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

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***Abstract***— **Online review comments have become a popular and efficient way for sellers to acquire feedback from customers and improve their service quality. 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, which influences future customer demand and hotels' financial performance and thus have significant business value. This paper proposes an approach for hotel quality evaluation according to online review comments and ratings using Fuzzy Pattern Matching (FPM) for mining customers' opinions and Fuzzy Cognitive Maps (FCM) for evaluating the attributes that contribute to the review rating. The proposed approach was applied to a 4-star hotels dataset in Athens, Greece and experiments were performed.**

***Keywords-e-tourism; data analytics; machine learning; tourism management; service quality.***

## I. INTRODUCTION

Online comments have become a popular and efficient way for sellers to acquire feedback from customers and improve their service quality [1]. According to a survey, 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% [2]. Customer online reviews of hotels have significant business value in the e-commerce and big data era, while they affect room occupancy [3], revenue, prices [4] and market share [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, which influences future customer demand and hotels' financial performance [6].

Hotel owners want to know the details about hotel guests' experiences, to improve the corresponding product and service attributes, and customers' overall evaluation of the hotel stay experience, to obtain a snapshot of the hotel's operational performance and overall customer satisfaction [7][8]. Although the direct measurement of customer ratings in terms of closed-ended survey questions can show overall customer satisfaction in a direct way [7][8], they suffer from confounding the data of customers' true evaluation because of variations in survey design from different approaches [9].

Recently, many studies have focused on textual reviews [8][10]. 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, and provide customers' perceptions in a detailed way through the open-structure form [8]. The provided information is free from obvious bias and is helpful in understanding and assessing hotel performance [11]. In addition, such information is inexpensive and efficient to collect [12]. However, the exploitation of online textual reviews is still largely under-explored [8], while there is a lack of advanced data analytics approaches and algorithms for modeling complex dynamics of online hotel review data.

Hotel quality evaluation from online reviews is an emerging research field; however, the vast majority of existing research works have been performed from a tourism management perspective. Therefore, the applied methods and algorithms are limited to descriptive statistics, e.g., using well-established regression models. However, the increasing amount of online reviews as the core means for customers to express their level of satisfaction about a hotel pose significant challenges to the data analytics and computer science community for the development of advanced data analytics models aiming at 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 both: (i) mines customers' opinions from online hotel reviews (review comments and rating); and, (ii) evaluates the hotel performance by identifying how the various attributes (e.g., location, cleanliness, breakfast, etc.) affect the overall review rating. The rest of the paper is organized as follows: Section II presents the related work on methods and approaches for hotel evaluation based on online review comments. Section III describes the research methodology and the proposed approach for hotel quality evaluation from online reviews using FPM and FCM. Section IV presents the results from the adoption of the proposed methodology on a dataset of six

4-star hotels in Athens. Section V concludes the paper and outlines our plans for future work.

## II. Related Work

The business value of online consumer reviews has emerged in recent year in the hotel industry aiming at solving the problems confronted by the traditional hotel service quality assessment methods [13]. For example, in [14], the authors performed hierarchical multiple regressions in order to examine the effects of traditional customer satisfaction relative magnitude and social media review ratings on hotel performance and found that social media review rating is a more significant predictor. In the traditional hotel quality assessment, domain experts or customers are asked to fill in a questionnaire and score each evaluation index to be used in a service quality assessment model [15]-[17]. On the contrary, online comments are made by a large amount of customers with actual user experience shortly after the consumption is completed. In addition, the increasing amount of reviews-related data pave the way for the use of advanced data analytics and machine learning algorithms that outperform traditional statistical methods based on sampling [2].

Technical attributes of online textual reviews can explain significant variations in customer ratings and can have a significant effect on customer ratings [18][19]. In this direction, in [8], the authors developed an approach for predicting overall customer satisfaction using the technical attributes of online textual reviews and customers' involvement in the review community. They calculated subjectivity and polarity measurements by using naïve Bayes classifier and sentiment analysis. The research work in [10] investigated the underpinnings of satisfied and unsatisfied hotel customers by applying text mining techniques on online reviews.

The literature is rich of methodologies based on descriptive statistics aiming at providing insights on hotel quality performance for various datasets. In [20], the authors applied statistical methods in order to assess how several characteristics, such as timeliness of the response, length of the response, number of responses, etc., contributes to the hotel's financial performance. The research work in [21] compared the rating dynamics of the same hotels in two online review platforms, which mainly differ in requiring or not requiring proof of prior reservation before posting a review (respectively, a verified vs a non-verified platform). In [22], the authors examined the effect of factors of online consumer review, including quality, quantity, consistency, on the offline hotel occupancy (i.e., how popular the hotel is among consumers).

In [3], the extent to which digital marketing strategies influence hotel room occupancy and revenue per available room and how this mechanism is different for different types of hotels in terms of star rating and independent versus chain hotels was investigated. In [23], the authors examined the determinants of customer satisfaction in hospitality venues through an analysis of online reviews using text mining and content analysis. The research work in [24] investigated the impacts of online review and source features (usefulness, reviewer expertise, timeliness, volume, valence and comprehensiveness) upon travelers' online hotel booking intentions by applying factor analysis and regression analysis. In [11], the authors compared customer satisfaction by classifying several attributes influencing customer satisfaction in: satisfiers, dissatisfiers, bidirectional forces, and neutrals. Reference [25] applied qualitative research methods and extracted six main factors influencing the positive or negative emotions of the comments of travelers staying in the hotel.

Reference [26] conducted a multilevel analysis of factors affecting customer satisfaction, such as service encounter, visitor, visitor's nationality, hotel, and destination. In [27], the authors applied a multi-group analysis and an importance-performance map analysis by means of PLS-SEM in order to differentiate between service quality performance scores and their influences on customer satisfaction across accommodation with a different star grading. Reference [28] assessed social media content produced by customers and related review-management strategies of domestic and international hotel chains with the use of multilevel regression.

As mentioned earlier, the increasing amounts of reviews-related data require advanced data analytics and machine learning methods for exploiting the full potential. To this end, the research work in [2] assessed whether terms related to guest experience can be used to identify ways to enhance hospitality services. They developed a model based on naïve Bayes classifier in order process vast amount of data and to classify reviews of hotels. Reference [29] developed a framework in order to integrate visual analytics and (deep) machine learning techniques, such as clustering for text classification and Convolutional Neural Networks (CNN), to investigate whether hotel managers respond to positive and negative reviews differently and how to use a deep learning approach to prioritize responses. Reference [1] combined fuzzy comprehensive evaluation and fuzzy cognitive maps aiming at identifying the causal relations among evaluation indexes from online comments. Based on this, their proposed approach recommends more economical solutions for improving the service quality by automatically getting more trustworthy evaluation from a large amount of less trustworthy online comments.

## III. Research Methodology

Our research methodology consists of three main steps: (i) Extracting the evaluation criteria from online comments; (ii) Mining customers' opinions using FPM; and, (iii) Applying FCM for attributes evaluation. These steps are described in detail in the following sub-sections.

### A. Extracting the Evaluation Criteria from Online Comments

The proposed approach utilizes three fields from the online hotel reviews: (i) *review title*; (ii) *review comments*; and, (iii) *review rating*. This step of the methodology processes the *review title* and the *review comments* in order to extract the evaluation criteria from the online comments.

More specifically, based upon an evaluation index for hotel service quality [1], this step identifies the criteria mentioned in the hotel reviews under examination, e.g., location, price, breakfast, room space, etc. In this way, the criteria are defined dynamically out of the pre-defined list, according to the dataset of the available online comments. The extracted evaluation criteria of the previous step play the role of a questionnaire and the online review comments can be considered as the answers to the questionnaire made by customers, so that they can be further processed with the use of Fuzzy Pattern Match Template (FPMT), as we describe in Section III.B. Moreover, along with the review rating, they constitute the concepts of the FCM, as we describe in Section III.C.

### B. Mining Customers' Opinions Using Fuzzy Pattern Matching

Since online comments are written in natural and informal language, there is the need to mine customers' opinions so that they subsequently feed into the FCM for further processing. FPM, alternatively mentioned as fuzzy string searching or approximate string matching, has been developed in the framework of fuzzy set and possibility theory in order to take into account the imprecision and the uncertainty pervading values, which have to be compared in a matching process [30]. This technique has proved effective for implementing patterns of approximate reasoning in expert system inference engines, and for designing retrieval systems capable of managing incomplete and fuzzy information data bases and vague queries.

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 [31] technology to identify the specific pattern strings from a long text. A simple example of regular expression is "[\s\S]∗?[room|bathroom][\s\S]∗?dirty[\s\S]∗?" that can match "The room was too dirty." However, the regular expression method causes a binary value result: match or not match.

In the proposed approach, we apply FPMT [1] as an effective fuzzy pattern matching method to deal with the vagueness of the free text online comments. FPMT is a set of pattern strings with membership degrees, denoted as:

$$FPMT = \{(p_1, w_1), (p_2, w_2), \ldots, (p_i, w_i), \ldots, (p_n, w_n)\}$$

where $p_i$ is a pattern string described by regular expression, and $w_i$ is the membership degree that a string falls into the object FPMT when the string matches $p_i$. When a string matches multiple pattern strings at the same time, the max membership degree of these pattern strings will be selected as the final membership degree. Although this method results in some mismatched cases due to the limitation of pattern strings, 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. Specifically, first, the extracted evaluation criteria of hotel quality are assigned to a five-level Likert scale (1 – Very Low, 2 – Low, 3- Neutral, 4 – High, 5 – Very High), which serve as an equivalent to responses of a Likert scale questionnaire. Then, following the approach proposed by [32], this step considers the median of the resulting responses in order to represent the magnitude of causality among the evaluation criteria to be used as FCM concepts in Section III.C.

### C. Applying Fuzzy Cognitive Maps for Attributes Evaluation

This step applies FCM in order to evaluate the quality of the hotels with respect to the extracted evaluation criteria, i.e., attributes, from Section II.A and to identify the effect of each criterion to the review rating. An FCM is a graph consisting of nodes $C_i$ that represent the concepts of the domain in study, connected to each other with weighted arcs $W(i,j)$ showing how concept $i$ is causally affected by concept $j$. The weights on the arcs connecting two concepts correspond to fuzzy qualifiers, such as 'a little', 'moderately', 'a lot', or fuzzy numbers can be assigned in order to show the extent to which a concept affects another. FCMs are used to model and study perceptions about a domain, to investigate the interrelationships among its concepts and to draw conclusions based on the implications of scenarios. The impact among the concepts of a FCM is estimated using the indirect effect i.e., the impact caused due to the interrelationships among the concepts along the path from a cause variable ($X$) to an effect variable ($Y$) and the total effect, i.e., the sum of all the indirect effects from the cause variable $X$ to the effect variable $Y$ [33].

FCMs can be represented by means of an N×N matrix E = $[e_{ij}]$, where N is the number of the concepts in the FCM with $i$ and $j$ representing concepts in the FCM. Every value $e_{ij}$ of this matrix represents the strength and direction of causality between interrelated concepts. The value of causality $e_{ij}$ is assigned values from the interval [-1, +1], as follows [34]:

- $e_{ij} > 0$ indicates a causal increase or positive causality from node $i$ to $j$.
- $e_{ij} = 0$ there is no causality from node $i$ to $j$.
- $e_{ij} < 0$ indicates a causal decrease or negative causality from node $i$ to $j$.

The multiplication between matrices representing FCMs produces the indirect and total effects [35] and allows the study of the impact that a given causal effect $D_1$ causes. Causal effects can be represented with a 1×N vector [36]. This impact is calculated through repeated multi-plications: $E \times D1 = D2$, $E \times D2 = D3$ and so on, that is, $E \times D_i = D_{i+1}$, until equilibrium is reached, which is the final result of the effect $D_1$. Equilibrium is reached when the final result equals to zero, i.e., all cells of the resulting vector are equal to zero (0) and there is no any further causal impact caused by any concept. Different thresholds, depending on the modelling needs, restrict the values that result from each multiplication within the range [-1, +1] [32].

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

 ISBN: 978-1-61208-816-7 

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*. The latter is affected by all the other concepts and does not affect any of them.

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", thus allowing the combination of multiple FCMs into a single knowledge-based representation. Multiple weighted FCMs are combined into a single averaged FCM by adding their scaled and augmented adjacency weight matrix. This procedure is based on the mathematical transformation of the causal weight matrices [37]. 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.

## IV. Results

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 superset of the FCM concepts is shown in Table I. These concepts represent the extracted evaluation criteria from FPMT (C1-C9) along with the review rating (C10).

TABLE I. THE EXTRACTED EVALUATION CRITERIA

| 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 |

After the fuzzy evaluation of the aforementioned concepts for each hotel, the weight matrix is created and is inserted to the FCM model. Figure 1 depicts the result for one indicative hotel, while Figure 2 depicts the augmented FCM topology of all the six hotels under examination. The C10: Review Rating has been put on the left so that the effect of the various attributes on the review rating is more visible. For these visualizations as well as for experimental purposes, we used the "FCM Expert" software tool [37]. The rest of the experimental analysis deals with the augmented topology, thus providing insights on a regional basis. As shown in Figure 2, the review rating (C10) is mainly affected by Location (C1), Cleanliness (C3), Room Space (C4) and Interior Design (C8).

Table II presents the values related to the degree centrality. It is a local centrality measure determined by only its directed connections. The degree centrality of a node is the summation of its absolute incoming (indegree) and outgoing (outdegree) connection weights. Furthermore, we performed inference using various reasoning rules (Kosko's activation rule, Kosko's activation rule with self-memory, Rescaled activation rule with self-memory) in order to compute the output vector including the weights of the concepts. Figure 3 presents an indicative visualization of our results. Specifically, Figure 3a depicts a chart and Figure 3b depicts a table with the iterations of the algorithm until convergence.

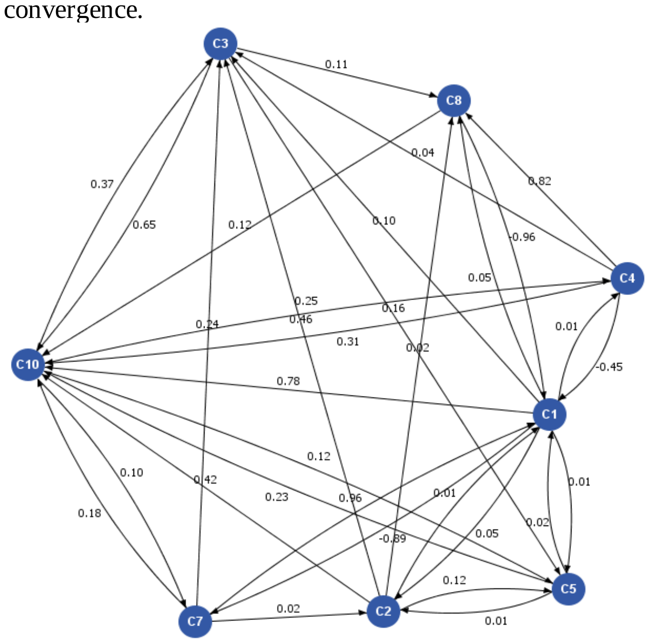



Figure 1. The resulting FCM of one indicative hotel.

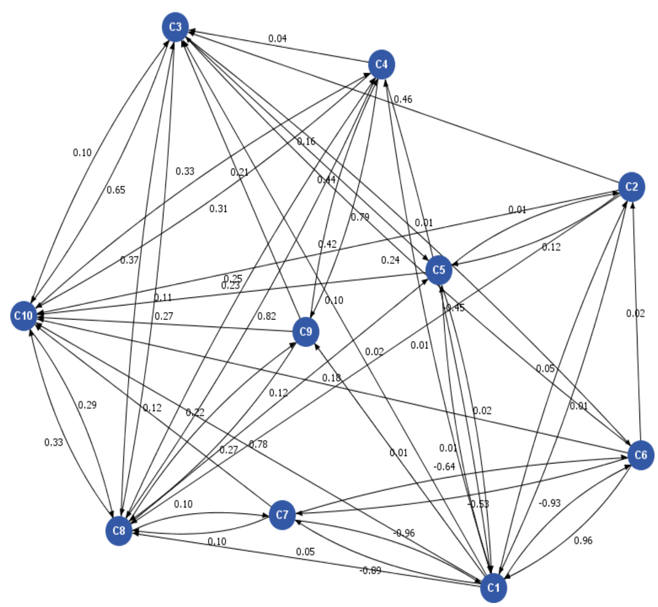
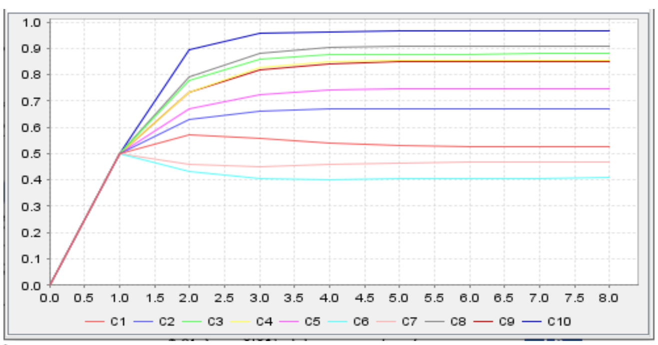



Figure 2. The augmented FCM topology for all the six hotels.

Table III presents and compares the output vector of weights by applying three different unsupervised learning methods using a Hebbian rule, i.e., non-linear Hebbian learning, differential Hebbian learning, and balanced differential Hebbian learning. Hebbian learning constitutes an unsupervised technique initially applied on the training of artificial neural networks [38]. The main feature of this learning rule is that the change of a synaptic is computed by taking into account the presynaptic and postsynaptic signals flow towards each processing unit (neuron) of a neural network [39].

TABLE II. OUTDEGREE, INDEGREE, AND CENTRALITY OF THE FCM

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




| 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 |

Figure 3. Results of inference until convergence: (a) Chart; (b) Table.

As shown in Table III, the outcome of the non-linear Hebbian rule varies significantly compared to the outcomes of differential Hebbian learning and balanced differential Hebbian learning. Non-linear Hebbian learning constitutes an extension of differential Hebbian learning and is able to capture effectively non-linear relationships [40]. However, despite the differences in the estimated weight vector of the criteria, all the aforementioned implementations result in the same order of significance in terms of their impact on the review rating (C10), i.e., C8 – C3 – C4 – C9 – C5 – C2 – C1 – C7 – C6.

TABLE III. COMPARATIVE ANALYSIS FOR THE OUTPUT WEIGHT VECTOR

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

## V. CONCLUSIONS AND FUTURE WORK

Hotel quality evaluation from online reviews is an emerging research field, while the use of data analytics and machine learning methods are able to exploit its full potential in an e-tourism context. This paper proposed an approach for hotel quality evaluation according to online review comments and ratings using FPM for mining customers' opinions and FCM for evaluating the attributes that contribute to the review rating. The results show that 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. Regarding our future work, we plan to apply our methodology to further datasets and to investigate the role of user profiling in hotel selection.

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 ISBN: 978-1-61208-816-7 