–197, 2019.

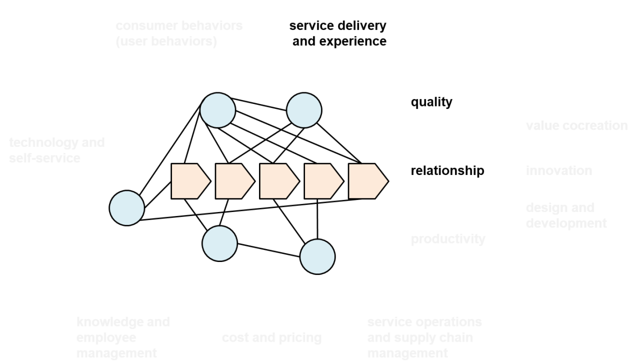
Revisiting the Questions and Learning Objectives

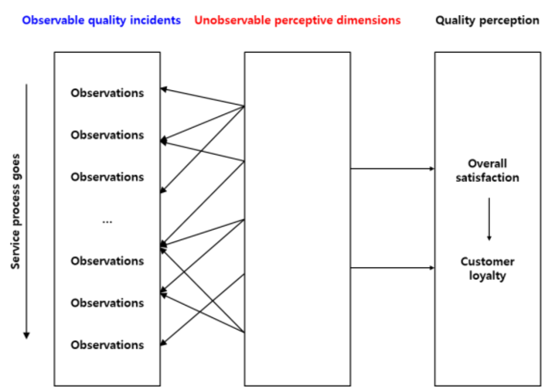
- How can we “explicitly” evaluate and improve the “implicit” quality of services?

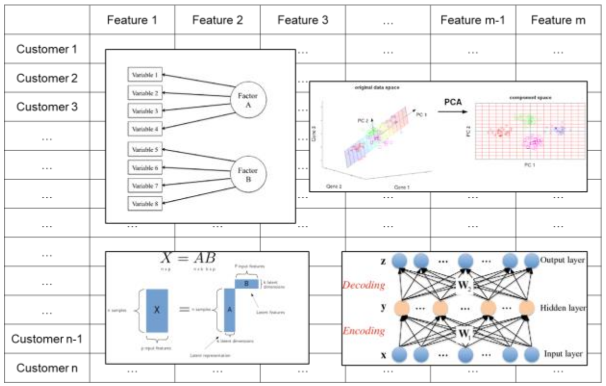
  → The service representation (quality dimension identification) is essential

- How can we use data and learning intelligence for service quality representation?

  → Observed data are varied. Estimations can be different depending upon the assumptions and models





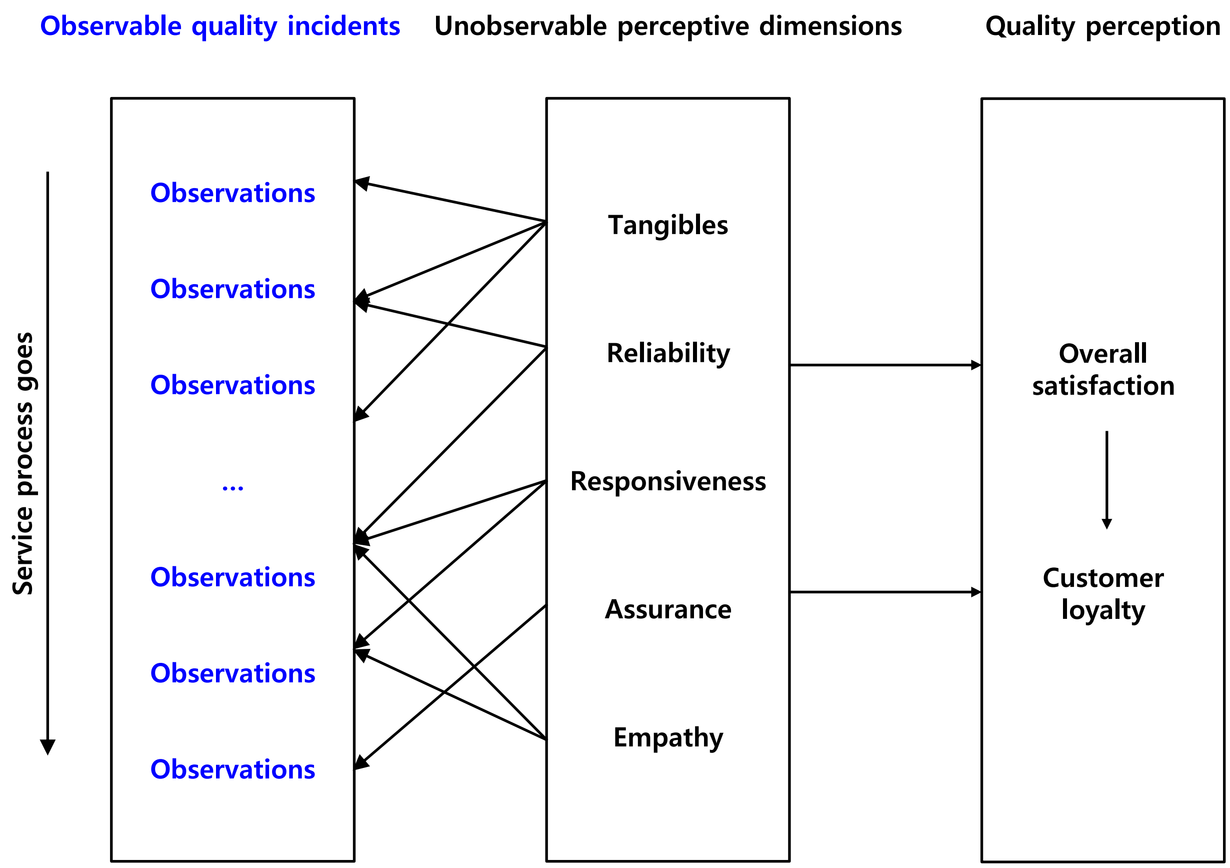


Discussion

- Think about
  - Fundamental reasons to use the latent factors rather than the observed variables
  - Directions from the factors to the observed variables
  - Implications of the unique loadings about the reliability of observations (i.e., raw data collection)
  - Factor Analysis vs. Principal Component Analysis
  - Use of covariance matrix vs. Use of correlation matrix
  - Estimation of the parameters depending upon the model assumptions
  - Pros and Cons coming from the ambiguity of factor rotations (i.e., $R = \Lambda\Lambda' + \Psi = (\Lambda M)(\Lambda M)' + \Psi$)
  - Validation of the factor analysis outcomes (i.e., Validity of the identified factors)
  - …

Classes of the Next Week

- What other observations are available these days?



Classes of the Next Week

- What other observations are available these days?

VS

Hotels.com

yelp

Tripadvisor

amazon

Further Readings Recommended

- Parasuraman, A., Zeithaml, V. A., & Berry, L. (1988). SERVQUAL: A multiple-item scale for measuring consumer perceptions of service quality. *1988*, *64*(1), 12-40.
- Mejia, J., Mankad, S., & Gopal, A. (2020). Service quality using text mining: Measurement and consequences. *Manufacturing & Service Operations Management*.