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Range Similarity Measures between Buyers and Sellers in e-Marketplaces

Lu Yang[1], Biplab K. Sarker[1], Virendrakumar C. Bhavsar[1], and Harold Boley[2]

[1] Faculty of Computer Science, University of New Brunswick,
Fredericton, New Brunswick, Canada
{lu.yang, sarker, bhavsar}@unb.ca
[2] Institute for Information Technology e-Business, National Research Council of Canada,
Fredericton, New Brunswick, Canada
harold.boley@nrc-cnrc.gc.ca

Abstract. Price is the omnipresent factor that determines buyers' and sellers' decision-making when trading products in real and virtual marketplaces. However, since a fixed price can often lead to unsuccessful transactions, in practice market players normally have price ranges in their minds, which imply some concessions when finding potential buyer-seller matches. In this paper, we propose a price-range similarity measure that is justified by price-range overlaps between buyers and sellers in several possible cases. Working independently, our price-range similarity measure provides a buyer (seller) with a list of ranked sellers (buyers) according to their price-range similarity values. Embedded into a similarity algorithm, our price-range similarity measure contributes, in a controllable way, to the overall similarity measures of products/services.

1 Introduction

On-line shopping is very common for buyers nowadays. For example, e-Bay (http://www.ebay.com) lists the details (price, payment, shipping, etc.) of particular products that are sought by buyers. For buying a specific product, buyers usually want to compare prices from various sellers in order to make decisions. Therefore, among the various product attributes, the price, having the greatest effect on buyers' and sellers' decision-making, is arguably the most important attribute.

To flexibly achieve successful transactions, buyers (usually) and sellers (often) have price ranges in their minds. While the buyer will not tell a seller, upfront, the maximum price he/she would be willing to pay, a match-making engine should be made aware of it to avoid unrealistic buyer-seller pairings. Conversely, the seller will hide the minimum price to a buyer until the latest moment in the negotiation phase, but the match-maker should use it for reasonable pairings. Providing a modular (price-)range extension to the similarity engine of the AgentMatcher architecture [4], we focus on the match-making phase here. An application of the AgentMatcher architecture is our Teclantic portal (http://teclantic.cs.unb.ca) which matches projects according to the project profiles.

In the price-comparison problem proposed by [5], a buyer was provided with products such that each had the lowest price that fell into his/her price ranges (minimum and maximum). But a problem appears in this approach when a product's price is less than the lower bound (minimum price) of the buyer's quoted price range: for a buyer's non-zero lower bound on a product's price we are never sure if he/she could not *imagine* the product to be cheaper or would not *like* a cheaper product. So, the consequence might be that a buyer unnecessarily loses some money. Some other systems such as PriceWatch [10], DealTime [6], MySimon [8], PriceScan [9] and BizRate [3] also have provided the functionality of price comparison. They allow buyers to specify price ranges and then display possible products within such a range from various vendors.

There are two disadvantages of these kinds of price-comparison systems. First, the systems only search corresponding products that fall into buyers' price ranges, but do not provide intelligent recommendations. Second, only one party, the buyer, is active in seeking sellers. In such a buyer-centric e-marketplace, the one-way interaction between buyers and sellers restricts sellers to find appropriate buyers. The e-marketplace embodied in MARI [13] aims to solve these two problems. It classifies product attributes as fixed and flexible. Fixed attributes have predefined permissible values and flexible attributes associate with ranges values. For fixed attributes, it only checks if the transaction party qualifies the specified values of those attributes. However, for flexible attributes, it values corresponding ranges by utility functions. The matching cost for a buyer and a seller is computed according to their valued ranges of flexible attributes. Price is not classified as flexible in this system and thus it does not affect the final matching cost.

Automated negotiation also makes use of a similarity measure [7] to approximate the preference structures between negotiators. The similarity between two contracts which contain quantitative and qualitative decision variables is an integration of the pair-wise similarities over the values of a set of decision variables for a given domain. Our tree similarity algorithm [1] recursively computes the intermediate subtree similarity values for the overall similarity computation between a buyer and a seller tree. Prices ranges represented by leaf nodes are appropriately located in the tree (see subsection 2.2). The prices in [7] are considered as a quantitative decision variable whose similarity is computed by a linear function. However, they are represented as fixed prices rather than price ranges. Thus, the corresponding price similarity cannot express the potential overlap between a buyer's and a seller's maximum, minimum and preferred prices existing in their minds.

In this paper, we propose a similarity measure to find the overlaps of buyer/seller price ranges for their semantic matching. We treat prices as ranges which are composed of minimum, preferred and maximum prices specified by buyers and sellers. Our semantic, decision-supporting, price-range similarity measure can be used independently when the price is the only decisive factor for decision-making or incorporated into other algorithms [1] as a subfunction.

This paper is organized as follows. In the following section, we describe how we symmetrically represent price ranges for buyers and sellers. Two sample trees that embed price ranges are also shown here. Section 3 derives our price-range similarity measure based on seven case studies. We also present the adaptation of the price-range similarity measure to other "range"-characterized product attributes (e.g. salary). The analysis of our algorithm with examples is provided in Section 4. Concluding remarks are given in Section 5.

2 Price Ranges for Buyer/Seller

We use arc-labeled and arc-weighted trees [1], [15] to represent product descriptions of buyers/sellers. The attribute "price range" and its corresponding values are represented as arc labels and node labels, respectively, in our trees.

2.1 Representation and Semantics of Price-Range

In most on-line systems that advertise products, a buyer needs to fill out an on-screen form to specify the particular product(s) that he/she wants to buy. The systems then provide buyer detailed descriptions of the product(s). For various product attributes in the on-screen form, price range (maximum and minimum prices) plays a leading role for the success of transaction.

However, in some cases (e.g. used-car buying/selling), sellers also seek buyers to find a good deal. In a common e-marketplace, both buyers and sellers have a preferred price in their minds that might be negotiable. The semantics of the "preferred price" is that buyers/sellers are satisfied to buy/sell a product at that price taking into account of other concerns (e.g. warranty, delivery time, quality, return policy etc.). It is natural that a buyer wants to buy a product as cheap as possible; on the other hand, a seller always wants to sell it as expensive as possible to obtain more benefit. Therefore, if a buyer specifies his preferred price as "$40", we can assume that he/she is also interested in those products that are cheaper than "$40". And for a seller, he/she will never refuse to consider the offers that are higher than his/her preferred price. However, in practice, it is quite common that both buyers and sellers would like to concede to some extent. So, buyers often have maximum and sellers have minimum prices in their minds.

In this paper, a price range such as [$40, $50] for a buyer indicates that he/she prefers to buy the product for $40 or even cheaper and the maximum price he/she can accept is $50. The price range, say [$30, $70], for a seller reveals that he/she prefers to sell a product at $70 or even higher but he/she can accept a price as low as $30.

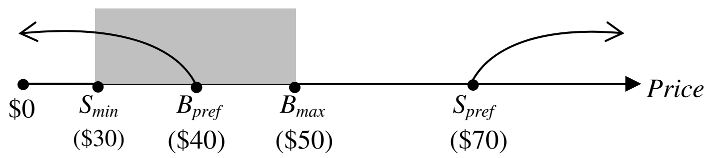

Fig. 1. An example of price range overlapping

We use B_{pref} and B_{max} to represent the preferred and maximum prices of buyers and S_{pref} and S_{min} for the preferred and minimum prices of sellers. B_{max} will always be equal to or greater than B_{pref} and S_{min} be equal to or less than S_{pref}. Therefore, the price ranges for buyers and sellers are [B_{pref}, B_{max}] (e.g. [\$40, \$50]) and [S_{min}, S_{pref}] (e.g. [\$30, \$70]), respectively. When $B_{pref} = B_{max}$ or $S_{min} = S_{pref}$, it means that the buyer or the seller will not concede in his/her future negotiation. In Fig. 1, we show an example of the price ranges of a buyer and a seller. Buyer and seller prices are shown on "Price" axis. Some example values are shown in brackets. Since negative prices are meaningless, all prices are equal to or greater than \$0. Therefore, the buyer is satisfied with the prices below his/her preferred price (B_{pref}). This is shown by a curve with a left arrow. Symmetrically, the seller is satisfied with prices above his/her preferred price (S_{pref}) and we show it by a curve with a right arrow. Mathematically, the overlaps of price ranges [\$40, \$50] and [\$30, \$70] are [\$40, \$50]. However, based on our real life experiences, we easily know that the transaction can take place within the grey range [S_{min}, B_{max}] (in this case, [\$30, \$50]). It is obvious that the bigger the grey range (buy/seller price-range overlap), the bigger the distance of S_{min} and B_{max} and thus the more successful their transaction and consequently, the more similar their price ranges.

Representing price ranges for buyers and sellers in this way, we can get a unique price-range similarity value for a pair of buyer and seller (see Section 3). Therefore, our price-range similarity measure is symmetric.

2.2 Price Ranges in Trees

The core of the similarity engine embedded in our AgentMatcher [4] architecture is our weighted-tree similarity algorithm [1] for buyer/seller matching [2], [12]. Product attributes and corresponding values are respectively incorporated into weighted trees as arc labels and node labels underneath. However, we only conducted exact string matching for values with "price" attribute which results in non-semantic similarity values. For example, for a buyer who wants to buy a product for \$50 and a seller who sells at \$51, the similarity value 0.0 is not reasonable because they have quite close offers.

Fig. 2 shows two example trees describing used cars from a buyer and a seller. Attribute "Price range" and its corresponding value (e.g. [\$40, \$50]) are now arc label and node label. We also allow buyers and sellers to specify an importance value for each attribute.

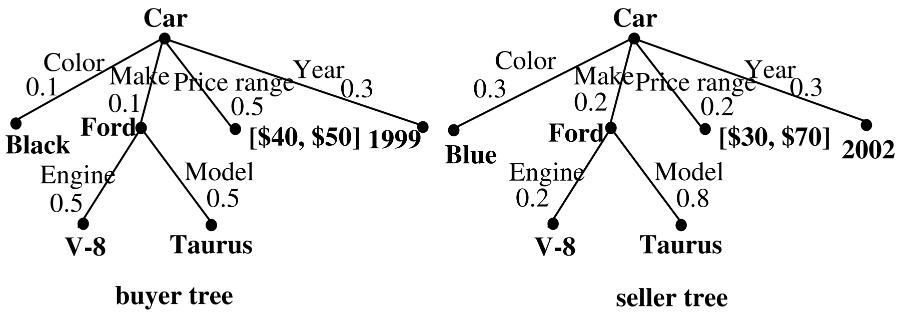

Fig. 2. Two example trees describing used cars

The similarity of two whole trees is recursively obtained by computing intermediate similarity values of each pair of subtrees. As it is not the main focus of this paper, please refer to [1] for more details on our tree similarity measure. Here, we present our similarity measure on nodes (e.g. "[$40, $50]" vs. "[$30, $70]") under "Price range" arc-label.

3 Range Similarity Measure

Buyers and sellers do not expose their prices to each other. However, similarity values computed by our price-range similarity measure imply the negotiation spaces [11] of them. Although we only match buyers and sellers and do not manage any negotiation between them, our proposed price-range similarity measure is directly proportional to their negotiation space. Intuitively, bigger overlap of buyer-seller price ranges leads to higher similarity value and thus implies bigger negotiation space. For a buyer (seller), we recommend a ranked list of sellers (buyers) according to their similarity values with the buyer (seller) in an e-marketplace. The recommended sellers (buyers) with the highest similarity values will have the maximum negotiation spaces with the buyer (seller). Thus, a buyer (seller) can select the most promising sellers (buyers) for their future negotiation.

3.1 Price-Range Similarity Algorithm

We propose a price-range similarity algorithm based on case studies described below. There are at most seven possible cases of buyer-seller price range overlapping. We use Sim_{price} to denote the similarity of price ranges of a buyer and a seller.

Case 1

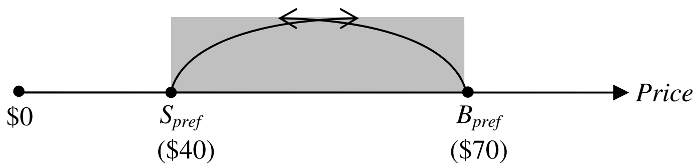

Fig. 3. Both buyer and seller are satisfied

Here in Fig. 3, buyer's preferred price is greater than or equal to that of seller's ($S_{pref} \leqslant B_{pref}$). Therefore, both of them are pleased with the transaction. We do not need to take into account the minimum and maximum prices specified by the seller and the buyer because [S_{pref}, B_{pref}] is the only range within which both buyer and seller are satisfied. We define Sim_{price} = 1.0 for this case.

From Case 2 to 6, there is no overlap between a buyer's and a seller's preferred prices (i.e. $B_{pref} < S_{pref}$). Therefore, successful transactions can only take place if one or both of them are willing to concede.

Case 2

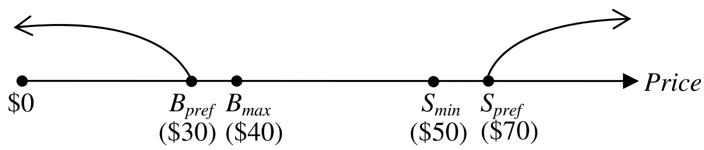

Fig. 4. Buyer's and seller's price ranges do not overlap even after concession

Both B_{max} and S_{min} stay in [B_{pref}, S_{pref}] but $B_{max} < S_{min}$ (Fig. 4). So, although both buyer and seller's prices are negotiable, they still do not have any overlap between their price ranges. We define Sim_{price} = 0.0.

From Case 3 to 6, there is overlap between buy/seller price ranges since $S_{min} < B_{max}$ always holds. Successful transactions only take place within the overlap range [S_{min}, B_{max}]. It is intuitive that the bigger the distance between S_{min} and B_{max}, the more chances for their successful transaction and thus the more similar their price ranges. Therefore, we define the price-range similarity as

$$Sim_{price} = d(B_{max}, S_{min}) \tag{1}$$

Where, $d(B_{max}, S_{min})$ is the distance of B_{max} and S_{min}.

We compute $d(B_{max}, S_{min})$ by $\frac{B_{max} - S_{min}}{\mathrm{MAX} - \mathrm{MIN}}$ [14] and thus equation (1) is changed into

$$Sim_{price} = \frac{B_{max} - S_{min}}{\mathrm{MAX} - \mathrm{MIN}} \tag{2}$$

where, MAX and MIN are the current maximum and minimum prices among all buyers and sellers in an e-marketplace. The values of the parameters MAX and MIN of equation (2) may change with time. When a new buyer or a new seller joins the market, the maximum or minimum prices carried by him/her may update the current values of MAX and MIN. Here, we consider the current values of MAX and MIN in the market are $75 and $25, respectively, for explaining the following cases.

Case 3

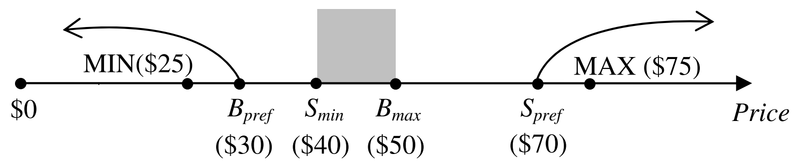

Fig. 5. Both buyer and seller are not satisfied but still can accept the transaction

Both B_{max} and S_{min} stay within [B_{pref}, S_{pref}] in Fig. 5. In this case, both the buyer and the seller are not satisfied because both of them have to concede for successful transaction. Equation (2) is employed without any change. The value of Sim_{price} of this example is 0.2.

Case 4

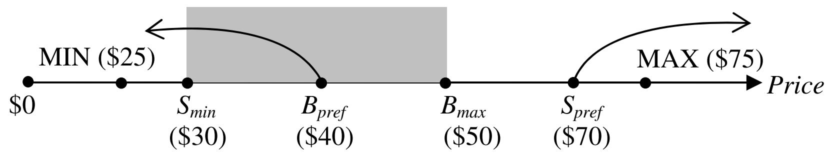

Fig. 6. Only buyer is satisfied

In Fig. 6, B_{max} stays within [B_{pref}, S_{pref}] and $S_{min}<B_{pref}$. The buyer is satisfied even if he does not concede since the seller would concede to a price below B_{pref}. If the value of S_{min} is smaller than MIN, we update MIN by S_{min}. We use the function min{MIN, S_{min}} to compute the smaller value between them. So, for this case, equation (2) is changed into

$$Sim_{price} = \frac{B_{max} - S_{min}}{\mathrm{MAX} - \min\{\mathrm{MIN}, S_{min}\}} \quad (3)$$

The value of Sim_{price} of this example is 0.4.

Case 5

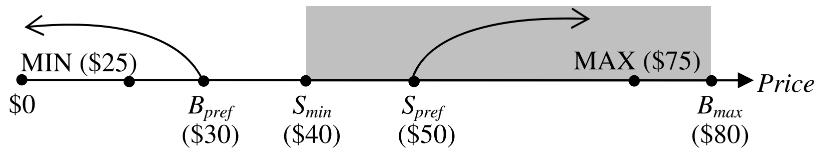

Fig. 7. Only seller is satisfied

This case (Fig. 7) is symmetric to Case 4. S_{min} is within [B_{pref}, S_{pref}] and $B_{max}>S_{pref}$. The seller is satisfied even if he does not concede since the buyer would concede to a price above S_{pref}. If the value of B_{max} is greater than MAX, we update MAX by B_{max}. We use the function max{MAX, B_{max}} to compute the bigger value between them. So, for this case, equation (2) is changed into

$$Sim_{price} = \frac{B_{max} - S_{min}}{\max\{\mathrm{MAX}, B_{max}\} - \mathrm{MIN}} \tag{4}$$

The value of Sim_{price} of this example is 0.7273.

Case 6

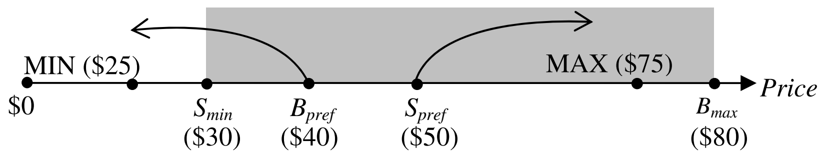

Fig. 8. Buyer and seller do not satisfy simultaneously

In this case (Fig. 8), both the buyer and the seller are willing to concede a lot compared to other cases. S_{min} is smaller than B_{pref} and B_{max} is greater than S_{pref}. This case covers the cases from case 3 to 5. Either the buyer or the seller is satisfied or both of them are not satisfied but they still can concede to a successful transaction. Similarly, we update MAX and MIN by B_{max} and S_{min} when $B_{max}>$MAX and $S_{min}<$MIN. So, equation (2) is changed into

$$Sim_{price} = \frac{B_{max} - S_{min}}{\max\{\mathrm{MAX}, B_{max}\} - \min\{\mathrm{MIN}, S_{min}\}} \tag{5}$$

When $B_{max}\geqslant$MAX and $S_{min}\leqslant$MIN, the value of Sim_{price} is 1.0. The reason for such a high similarity is that both buyers and sellers extremely compromise in order to make the transaction successful. The value of Sim_{price} of the example in Fig. 8 is 0.9091.

Case 7/Special Case

In the discussions from case 2 to 6, we omit one special case that S_{min}=B_{max} and it is shown in Fig. 9. It might happen that the buyer's maximum price is the same as the seller's minimum price. In practice, transactions in such a case tend to fail because only if both buyers and sellers concede toward their price limits then the transactions could be successful. However, if we use equation (2), we obtain similarity 0.0 which is not reasonable since price ranges of the buyer and seller still have one common point overlapping. We expect a similarity value that is small but greater than 0.0.

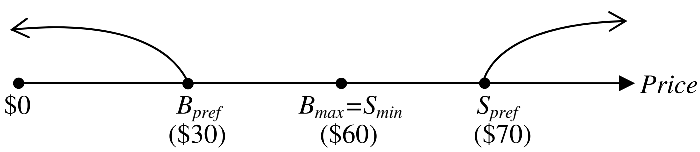

Fig. 9. Buyer and seller price ranges only have one point overlapping

In most on-line buying/selling systems, prices are presented as precise as two decimal digits (i.e. $30.59). So, the minimum difference between two different prices is 0.01. Therefore, if two price ranges have different values of S_{min} and B_{max}, their similarity Sim_{price} must be equal to or greater than $\frac{0.01}{\text{MAX}-\text{MIN}}$.

Thus, we fix the difference for identical S_{min} and B_{max} as 0.005. And consequently, we get their price-range similarity

$$Sim_{price} = \frac{0.005}{\text{MAX}-\text{MIN}} \tag{6}$$

This value is a number that is greater than 0.0, but smaller than any cases when S_{min} and B_{max} are not identical.

```
PriceRangeSim ([B_pref, B_max], [S_min, S_pref])
Begin
    If S_pref <= B_pref    similarity = 1.0
    else if B_max < S_min  similarity = 0.0
    else if  B_max = S_min
       similarity = 0.005 / (MAX - MIN)
    else
      {   MIN = min{MIN, S_min}
          MAX = max{MAX, B_max}
          similarity = (B_max - S_min) / (MAX - MIN)
      }
 End.
```

Fig. 10. Pseudo-code of the price-range similarity algorithm

Fig. 10 presents the pseudo-code of our price-range similarity algorithm based on the case studies above which can be embedded into other similarity algorithms.

3.2 Application of the Range Similarity Measure in Other Domains

There are some other product/service attributes such as salary, date, age etc., which can be represented as ranges as well. Our price-range similarity measure can be easily adapted to these attributes.

Here, as an example, we present how to adapt our price-range similarity measure to the attribute "salary range". In a common e-marketplace for job seeking and recruiting, buyers and sellers can be treated as job seekers and employers, respectively. Unlike the price ranges described above, job seekers (buyers) can specify their preferred and minimum salaries and employers (sellers) can offer their preferred and maximum salaries. So, the buyer and the seller price ranges [B_{pref}, B_{max}] and [S_{min}, S_{pref}] discussed in previous sections can be changed into [B_{min}, B_{pref}] and [S_{pref}, S_{max}] for salary-range similarity measure. We can denote the similarity of salary ranges as Sim_{salary}. There are also seven cases that are symmetric to those described in subsection 3.1. For the first case, Sim_{salary} is defined as 1.0 when $B_{pref} \leqslant S_{pref}$. For case 2 to 6, equation (2) can be easily changed for salary-range similarity as below (equation (7)).

$$Sim_{salary} = \frac{S_{max} - B_{min}}{\mathrm{MAX} - \mathrm{MIN}} \tag{7}$$

MAX and MIN can also be changed at different situations in symmetric ways described as in subsection 3.1. For the special case (case 7), equation (6) can be used without any change. Thus, as a whole we can say that more range similarity measures on various product/service attributes can be developed based on our proposed price range similarity measures.

4 Analysis of Algorithm with Examples

In this section, we present the analysis of our price-range similarity algorithm with examples.

As described in Section 3, when the seller's preferred price is less than or equal to the buyer's preferred price, both of them are satisfied with the similarity value 1.0. They even do not need to negotiate for their successful transaction. However, when the seller's preferred price is greater than the buyer's preferred price and also the seller's minimum price is greater than the buyer's maximum price, then there is no overlap between their price ranges and a zero similarity value is defined. In this case, there is no negotiation space for the buyer and the seller.

However, buyers and sellers can have overlaps after their concession. Although they cannot be satisfied simultaneously, they might be willing to negotiate in the future. Therefore, the difference between a buyer's maximum price and a seller's minimum price is decisive to their price-range similarity which is computed by equation (2).

For a given buyer, to buy a specific product, the value of the buyer's maximum price (B_{max}) is fixed (say, $60). If we assume the values of MAX and MIN in the e-marketplace are $90 and $20 respectively, the similarity values of this buyer and other sellers are decided by the sellers' minimum prices (S_{min}). Symmetrically, for a given seller, to sell a specific product with minimum price S_{min} (say, $45), buyers' maximum prices (B_{max}) are crucial to their similarity values with the seller. Therefore, for a given buyer and a seller mentioned above, equation (2) is changed into equation (8) and (9) respectively.

$$Sim_{price} = \frac{60 - S_{min}}{90 - 20} \tag{8}$$

$$Sim_{price} = \frac{B_{max} - 45}{90 - 20} \tag{9}$$

According to equation (8) and (9), for a buyer or a seller in a given e-marketplace, his/her similarity values with other sellers or buyers should be linearly distributed.

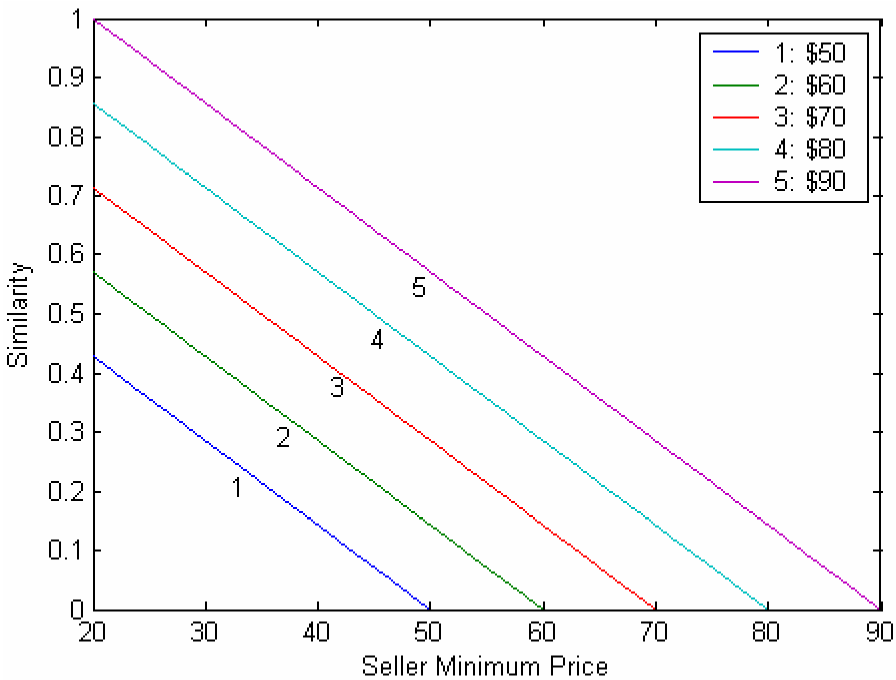

Fig. 11. Price-range similarity for given buyers

Fig. 11 shows the similarity values of several given buyers with other sellers in an e-marketplace. We plot the relationship between seller minimum prices and similarity values for each buyer. Seller minimum prices range from \$20 to \$90. Each buyer's maximum price is shown in the legend. Plot 2 represents equation (8). Other plots (1, 3, 4 and 5) correspond to buyers with maximum prices (\$50, \$70, \$80 and \$90). We see that for each buyer, his/her similarity values with sellers decrease when sellers' minimum prices increase because their overlaps decrease. One extreme case is curve 5. When the buyer's maximum price is \$90 (identical to MAX), the seller whose minimum price is \$20 (identical to MIN) has similarity value 1.0. The reason is that, in order to make the transaction successful, the buyer and the seller would like to concede to the maximum (MAX) and minimum (MIN) prices of the e-marketplace, respectively.

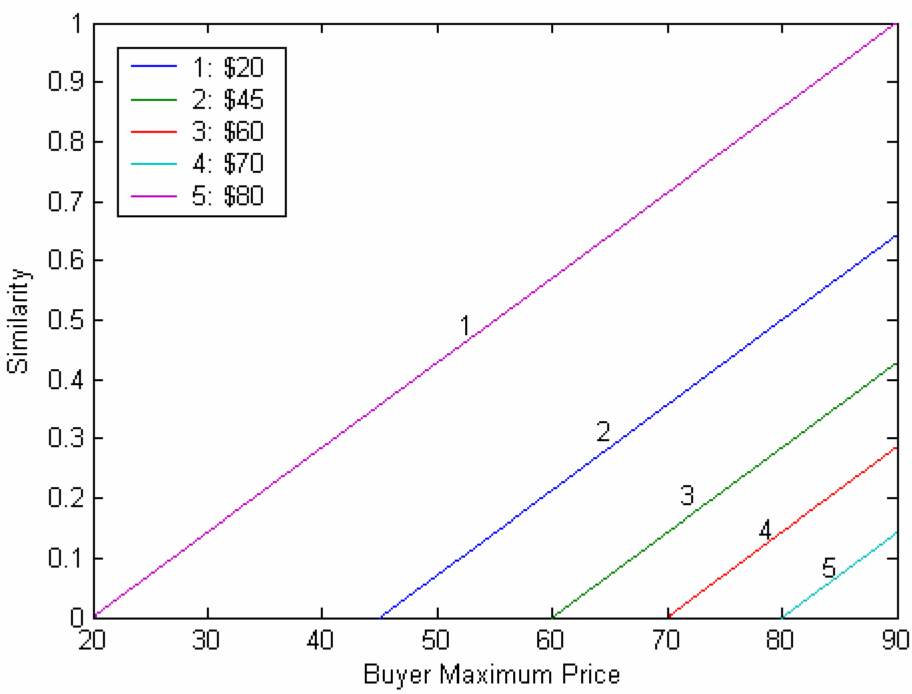

Fig. 12. Price-range similarity for given sellers

We also plot the trend of the similarity variation for given sellers in Fig. 12. Similarly, we show the relationship of the similarity values and the buyers' maximum prices for 5 given sellers. The minimum prices of these sellers are shown in the legend. Equation (9) corresponds to plot 2. Plots 1, 3, 4 and 5 represent sellers having minimum prices \$20, \$60, \$70 and \$80. It is intuitive that the bigger the buyer maximum price, the bigger his/her overlap with a seller's minimum price. Therefore, for a given seller, his/her similarity values increase when the buyers' maximum prices increase. One extreme case in plot 1 is when the seller's minimum price equals to \$20, the minimum price (MIN) in the e-marketplace. The buyers with maximum price \$90 (MAX) also have similarity value 1.0 with this seller for the similar reason explained in the previous paragraph.

5 Conclusion

Price is a decisive product attribute for buyer-seller matching in e-marketplaces. Furthermore, prices in buyers' and sellers' minds might often range so as to concede to some extent. In this paper, we have proposed a price-range similarity measure for buyers and sellers. This price-range similarity measure can be used independently if the price comparison is the only target or can be embedded into other algorithms to obtain similarity values combining with other product attributes.

In our approach, we allow the buyer and the seller to specify their preferred prices so that both buyer and seller are satisfied when their preferred prices overlap. Buyer and seller can also respectively provide their maximum and minimum prices for the purpose of finding more promising sellers and buyers. Thus, we use price ranges $[B_{pref}, B_{max}]$ and $[S_{min}, S_{pref}]$ for the buyer and seller, respectively. Our price-range similarity measure computes buyers' and sellers' price-range similarities based on the semantics of their overlaps. The bigger the overlaps, the more similar their price ranges and the more successful their transactions. This is justified by the analysis and examples.

We show that our price-range similarity measure can be adapted to other product attributes with "range" characteristics, for example, salary, tuition, date and so on. Therefore, our future work will focus on providing more case studies on similarity measures of these and other real-life product/service attributes.

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