On the Role of Compensatory Operators in Fuzzy Result Merging for Metasearch

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Abstract. A key metasearch engine task is result merging of search results from multiple search engines in response to a user query. The problem of result merging has been widely studied as a multi-criteria decision making model (MCDM). While many MCDM techniques have been employed to create experimental models for result merging, the most notable have used fuzzy aggregation operators such as the OWA operators and its extensions and variations. In this work we study the role of applying fuzzy algebraic t-norms, s-norms and compensatory operators in fuzzy result merging for metasearch. Our results will demonstrate the superiority of compensatory operators over t-norm aggregation functions in the context of result merging for metasearch.

Keywords: Information Retrieval, Metasearch Engines, Fuzzy Sets, Fuzzy Aggregation Operators.

1 Introduction

A metasearch engine is a search engine that can be used to search multiple search engines systems concurrently. Metasearch engines are particularly useful in searching through topic specific search systems like PUBMED, MEDILE etc. A typically search engine output comprises of a list of results (documents/URLs/database records), ranked in the order of relevance. However, different search engines evaluate and consequently rank results differently. The problem of result merging is to aggregate the rankings of each result to come up with a composite rank, such that the final ranking preserves the order of relevance. In this paper we propose two models Compensatory Ordered Weights Average (COWA) and Importance Guided Compensatory Ordered Weights Average (IGOWA) models for result aggregation using the OWA operator [11] and compensatory aggregation function [15]. We compare our models with the existing OWA [5], IGOWA, t-norm OWA and t-norm IGOWA [3, 4]. This paper is organized as follows. In Section 2, we discuss previous models for result merging, including a discussion on the OWA, IGOWA, t-norm OWA and t-norm IGOWA models. In Section 3 we describe our proposed models, COWA and IGCOWA. In Section 4 we describe experiments comparing COWA and IGCOWA with OWA, IGOWA and t-norm IGOWA and discuss our results. In Section 5 summarize our findings in a conclusion.

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2 Previous Work

In early work on aggregation, includes the work of Fox and Shaw [6, 7] and Aslam and Montague [1]. The latter proposed two models Borda-Fuse and Weighted Borda-Fuse based on the political election strategy, Borda Count [2].

Diaz [5] developed the first fuzzy result aggregation model OWA, based on Yager Ordered Weighted Average (OWA) [11, 12] operator. The OWA model uses a *positional value* (PV) to quantify the rank of a result in a result list. The positional value (PV) of a result ranked r in a result list is (n – r + 1) where n is the total number of results in the list. The OWA model uses the OWA operator to aggregate the PVs of each result. Let us say we have n criteria and an alternative x. Let a_i represent the degree to which x satisfies the i^{th} criteria. Thus we have a set $\{a_1 \ldots a_n\}$. Let b_j is the j^{th} largest value within the set $\{a_1, a_2, \ldots, a_n\}$. Then F (eq. 1) defines the OWA operator.

$$F(a_1, a_2, a_3, \ldots, a_n) = \sum_{j=1}^{n} w_j b_j \tag{1}$$

In the OWA model for metasearch, the PV (or inverse of rank) is considered extent to which the result (alternative) satisfies a search engine (criteria). The ordered weights are computed using a linguistic RIM quantifier $Q(r) = r^{\alpha}$ as described in equation (2). The orness associated with the quantifier, orness (Q) = $(1+\alpha)^{-1}$. Experiments in [10, 11] demonstrate the OWA model outperforms the Borda Fuse and Weighted Borda Fuse models.

$$w_i = Q\left(\frac{i}{n}\right) - Q\left(\frac{i-1}{n}\right) \tag{2}$$

The OWA model however, does not consider search engine importance weights in result aggregation. To overcome this, De [3, 4] proposed the IGOWA (importance guided) model for metasearch. The IGOWA model uses Yager's [12] Importance Guided Aggregation technique to generate the ordered weights for aggregation using the OWA operator. Once again PVs of results from result lists are aggregated using the OWA operator. However, weights are generated as per equation (3) below. Let the importance weight for the i^{th} criteria be V_i. Let V_i ε [0, 1]. For an alternative x there will be a pair (V_i, a_i) for each criteria i. The criteria scores can be sorted in descending order with b_k being the k^{th} largest a_i. Let u_k be the importance weight attached to b_k. We can now associate, with alternative x, a collection of n (u_k, b_k) pairs, where the b_k's are degrees to which x satisfies the n criteria in descending order. The ordered weights can now be obtained using equation (3) and where $T = \sum_{j=1}^{n} u_j$ .Yager [12] proposes a set of extensions of the OWA operator, which he calls the triangular norm (t-norm) OWA operators. This is essentially a quantifier guided aggregation decision function that strikes a balances the RIM quantifier Q, defined previously, that stipulates the degree of satisfaction that is attained when satisfying i^{th} criteria with the need to find i criteria that are satisfied. Combining these two factors, Yager arrives at the aggregation function shown in eq. (4). Here b_j is j^{th} greatest a_i and T is a t-norm function.

$$w_k(x) = Q\left(\frac{\sum_{j=1}^{k} u_j}{T}\right) - Q\left(\frac{\sum_{j=1}^{k-1} u_j}{T}\right) \tag{3}$$

$$F(a_1, a_2, a_3, \ldots, a_n) = \sum_{j=1}^{n} w_j T(b_1, \ldots, b_j) \tag{4}$$

De [3, 4] used an algebraic t-norm eq. (5) to propose two models for result merging. The first was the t-norm OWA result merging model for metasearch and did not consider search engine importance weights. The second was the importance guided t-norm IGOWA model that use search engine weights to generate ordered weights using equation (3). In each case multiple PVs for each result (obtained from different search engine result lists) are obtained. Experiments of De [3, 4] demonstrated that when using an algebraic t-norm the t-norm OWA model outperformed the OWA model and the t-norm IGOWA model outperformed the IGOWA model for metasearch. The IGOWA and t-norm OWA model both outperformed the OWA model in creating improved relevance order ranking.

$$T(b_1, \ldots\ldots b_n) = \prod_{i=1}^{n} b_i \tag{5}$$

3 Proposed Models

Several researchers working in the area of fuzzy decision making noticed that t-norms and their dual s-norms lack the compensation behavior crucial to any aggregation process. Zimmermann and Zysno [15] were the first to notice that in a decision function making context humans neither follow the behavior of a t-norm or an s-norm strictly when aggregating. Zimmermann and Zysno [15] proposed an aggregation function on the unit interval based on t-norms and s-norms as described in equation (6). Here γ is the extent of compensation provided. Yager [14] proposes a function to calculate the value of γ as described in equation (7).

The motivation of our work was to study how using compensatory operators, affects the result of merging result merging for metasearch. We build two models. Our first model was the Compensatory Ordered Weighed Aggregation (COWA) model. This model employs the Zimmermann [15] compensatory aggregation function in result aggregation using the OWA operator as defined in eq. (8). This model does not take into consideration search engine weights in result merging. In our model we use the algebraic t-norm for aggregation as described in eq. (5). We compare the performance of this model to the OWA model [5] and t-norm OWA model [3, 4].

Our second model is the Importance Guided Compensatory Ordered Weighted Aggregation (IGCOWA) model for result merging. The model is similar as it user the

Zimmerman [15] aggregation function in conjunction with the OWA operator as described in eq. (8). However the ordered weights for aggregation are generated using equation (3) as in IGOWA and t-norm IGOWA [3, 4]. Both our models use a Regular Increasing Monotone (RIM) quantifier as described earlier of the form $Q(r) = r^{\alpha}$ as a function to generate ordered weights.

$$Z_{\gamma}(b_1, b_2, b_3, \ldots, b_n) = \left(\prod_{i=1}^{n} b_i\right)^{1-\gamma} \bullet \left(1 - \prod_{i=1}^{n}(1 - b_i)\right)^{\gamma} \tag{6}$$

$$\gamma = \frac{T(b_1, \ldots, b_n)}{T(b_1, \ldots, b_n) + T(1 - b_1, \ldots, 1 - b_n)} \tag{7}$$

$$F(a_1, a_2, a_3, \ldots, a_n) = \sum_{j=1}^{n} w_j Z_{\gamma}(b_1, \ldots, b_j) \tag{8}$$

4 Experiments and Results

For our experiments, we use Hersh's [8] OHSUMED collection within the LETOR 2 (**L**earning **TO R**ank) [9] dataset from Microsoft Research Asia. The LETOR2 dataset comprises of a collection of OHSUMED documents (results), a query set of size of 106, a set of 25 algorithms (search engines) that are used to judge the relevance of each document to each query. For our experiments, our performance metric is Recall-Based (RB) Precision as defined by Bollmann and Raghavan [16]. We compare our proposed models COWA and IGCOWA against existing models OWA, t-norm OWA, IGOWA and t-norm IGOWA. Odd numbered queries are used for learning search engine importance weights based on performance of search engines over the query set. For our experiments for each odd numbered query, we randomly pick N search engines from the 25 available. The value of N is varied from 2 to 12. Overall 1000 sets of experiments are done for each value of N. Table 1 shows the results. We compute the average precision at recall levels of 0.25, 0.5, 0.75 and 1. The results are shown in Table 1 and Table 2.

Table 1. Results comparing COWA, IGCOWA vs. OWA, IGOWA, t-norm OWA and t-norm IGOWA when number of lists varies from 2 to 12.

N (Number of lists merged)	Average Precision of the Merged List					
	OWA	IGOWA	t-norm OWA	t-norm IGOWA	COWA	IGCOWA
2	0.4051	0.4231	0.4233	0.4472	0.4538	0.4638
4	0.4237	0.4445	0.4453	0.4491	0.4573	0.4783
6	0.4297	0.4593	0.4597	0.4638	0.4791	0.4891
8	0.4332	0.4682	0.4712	0.4783	0.5011	0.5013
10	0.4681	0.4783	0.4813	0.4891	0.5113	0.5291
12	0.4732	0.4813	0.4913	0.5013	0.5231	0.5345

Table 2. Results comparing COWA, IGCOWA vs. OWA, IGOWA, t-norm OWA and t-norm IGOWA when orness of aggregation varies from 0.8 to 0.2.

Orness (O)	Average Precision of the Merged List					
	OWA	IGOWA	t-norm OWA	t-norm IGOWA	COWA	IGCOWA
$O \geq 0.8$	0.4371	0.4413	0.4417	0.4472	0.5146	0.5292
$0.8 \geq O \geq 0.6$	0.4251	0.4345	0.4453	0.4491	0.4629	0.5177
$0.6 \geq O \geq 0.4$	0.4108	0.4139	0.4397	0.4428	0.4439	0.5237
$0.4 \geq O \geq 0.2$	0.4332	0.4428	0.4712	0.4783	0.5211	0.5378

5 Conclusions

From Table 1 it is clear that the COWA model outperforms the models in its class (without search engine importance weights), namely the OWA and the t-norm OWA (with algebraic t-norms) models. The overall improvements over t-norm OWA model are 7.20, 2.69, 4.22, 6.34, 6.23 and 6.47 % when merging 2, 4 6, 8, 10 and 12 search engines respectively. Similarly, in its class of models (requiring search engine importance weights) IGCOWA model improves upon the IGOWA model by 3.7, 6.5, 5.45, 4.80, 8.17 and 6.62 % when merging 2, 4, 6, 8, 10 and 12 search engines. . In Table 1 it is also observed that as the number of search engines increases the overall performance in terms of average precision increases. This is primarily because when more search engine results are merged more relevant results are present in the merged list.

Orness is a key measure in fuzzy aggregation. For the OWA, t-norm OWA and COWA models orness is computed as $1/(1+\alpha)$. Here α is the parameter of the RIM quantifier $Q(r) = r^{\alpha}$ used to compute ordered weights. We also measured the performance of aggregation for different levels of orness. In previous findings [3,4, 5] it was observed that as orness of aggregation decreases, the performance in terms of average precision decreases, till averaging conditions are achieved. When orness =0.5 then the average precision falls to its lowest value. Following this as orness decreases and andness increases the average precision increases.

This is consistent with findings in [3, 4 and 5] illustrated in results from Table 2. Also for each level of orness the performance of COWA is better than that of algebraic t-norm OWA and OWA. For the models that require importance weights the IGCOWA model also outperforms the t-norm IGOWA and IGOWA models.

The overall improvements of COWA over OWA and t-norm OWA are 9.98% and 8.01%. The overall improvements of IGCOWA over IGOWA and t-norm IGOWA are 5.52% and 5.87%. Clearly compensatory operators clearly improve the performance of aggregation in terms of average precision.

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