The importance of Diversity in Profile-based recommendations: A Case Study in Tourism

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ABSTRACT
The paper explores the concept of similarity between two users measured in user profile space rather than the traditional rating space. The study aims at discovering the most relevant user profiles in order to provide recommendations to any given target profile. Closer profiles were found to be the most accurate in terms of prediction error. However, the best results were obtained when including profiles far away from the target one. This striking result is explained in light of the diversity prediction theorem.

Keywords
User profile, Diversity Prediction Theorem, tourism, gastronomy.

1. INTRODUCTION
A search on a tourism website typically involves a user filling a form to choose the item of interest (hotel, travel package and so on) as well as the relevant dates of the trip. The response usually includes prices and availability of those items fulfilling the request, which actually assists the consumer to make an informed decision. In the Tourism 2.0 era, the decision-making process has been further facilitated by means of specialized websites that include additional feedback provided by travelers who previously experienced the evaluated item. This feedback comes under different flavors (reviews, ratings and comments) and serves to further clarify the quality of services or to uncover issues or problematic situations. However, the relevancy of this additional experience-based information is not the same for all future users. Recently, some advanced websites started to pave the way for personalization services by classifying user feedback on the basis of user profiles, like Families, Couples and Business profiles. The motivation for this move comes from the fact that a touristic product could be a wonderful experience for, let's say, a Family, but not appropriate for a Couple. The perceived trend is to increase the tourist satisfaction by providing better personalization services on the basis of relevant consumer attributes, both personal and contextual [1].

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A number of Recommender strategies based on consumer attributes have been proposed in the literature. They can be classified according the scheme followed to generate the predictions: (1) probabilistic predictors, and (2) rule predictors. Among the first ones, an algorithm proposed by Ono et al. (2007) uses contextual information including user, item and context attributes, to recommend movies. The interaction scenario is modeled by: (1) a set of user profile attributes (U), with attributes like age and sex, (2) a set of context attributes (S), with attributes like mood and location, (3) a set of item attributes (C) with attributes like film genre and director, (4) a set of film ratings enhanced with contextual information. Their approach applies Bayesian networks to obtain the probability $P(V|u, s, c)$ of a rating for the target user $U = u$, specific context $S = s$ and candidate movie $C = c$. The Bayesian paradigm is also used in another recommender system but pointing out a difference between a fixed profile stated by the user, and an adaptive profile that is built dynamically based on user activity [3]. A naive Bayes network was also applied to generate recommendations adapted to contexts that were previously predicted by means of behavioral pattern analysis [4]. In the field of tourism, Costa et al. (2012) propose a probabilistic classifier and an agent-based approach in which a set of user attributes, a user context attributes and some item context attributes are defined: the restaurant category, the price, the schedule, the kind of day, the distance, the timeOfDay, the day of the week and the goal of the user interaction. The recommendations are conditioned by the users goal on any given moment. Among the second ones, a restaurant recommender system made up with a set of semantic rules was proposed by Vargas et al. (2011). The rules depend on user properties and context information. The key aspect of this work is the selection of the most relevant context attributes among an original set of 23 restaurant attributes, 21 user attributes and 2 environmental attributes.

In this paper we aim at exploring the value added by user attributes under the traditional k-Nearest Neighbors (k-NN)

Figure 1: TapasPassport of Santiago(é)Tapas contest. The official information of the contest, including the set of available tapas as well as the location of the restaurants, was published in the TapasPassport.

scheme [7, 8]. User attributes are used to characterize user profiles, and then k-NN predictors can work with a similarity measure built on top of a user profile space rather than a rating space. In what follows, we present the hypothesis underlying the research work, the experiment carried out to test the hypothesis, the exploratory analysis that provided the key findings to develop the profile-based algorithms, the evaluation of those algorithms, and finally, the application of the diversity prediction theorem to understand an striking result obtained with our algorithms.

2. HYPOTHESIS

The line of thought behind this work is that k-Nearest Neighbors predictors in the user profile space, i.e user attribute space, should have to work better than in rating space. The rationale is that the similarity metrics behind the traditional user-based approach, a k-NN predictor in rating space, is not really measuring the similarity in tastes between two users. In other words, the fact that two users present the same set of ratings on a number of items does not mean that the two share the same tastes on those items. A coincidence on ratings does not imply a coincidence on tastes. Ratings measure satisfaction, an outcome of the experience process, while tastes measure preference on the attribute space of a choice set. In short, we believe that the probability of two users having similar tastes is higher when the two are closer in profile space rather than in Rating space.

3. EXPERIMENTAL DESIGN

3.1 Santiago(é)Tapas contest

In the context of the RECTUR project, an experiment was carried out with real users in the context of Santiago(é)Tapas, a gastronomic contest that takes place every year in Santiago de Compostela. In 2011 the fourth edition was held with a total of 56 participating restaurants proposing and elaborating up to three tapas that were sold at a price of 2 euro. The experiment was designed to gather relevant data while preserving the spirit of the contest. Participants were local users as well as Spanish and international tourists. A TapasPassport with the official information about the contest was made available to all participants (Fig. 1). It contained: (i) the contest guidelines and other related information to the participants, (ii) restaurants location, (iii) the tapas offered on each restaurant, (iv) an official seal to demonstrate that a participant has visited the minimum number of restaurants required to obtain contestś gifts. Restaurant staff had to sign the TapasPassport to certify that its owners have visited the place.

After consuming a tapa, participants were asked to evaluate their experience by covering the vote shown in Fig. 2. Users had to provide two ratings ranging from 0 to 5: (i) a rating of the tapa, and (ii) a rating of the overall experience (service, place atmosphere, etc.). In addition, they were informed about our research experiment and asked to extend their feedback providing information about the temporal and social context in which the experience took place.

3.2 RECTUR Dataset

The data gathered in the experiment was collected in the RECTUR dataset. It is assumed that the choice of a tapa

Figure 2: Santiago(e)Tapas Vote. The participants had to fill the Tapa Votes with both the tapa and the overall experience rating.

depends on the user preferences about the levels of tapa attributes, which will in turn depend on the user attributes and context elements. The consumption of a tapa on a given moment determines an *Interaction* of a *User* with a *Tapa* that will elicit a satisfaction response quantified as a user *Rating*. Table 1 shows some relevant figures of the experiment.

In order to avoid the overload of contest participants with a large list of feedback questions, only a set of attributes of the full research model has been included in the evaluation process. These attributes were selected with the help of experts in the field of gastronomy. Figure 2 shows the tapa vote that was finally designed to gather the experience of the user after a tapa consumption (user-tapa interaction).

For each tapa, we gathered the following attributes:

- Type: Meat, Fish, Vegetables, etc. The main ingredient defined the type of the tapa.
- Character: Traditional or Daring. Traditional tapas are those that follow popular well-known recipes, while daring tapas are creative and provide innovative recipes.
- Restaurant. The restaurant that offers the tapa was also categorized in terms of its location, atmosphere and style.
- Average Rating. The average of ratings provided by consumers.

The consumers, in turn, were characterized with the following attributes:

- Origin: There will be differences between local, Spanish and foreign users as the first ones have a deeper knowledge of both restaurants and gastronomy.
- Character: Users are classified either as daring or as traditional based on the tapas they have consumed. A group of experts grouped the tapas offered in the contest in two groups, traditional and daring. Experts considered several attributes like tapa ingredients or tapa presentation in order to classify them.
- Experience: User domain knowledge will increase owing to the consumption of new tapas. Due to this, it was assumed that user ratings accuracy will increase with the experience she has.

At each tapa consumption, the user had a user context that was described as follows:

- Social context defined by the user company
- Temporal context defined by the time frame when she consumes the tapa, the hour, the day, the kind of day (work day or holiday)
- Climatological context defined by weather conditions
- Location context defined by the position of the user when she decides to start a tapa consumption.

Table 1: Experiment Info

Participating restaurants	56
Different tapas offered	109
Tapas consumed	35.000

Table 2: Attributes and Levels of User Profiles

Attributes	Levels
Character	Traditional, Daring
Origin	Local, Spanish, Foreign
Experience	Low, Medium, High

4. EXPLORATORY ANALYSIS

4.1 Methods

Exploratory data analysis was developed by John Tukey in the field of Statistics to encourage researchers to explore the data in some informal way in order to discover patterns or relationships between different variables [9]. The idea behind this approach is to generate hypothesis that could lead to further experiments and/or specific confirmatory analysis.

We found this strategy suitable to explore our idea about the usefulness of user profile information to generate better recommendations. On the basis of the available user attributes and attribute levels (see Table 2 for details), 18 profiles were identified and every user of the Rectur Dataset were categorized on each one of those profiles. Thereafter, a number of target users as well as their collection of tapa ratings was chosen. For each tapa rating, a prediction was generated by averaging just the ratings of those users in profile k (k ranging from 1 to 18)). The Mean Absolute Error (MAE) was used to test the accuracy of the prediction according to each profile k. MAE is estimated by comparison of the prediction with the real rating value in the following way:

$$MAE = \frac{1}{n_k} \sum_{i=1}^{n_k} |\hat{r}_i - r_i| \tag{1}$$

where n_k is the number of users in profile k, $\hat{r}_i$ is the predicted rating, and r_i is the real rating provided by the target user.

4.2 Results

The results of the exploratory analysis are shown in table 3. For brevity, only five target user profiles are presented. For each target profile, the best as well as the worst predictor in terms of MAE are presented. From this sample it can be observed that the best predictors correspond to those that are closer to the target profile according to their attribute values. There seems to be a correlation between the accuracy of the prediction and the similarity between profiles in the user attribute space. This finding motivated the development and evaluation of profile-based algorithms.

5. PROFILE-BASED ALGORITHM

5.1 Methods

The similarity between user profiles is determined by means of a distance measure in the user profile space. The contribution of each rating to the final prediction is weighted using this profile similarity among the active user and the target user instead of the traditional rating similarity between users.

Table 3: Exploratory Analysis: MAE per user profile. Abbreviations stand for: DAR (Daring), TRA (Traditional, FOR (Foreign), SPA (Spanish), MED (Medium).

Target	Predictor	MAE
DAR,FOR,HIGH	Best: DAR,FOR,HIGH	0,50
	Worst: TRA,FOR,LOW	1,21
DAR,SPA,MED	Best: DAR,SPA,MED	0,00
	Worst: DAR,FOR,HIGH	1,50
TRA,FOR,HIGH	Best: DAR,FOR,HIGH	0,67
	Worst: DAR,SPA,MED	1,50
TRA,FOR,MED	Best: DAR,FOR,MED	0,50
	Worst: TRA,SPA,HIGH	1,66
TRA,SPA,MED	Best: TRA,SPA,HIGH	0,33
	Worst: TRA,FOR,MED	1,25

A metric of profile distance has been defined on the basis of the distances between profile attributes, which are shown in Tables 4, 5 and 6. To compute the profile distance between a user with profile i and a user with profile j, the following equation was used:

$$d_{i,j} = \sum_{a \in A} d^a_{i,j} \tag{2}$$

where A is the set of attributes and $d^a_{i,j}$ are the distances between profiles i and j regarding to attribute a . Finally, the similarity between profiles is calculated as follows:

$$s_{i,j} = \frac{1}{1 + d_{i,j}} \tag{3}$$

where $d_{i,j}$ the distance between profile i and j. When $d_{i,j} = 0$, the similarity $s_{i,j} = 1$, the maximum value. Similarity then decreases as long as the distance between profiles increases.

The prediction was estimated in two different ways: (1) basic weighted average of neighboring users ratings (equation 4) , and (2) compensated weighted average of neighboring users ratings (equation 5) [10]. The equations for both schemes are:

$$\hat{r}_{j,k,l} = \frac{\sum_{i \in profile_k} s_{j,i} \times r_{i,k,l}}{\sum_{i \in profile_k} s_{j,i}} \tag{4}$$

Table 4: Distances between Character values.

u_k/u_l	Daring	Traditional
Daring	0.0	1.0
Traditional	1.0	0.0

Table 5: Distances between Origin values.

u_k/u_l	Local	Spanish	Foreign
Local	0.0	1.0	2.0
Spanish	1.0	0.0	1.0
Foreign	2.0	1.0	1.0

$$\hat{r}_{j,k,l} = \overline{r_l} + \frac{\sum_{i \in profile_k} s_{j,i} \times (r_{i,k,l} - \overline{r_i})}{\sum_{i \in profile_k} s_{j,i}} \quad (5)$$

where $\hat{r}_{j,k,l}$ is the predicted rating for user j in profile k for item l, $s_{j,i}$ the similarity computed under equation 3, $r_{i,k,l}$ the rating of user i of profile k on item l, and $\overline{r_i}$ the average of ratings of user i.

5.2 Results

The first analysis was focused on estimating the MAE for predictors based on all user profiles at the same distance $d_{i,j}$ from target user i. Results with increasing distances from the target user are shown in table 7 and plotted in figure 3. It is observed that lower MAEs correspond to closer distances, i.e. higher similarities according to equation 2. The error increases with distance until reaching its maximum value. These results confirm the exploratory analysis performed in the previous section. However, the traditional user-based algorithm still outperforms the best profile-based predictor, the one with user profile at distance $d = 1$ (see Table 10).

The second analysis was aimed at analyzing the impact of aggregating the users at different distance profiles. In short, we have generated the predictions at distance d with all users in profiles with distances lower or equal to d. The results of such aggregation profile scheme is shown in Table 8. A striking pattern is found here, as the MAE decreases when increasing the profile distance. This behavior was confirmed under the compensated weighting prediction of equation 5 (results in Table 9). However, the consequence of this outcome is that Profile-based algorithms with aggregation and compensated weighting prediction could work slightly better than traditional user-based approaches (see Table 10).

The question now opened is how to explain the fact that aggregating lower accurate predictors, i.e. those with higher distance and independent higher MAE, results on a decrease in MAE. The next section is focused on answering this question.

6. DIVERSITY PREDICTION THEOREM

Lu Hong and Scott Page propose what they called Diversity Prediction Theorem which states that the squared error of a collective prediction equals the average squared error of individual predictions minus the predictive diversity [11]. This

Table 6: Distances between Experiences values.

u_k/u_l	Low	Medium	High
Low	0.0	1.0	2.0
Medium	1.0	0.0	2.0
High	2.0	1.0	0.0

Table 7: MAE Results for predictors based on user profiles with increasing distances: basic weighting prediction.

Distance	MAE	Average Predictors
0	0.87236	16.30981
1	0.86204	20.56839
2	0.86851	16.14271
3	0.93652	7.27814
4	1.02836	3.03665
5	1.03636	2.33515

Table 8: MAE Results for predictors based on aggregation of user profiles with increasing distances: basic weighting prediction.

Distance	MAE	Average Predictors
0	0.87236	16.30981
0+1	0.8424	35.9854
0+1+2	0.83232	51.86515
0+...+3	0.83149	58.70979
0+...+4	0.83132	60.21792
0+...+5	0.83112	60.59597

Table 9: MAE Results for predictors based on aggregation of user profiles with increasing distances: compensated weighting prediction.

Distance	MAE	Average Predictors
0	0.7981	16.30981
0+1	0.78246	35.9854
0+1+2	0.77478	51.86515
0+...+3	0.77316	58.70979
0+...+4	0.77296	60.21792
0+...+5	0.77288	60.59597

Table 10: Comparison between profile-based and user-based algorithms.

Algorithm	MAE
Profile-based (Best predictor at d=1)	0.86
Profile-based (Aggr. + Basic Weight)	0.83
Profile-based (Aggr. + Comp. Weight)	0.77
User-based(k=500,minxy=3,x=3)	0.78

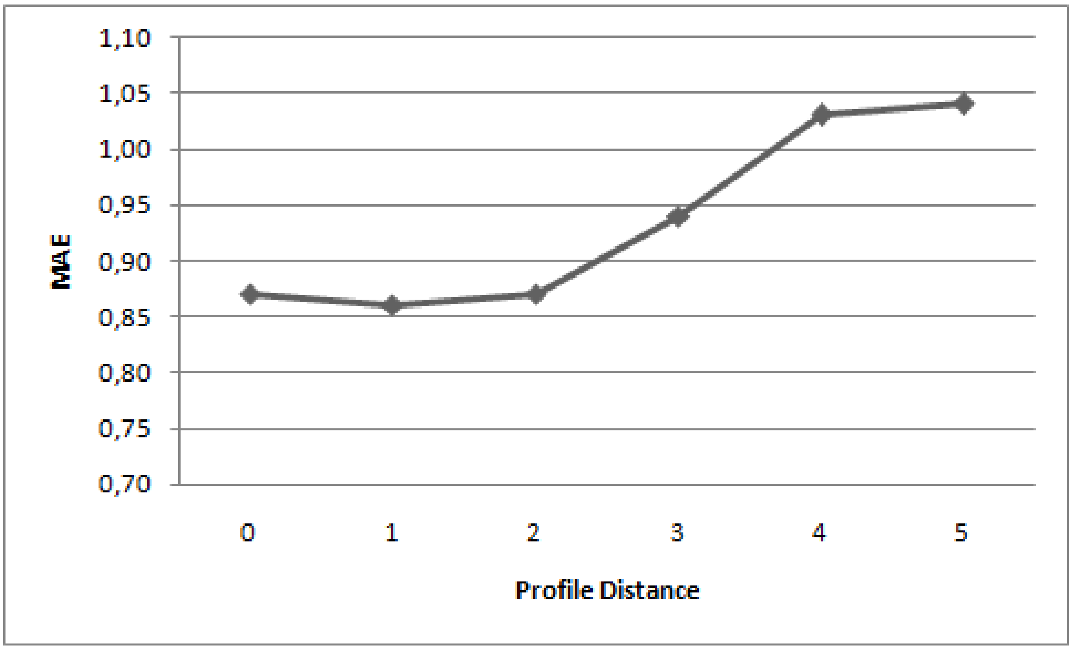

Figure 3: Plot of MAE for different profile distances.

theorem builds on a well know statistical principle, the bias-variance tradeoff, and its formulation is shown in Equation 6:

$$SqE(\bar{r}_{j,k,l}) = SqE(\hat{r}_{i,k,l}) - PDiv(\hat{r}_{i,k,l}) \tag{6}$$

where $\bar{r}_{j,k,l}$ is the global predicted value for user j on profile k for item l. It is calculated as the arithmetic mean of the individual predictions, as it is shown in Equation 7:

$$\bar{r}_{j,k,l} = \frac{1}{K \times n_k} \sum_{k=1}^{K} \sum_{i=1}^{n_k} \hat{r}_{i,k,l} \tag{7}$$

where K is the total number or user profiles, n_k the number of users with profile k, and $\hat{r}_{i,k,l}$ the individual prediction of user i.

$SqE(\bar{r}_{j,k,l})$ is the squared error of the global prediction. It is calculated as shown in Equation 8, being $r_{j,k,l}$ the true value.

$$SqE(\bar{r}_{j,k,l}) = (\bar{r}_{j,k,l} - r_{j,k,l})^2 \tag{8}$$

$SqE(\hat{r}_{i,k,l})$ is the squared error of the individual predictions used to compute the global prediction, the individual prediction being just the single rating generated by user i on profile k for item l. The error is calculated as shown in Equation 9:

$$SqE(\hat{r}_{i,k,l}) = \frac{1}{K \times n_k} \sum_{k=1}^{K} \sum_{i=1}^{n_k} (\hat{r}_{i,k,l} - r_{j,k,l})^2 \tag{9}$$

$PDiv(\hat{r}_{i,k,l})$ is the predictive diversity of the individual predictions used to compute the global prediction. It is calculated as shown in Equation 10

$$PDiv(\vec{s}) = \frac{1}{K \times n_k} \sum_{k=1}^{K} \sum_{i=1}^{n_k} (\hat{r}_{i,k,l} - \bar{r}_{j,k,l})^2 \tag{10}$$

The theorem states that the error of the collective prediction can be explained not only in terms of the error of the individual predictions, but also in terms of the diversity of the individual predictions. This is a possible explanation of the results shown in Tables 8 and 9. The aggregation of predictors that individually show higher MAEs could be balanced by the fact that the diversity of predictions increase in a higher rate. If this would happen in our case, the theorem could therefore explain our results.

6.1 Results

The application of the Diversity Prediction Theorem for predictors based on user profiles with increasing distances generated the results shown in Table 11. While the error values of $SqE(\bar{r}_{j,k,l})$ are different to MAE values of Table 7, a positive correlation with distances is also observed. However, the values of $SqE(\hat{r}_{i,k,l})$ and $PDiv(\hat{r}_{i,k,l})$ indicate that the reason behind the error increase is not because of the lower accuracy of the individual predictors at higher distances, but due to the poorer diversity of such predictors.

The unexpected results shown in tables 8 and 9 are explained

Table 11: Diversity Prediction Analysis for predictors based on user profiles with increasing distances: basic weighting prediction.

Distance	$SqE(\bar{r}_{j,k,l})$	$SqE(\hat{r}_{i,k,l})$	$PDiv(\hat{r}_{i,k,l})$
0	1.26678	2.14481	0.87803
1	1.19857	2.17998	0.98142
2	1.2202	2.19183	0.97163
3	1.48458	2.27204	0.78746
4	1.89438	2.24763	0.35325
5	1.85749	2.15699	0.2995

Table 12: Diversity Prediction Analysis for predictors based on aggregration of user profiles with increasing distances: basic weighting prediction.

Distance	$SqE(\bar{r}_{j,k,l})$	$SqE(\hat{r}_{i,k,l})$	$PDiv(\hat{r}_{i,k,l})$
0	1.26678	2.14481	0.87803
0+1	1.14378	2.15894	1.0139
0+1+2	1.10859	2.15455	1.04469
0+...+3	1.10515	2.16903	1.06132
0+...+4	1.10491	2.16971	1.0619
0+...+5	1.1046	2.16927	1.06234

in light of the application of the Diversity Prediction Theorem for predictors based on aggregation of user profiles. Table 12 show the results for increasing distances. It is clearly observed that error $SqE(\bar{r}_{j,k,l})$ decreases as the aggregation of user profiles increases with higher distances. This is explained by the values of $PDiv(\hat{r}_{i,k,l})$, which indicates that the diversity of predictors also increases with higher distances but at a higher rate than the errors of the individual predictors $SqE(\hat{r}_{i,k,l})$.

7. DISCUSSION

The first point to be discussed is the explanatory power of the Diversity Prediction Theorem. In order to test the aggregation effect in other algorithms, we applied the theorem to the traditional user-based algorithm. Table 13 illustrates how the error $SqE(\bar{r}_{j,k,l})$ again decreases as users with lower similarity to the target user are aggregated to the prediction equation. As in the case with our profile-based algorithms, this result can be explained by means of the increase of $PDiv(\hat{r}_{i,k,l})$.

The second point regards with our original hypothesis. The results show that profile-based algorithms only outperform traditional user-based algorithms when an aggregation scheme and a compensated weighting prediction are used. The aggregation works only when individual predictors with high prediction errors bring diversity to the pool of predictors. If this condition is satisfied, then the aggregation of such predictors could improve substantially the final prediction.

As a conclussion, profile-based algorithms can be particularly useful in the field of tourism in which users can show different profiles under different contexts. As future work we believe that preference learning, i.e. the discovery of user preferences associated to different user context, will be the key for improving predictions and generate better recommendations.

Table 13: Diversity Prediction Analysis for the User-Based Algorithm.

User Sim Th	$SqE(\bar{r}_{j,k,l})$	$SqE(\hat{r}_{i,k,l})$	$PDiv(\hat{r}_{i,k,l})$
1	1.19533	2.09803	0.9027
0.99	1.14034	2.08211	0.94185
0.98	1.11217	2.08478	0.972741
0.97	1.09727	2.08696	0.98983
0.96	1.09228	2.0948	1.00263
0.95	1.0924	2.10321	1.01078
0.94	1.09589	2.11771	1.02157
0.93	1.0983	2.12571	1.02696
0.92	1.09905	2.13274	1.03312
0.91	1.09871	2.13686	1.03751
0.90	1.10166	2.14358	1.04101
0.89	1.10268	2.14762	1.04392
0.88	1.10262	2.14945	1.04578
0.87	1.10197	2.1498	1.04681
0.86	1.10179	2.15093	1.04811
0.85	1.10062	2.15116	1.04958
0.84	1.10023	2.15226	1.0511
0.83	1.09975	2.15284	1.0522
0.82	1.10031	2.15422	1.0529
0.81	1.10057	2.15531	1.05368
0.80	1.10059	2.15545	1.05377
0.79	1.1007	2.15607	1.05425
0.78	1.10048	2.15584	1.05428
0.77	1.10067	2.15626	1.05446
0.76	1.1013	2.15743	1.05484
0.75	1.10089	2.15739	1.05531
0.74	1.10109	2.15806	1.05571
0.73	1.10103	2.15827	1.05598
0.72	1.10097	2.15818	1.05598
0.71	1.10078	2.15797	1.05602
0.70	1.10158	2.1592	1.05618
0.69	1.10138	2.15905	1.05629
0.68	1.10154	2.15928	1.0563
0.67	1.10168	2.15954	1.05635
0.66	1.10156	2.15957	1.05654
0.65	1.10158	2.15957	1.05652
0.64	1.10154	2.15958	1.05658
0.63	1.10165	2.15975	1.05659
0.62	1.1016	2.15955	1.05646
0.61	1.10154	2.15942	1.05641
0.60	1.10157	2.15972	1.05666

Acknowledgments

This research was sponsored by the Ministry of Science and Innovation of Spain under grant TIN2014-56633-C3-1-R as well as EMALCSA/Coruña Smart City under grant CSC-14-13.

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