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Hotel Quality Evaluation from Online Reviews Using Fuzzy Pattern Matching and Fuzzy Cognitive Maps

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Presenter's Resume



Alexandros Bousdekis

- **Current position**

- Post-doctoral Researcher (Athens University of Economics and Business)
 - Title of postdoctoral research: “Advanced data analytics and knowledge discovery for e-service customization”

- **Education**

- PhD in Information Systems (National Technical University of Athens)
- MSc in Manufacturing Systems Engineering (University of Warwick, UK)
- BSc in Production and Management Engineering (Technical University of Crete)

Outline

- Introduction
- Research Methodology
- Results
- Conclusions & Future Work

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Motivation

- With the increased popularity of online bookings, **53% of travellers** state that they would be **unwilling to book a hotel that had no reviews**, while a **10% increase in travel review ratings would increase bookings by more than 5%**.
- These online reviews in the e-tourism era, in the format of both textual reviews (comments) and ratings, generate an **electronic Word Of Mouth (eWOM) effect**.
- In contrast to a pre-designed questionnaire survey, online textual reviews have an **open-structured form** and can:
 - show **customer consumption experiences**
 - highlight the product and service **attributes customers care about**
 - provide customers' **perceptions in a detailed way**.

Research Objective

- **Hotel quality evaluation from online reviews** is an **emerging research field**. However:
 - the exploitation of online textual reviews is still largely **under-explored**
 - there is a **lack of advanced data analytics** approaches for modelling complex dynamics of **online hotel review data**.
- The **increasing amount of online reviews** pose significant challenges for the development of advanced data analytics models providing a **higher level of intelligence** and thus, **increased business value**.
- In this paper, we propose an approach for **hotel quality evaluation from online reviews** using **Fuzzy Pattern Matching (FPM)** and **Fuzzy Cognitive Maps (FCM)**.
- The **objective** is to provide a unified algorithm, which :
 - **mines customers' opinions from online hotel reviews** (review comments and rating)
 - **evaluates the hotel performance** by identifying **how the various attributes** (e.g., location, cleanliness, breakfast, etc.) **affect the overall review rating**.

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The Proposed Methodology

- The research methodology consists of 3 main steps:
 - Extracting the evaluation criteria from online comments
 - Mining customers' opinions using FPM
 - Applying FCM for attributes evaluation

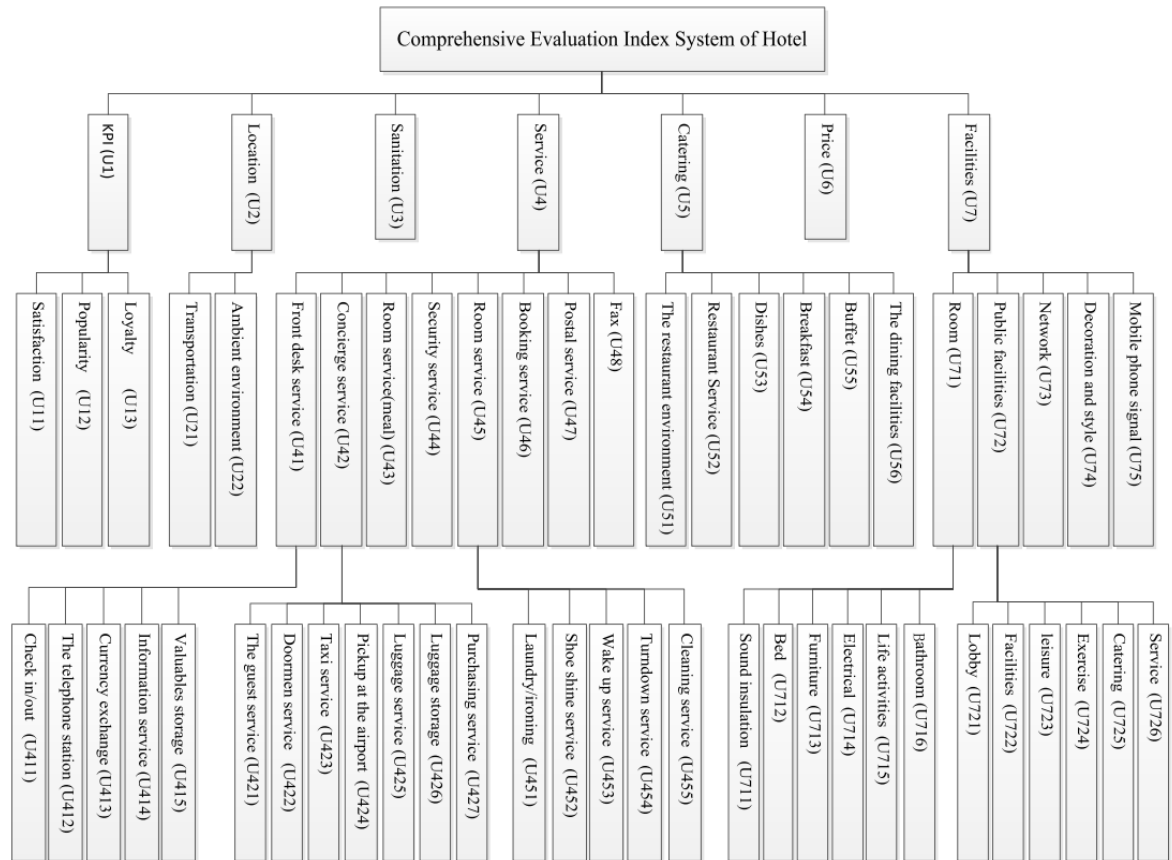
Extracting the Evaluation Criteria from Online Comments

- The proposed approach utilizes **3 fields from the online hotel reviews** in order to extract the evaluation criteria:

- **review title**
- **review comments**
- **review rating**

- Based upon an evaluation index for hotel service quality, this step identifies the **criteria mentioned in the hotel reviews**. E.g.

- Location
- Price
- Breakfast
- room space
- ...



Mining Customers' Opinions Using Fuzzy Pattern Matching (1/2)

- Since online comments are written in natural and informal language, there is the need to **mine customers' opinions**.
- FPM is able to take into account the **imprecision** and the **uncertainty** pervading values, which have to be compared in a matching process.
- In online review comments, **different customers may use different words or phrases to express their opinions**, while **the comments may be vague**.
 - For example, poor cleanliness can be expressed as: “The room was too dirty”, “Very dirty”, etc.
 - Regular expression is an efficient pattern match technology to identify the specific pattern strings from a long text.
 - However, the regular expression method causes a binary value result: match or not match.

Mining Customers' Opinions Using Fuzzy Pattern Matching (2/2)

- In the proposed approach, we apply **FPMT** as an effective **fuzzy pattern matching method** to deal with the vagueness of the free text online comments.
 - Although this method results in some mismatched cases, this causes little impact on the final result, because there are **many redundant comments with similar semantics**.
- The **output** of customers' opinions mining is a **fuzzy evaluation of the extracted criteria**.
 - First, the extracted evaluation criteria of hotel quality are assigned to a **5-level Likert scale**.
 - Then, we consider the **median of the resulting responses** in order to represent the magnitude of causality among the evaluation criteria **to be used as FCM concepts**.

Applying FCM for attributes evaluation (1/2)

- This step applies **FCM** in order to:
 - **evaluate the quality of the hotels with respect to the extracted evaluation criteria (attributes)**
 - **to identify the effect of each criterion to the review rating.**
- The FCM suitability for hotel quality evaluation through online review is argued by considering that a **variety of what – if sensitivity simulations** can be performed effectively.
 - Through what – if simulations, hotels can **identify a set of relevant review factors**, pertaining to the **customer satisfaction** as well as **hotel services that need to be improved.**
- In the proposed approach, the **FCM concepts matrix** consists of the **extracted evaluation criteria** plus an additional concept referring to the review rating.

Applying FCM for attributes evaluation (2/2)

- The FCM is applied **separately for each hotel** in order to allow each hotel gaining meaningful insights for its performance.
- However, there is also the possibility for **aggregated results** of more than one hotel (e.g., in one region of interest, specific number of stars, same overall review rating, etc.) in the sense of an “**augmented topology**”.
 - Multiple weighted FCMs are combined into a single averaged FCM by adding their scaled and augmented adjacency weight matrix.
- If the FCMs involve different concepts, each causal matrix is augmented by adding a new column and row filled with zeros for each additional concept.

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Data Collection and Evaluation Criteria

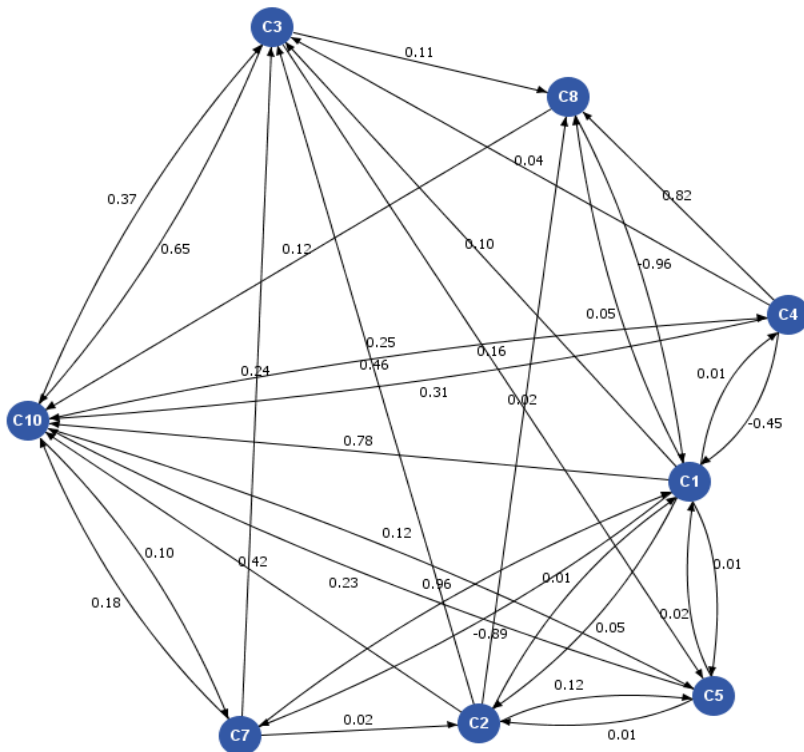
- The proposed methodology was applied to a **dataset including six 4-star hotels in Athens, Greece**.
- **Each hotel had 60 reviews** consisting, among others, of the review title, the review comments, and the review rating.
- The FCM concepts represent the **extracted evaluation criteria from FPMT (C1-C9) along with the review rating (C10)**.

| ID | Concepts | ID | Concepts |
|----|-------------|-----|-----------------|
| C1 | Location | C6 | Quiet |
| C2 | Personnel | C7 | Parking |
| C3 | Cleanliness | C8 | Interior Design |
| C4 | Room Space | C9 | Bed |
| C5 | Breakfast | C10 | Review Rating |

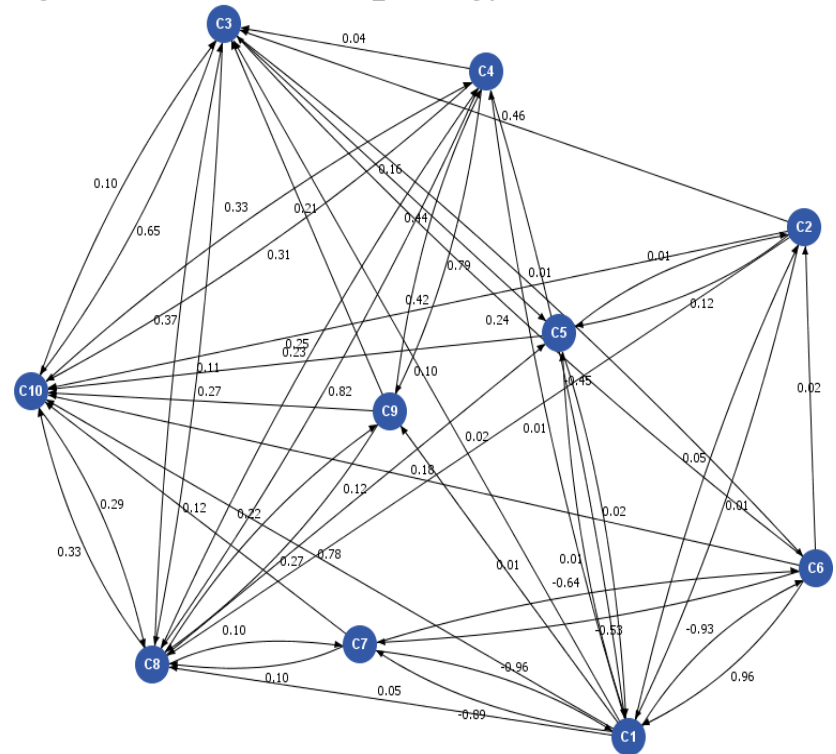
The FCM Topology

- After the fuzzy evaluation of the aforementioned concepts for each hotel, the **weight matrix** is created and is inserted to the FCM model.
- For all the 6 hotels, the review rating (C10) is mainly affected by Location (C1), Cleanliness (C3), Room Space (C4) and Interior Design (C8).

FCM for 1 indicative hotel



Augmented FCM topology of all the 6 hotels



Degree Centrality of the FCM

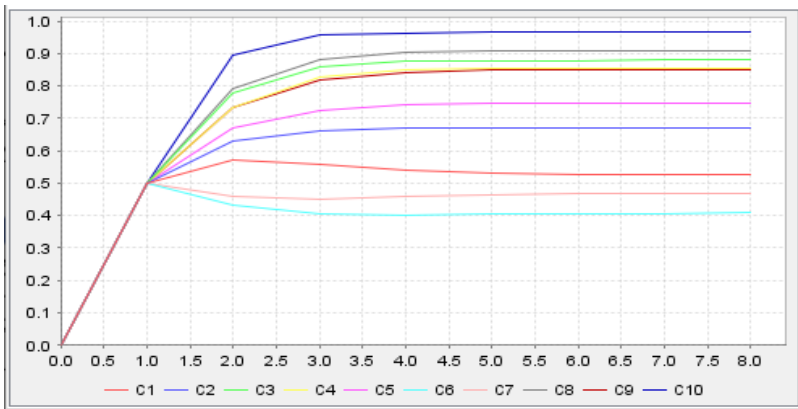
- A local centrality measure determined by only its directed connections.

| Concepts | Outdegree | Indegree | Centrality |
|------------|-----------|----------|------------|
| <i>C1</i> | 2.06 | 2.40 | 4.46 |
| <i>C2</i> | 0.64 | 0.08 | 0.72 |
| <i>C3</i> | 0.49 | 1.52 | 2.01 |
| <i>C4</i> | 2.78 | 1.03 | 3.81 |
| <i>C5</i> | 0.03 | 0.41 | 0.44 |
| <i>C6</i> | 1.75 | 1.58 | 3.33 |
| <i>C7</i> | 1.70 | 1.52 | 3.22 |
| <i>C8</i> | 1.44 | 1.66 | 3.10 |
| <i>C9</i> | 0.92 | 1.02 | 1.94 |
| <i>C10</i> | 0.72 | 1.31 | 2.03 |

Inference until Convergence

- We performed **inference using various reasoning rules** in order to compute the **output vector including the weights of the concepts**:
 - Kosko's activation rule
 - Kosko's activation rule with self-memory
 - Rescaled activation rule with self-memory.

Indicative visualization of the iterations until convergence



| Step | C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 | C9 | C10 |
|------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| 0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| 1 | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 |
| 2 | 0.572 | 0.6318 | 0.779 | 0.734 | 0.6693 | 0.4305 | 0.4601 | 0.7908 | 0.733 | 0.8952 |
| 3 | 0.558 | 0.6628 | 0.8576 | 0.8257 | 0.7252 | 0.4042 | 0.4506 | 0.8832 | 0.8165 | 0.9563 |
| 4 | 0.5406 | 0.6695 | 0.8746 | 0.849 | 0.7414 | 0.4026 | 0.4571 | 0.9037 | 0.8414 | 0.964 |
| 5 | 0.5319 | 0.6708 | 0.8781 | 0.8543 | 0.7457 | 0.4052 | 0.4633 | 0.908 | 0.8477 | 0.9652 |
| 6 | 0.5283 | 0.6711 | 0.8789 | 0.8555 | 0.7467 | 0.4068 | 0.4665 | 0.9089 | 0.8491 | 0.9653 |
| 7 | 0.5269 | 0.6711 | 0.879 | 0.8557 | 0.7469 | 0.4075 | 0.468 | 0.9091 | 0.8494 | 0.9653 |
| 8 | 0.5263 | 0.6711 | 0.8791 | 0.8558 | 0.747 | 0.4078 | 0.4685 | 0.9092 | 0.8495 | 0.9653 |

Comparative Analysis for the Output Weight Vector

- The outcome of the non-linear Hebbian rule varies significantly compared to the outcomes of differential Hebbian learning and balanced differential Hebbian learning.
- However, all the implementations result in the same order of significance.
 - For this example: C8 – C3 – C4 – C9 – C5 – C2 – C1 – C7 – C6.

| Concepts | Non-linear Hebbian Learning | Differential Hebbian Learning | Balanced Differential Hebbian Learning |
|------------|-----------------------------|-------------------------------|--|
| <i>C1</i> | 0.5825 | 0.6466 | 0.6674 |
| <i>C2</i> | 0.6712 | 0.6624 | 0.6663 |
| <i>C3</i> | 0.8266 | 0.7079 | 0.6851 |
| <i>C4</i> | 0.8090 | 0.6942 | 0.6757 |
| <i>C5</i> | 0.7256 | 0.6740 | 0.6713 |
| <i>C6</i> | 0.4731 | 0.6131 | 0.6556 |
| <i>C7</i> | 0.5145 | 0.6211 | 0.6572 |
| <i>C8</i> | 0.8609 | 0.7133 | 0.6860 |
| <i>C9</i> | 0.8008 | 0.6920 | 0.6730 |
| <i>C10</i> | 0.9200 | 0.7542 | 0.6997 |

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- This paper proposed an approach for **hotel quality evaluation from online review comments and ratings** using FPM for mining customers' opinions and FCM for **evaluating the attributes that contribute to the review rating**.
- The proposed approach is able to **model the complex dynamics of online hotel review data**, which are derived from both the **textual nature** of the review comments and the **uncertain relationships** between these comments and the review rating.
- In our **future work**, we plan to:
 - apply our methodology to further datasets
 - to investigate the role of user profiling in hotel selection.

Thank you!