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D3.2 Diversity-aware social relation learning

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Abstract	This deliverable describes the diversity-aware version of the Social Context Builder and presents the functionality of the three components that it consists of. These three components are the social relationships, the social preference and the social explanations component. The social relationships component monitors the interaction among users and specifies the tie strength of their relation. The social preference component aims to learn the preferences of a user and performs proper ranking of volunteers on a user's task. Finally, social explanations aim to provide personalized explanations for assisting the user in determining which among the volunteers for a task would be appropriate to be included into the task. The deliverable presents the diversity-aware functionality of the three components and illustrates various example case studies.
Keywords	social relations, social preferences, social explanations, tie strength, diversity awareness, diversity estimation, diversity evolution

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PU	Public, fully open, e.g. web	✔
CL	Classified, information as referred to in Commission Decision 2001/844/EC	
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** R: Document, report (excluding the periodic and final reports)*

DEM: Demonstrator, pilot, prototype, plan designs

DEC: Websites, patents filing, press & media actions, videos, etc.

OTHER: Software, technical diagram, etc.

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EXECUTIVE SUMMARY

The Social Context Builder module is responsible for maintaining the social part of the profile of the users by leveraging the data collected by the various streams connected through the WeNet platform. The Social context builder consists of three components that are the social relationships, the social preferences and the social explanations. The social relationships component aims to monitor the interactions among users and determine the tie strength of their relationships. The social preferences component is responsible for learning the preferences of a user and perform ranking of volunteers with respect to a specific task that the user creates. The social explanations component is responsible for providing arguments to the user about the acceptability of each volunteer.

A special aim of the Social Context Builder and the three components is to consider and take into account diversity. Diversity is acknowledged to be an aspect that does not exist within individuals, but can be considered between individuals when two or more individuals form a community or interact. This iteration round of the design of the Social Context Builder focuses on the integration of diversity into the functionality of the components. Accordingly, this deliverable presents the methodology to calculate diversity in the context of the components and also the way that the three components take into consideration diversity. In addition, the deliverable presents a Facebook application that was designed to solve the cold-start problem regarding the initialization of the social relationships of the users by utilizing users' Facebook accounts in a secure way and that complies with ethical and personal protection protocols. The deliverable also includes various case studies that demonstrate the workflow of the interaction with the components in example scenarios while encompassing issues of privacy and diversity.

The Social Context Builder will keep being extended and refined through the lifetime of the project, guided by the data that will be collected through the use of the WeNet platform in the next pilot studies. For this round of iteration, we have focused on the development of the diversity-awareness of the three components in a manner that accounts for their future refinement, based on the following WeNet pilot studies and the meaningful data that will be gathered.

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ABBREVIATIONS

SCB	Social Context Builder
DoA	Day of Arrival
WP	Work-package
KB	Knowledge Base

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1. INTRODUCTION

The WeNet project will create a sociotechnical platform that allows people to connect through a machine-mediated process, and complete everyday tasks while respecting their individual differences, and embodying fundamental features of transparency and privacy.

A part of the WeNet platform is the design and the development of the Social Context Builder module that maintains the social part of the profile of the users. The Social Context Builder consists of three components that are the social relationships, the social preferences and the social explanations. The social relationships component aims to monitor the interactions among users and determine the tie strength of their relationships. The social Preferences component is responsible for learning the preferences of a user and perform ranking of volunteers with respect to a specific task that the user creates. The Social Explanations component is responsible for providing arguments to the user about the acceptability of each volunteer.

A special aim of the Social Context Builder is to consider and take into account diversity. Diversity is an aspect that does not exist within individuals, but can be considered between individuals when two or more individuals form a community or interact. This means that we can recognize diversity only when we compare two or more people and, therefore, when we move at the level of a group or a community. With that consideration in mind, in this iteration round of design of the Social Context Builder, we have focused on the integration of diversity into the functionality of the components. Accordingly, this deliverable presents the methodology and the metrics to assess diversity in the context of the components and also the way that three components take into consideration diversity.

The deliverable also presents a Facebook Application that was designed to utilize prior information with an aim to solve the cold-start problem regarding the initialization of the social relationships of the users. It addresses the need for a user's social profile to be initiated in some meaningful manner from the moment that a user joins the WeNet platform, even before having access to WeNet interaction data, so that it can immediately be utilized to provide the user with meaningful suggestion and to enhance the user's WeNet experience.

The deliverable presents various case studies that illustrate the functionality of the methods in different scenarios and contexts. The social context builder will be constantly extended throughout the lifetime of the project, following an agile methodology. The main task, whose progress is reported in the current deliverable, aims to develop diversity-aware functionalities, prior to having a direct use and evaluation on the data collected during next pilot studies via the WeNet platform. After such data are gathered, the components will be expanded and further refined for the last iteration of its design and development, to be used with the final version of the platform.

Based on these requirements, we have integrated diversity into the functionality of the three components. The remainder of this deliverable presents the design and development of algorithms for each of those components of the Social Context Builder. Accounting for the fact that WeNet piloting studies will follow in M35 and interaction data will be available, we have accordingly focused our case studies to illustrate the functionality of the methods developed and the added value of our components for the users and the WeNet ecosystem. At the same time, our solutions were developed in a manner that supports the refinement of the social profile of the user after their joining the platform, and as soon interaction data with other users are available.

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The document consists of 7 chapters. Chapter 2 briefly presents the diversity-aware social context builder and analyses its main diversity-aware functionalities with respect to the components for social relationships, social preferences, and social explanations. Chapter 3 presents the methodology for the tie strength specification of the users' social relationships, the specification of diversity among users and the analysis of the behavior of users' relationships in terms of diversity. Chapter 4 presents the methodology for the social preferences of the volunteers with respect to a task that a user set and how diversity is taken into account. Chapter 5 presents the methodology for providing explanations to the user about the selection of each volunteer and the way of capturing diversity with machine coaching. Following the description of the three components, Chapter 6 describes case studies that illustrate the workflow and the functionality of the components. Chapter 7 concludes the deliverable and outlines the next steps towards deliverable D3.3.

2. DIVERSITY-AWARE SOCIAL CONTEXT BUILDER

The Social Context Builder is responsible for building and maintaining the social details of a user profile, by leveraging the data collected by the various streams connected through the WeNet Commons APIs and by analyzing them. The Social Context of a user is represented as in the standard way of major social networks. There, a user follows some other users ("friends"), which can be either individual, or groups. Similarly, the user is followed back by other users. Thus, the Social Context is represented as a directed graph between users, which is the standard practice in social network analysis [1] . The most important factor for us is being able to access the strength of a relationship. This is captured by the notion of "tie strength" [2] . Social relations are characterized as strong or weak ties, where strong ties indicate close relationships, and weak ties simpler acquaintances. Tie strength is dependent on various variables, such as time spent together, intimacy, reciprocal services, and others. An important study of these in the context of social networks can be found in [3] , where the authors attempt to measure those variables from Facebook data, and then access their predictive power for tie strength.

Tie strength plays a significant role in determining the trust level of a social relationship, and thus the likelihood of that relationship to be used to disseminate information and to provide assistance with respect to some task [13] .

To summarize, the main functionalities of the components are the following:

i) Specification of the tie strength of the social relationships of the users.
ii) Monitor the actions of a user and learn social preferences. Provide proper ranking procedures of volunteers with regards to a task that a user created.
iii) Provision of the social explanations about the inclusion of volunteers. Such information is meant for both the task creator and for the identified volunteers as it allows the motivation and explains the reasons why a match was identified.

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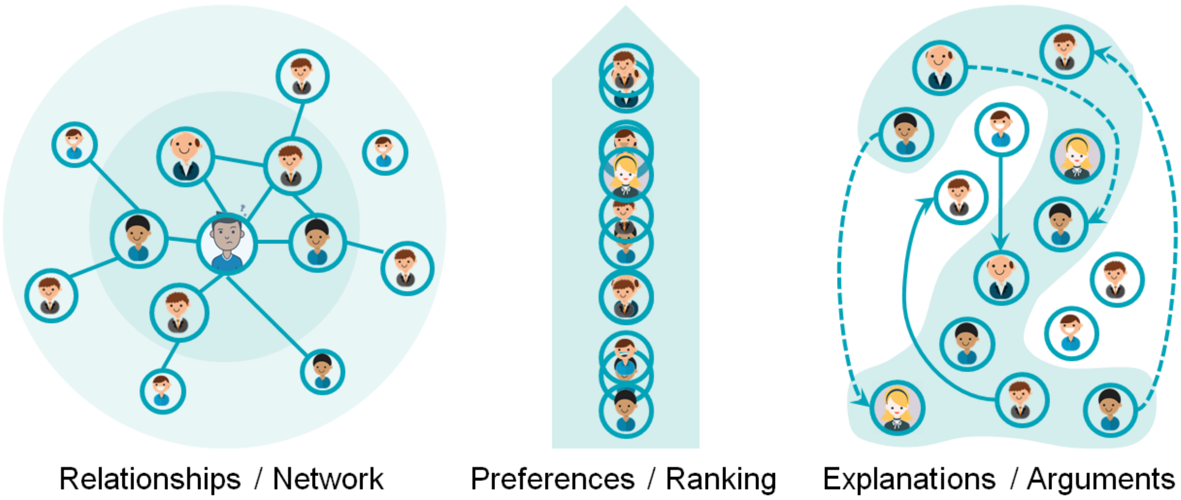

Figure 1: Illustration of social learning processes and representations

The Social relationships component aims to specify the social network of the user and the tie strength of the relationships with other users. This piece of information provides indicative and meaningful information for a user and will be taken into account by the procedures of WP5 for the identification of the volunteers for a task initiated by a requestor user as well as in the social preference component in the ranking procedure. After the formulation of the list of the volunteers by WP5, the list is returned to the Social Context Builder for further analysis. Initially, the Social Preferences component takes as input the list of volunteers that was formulated by WP5, and analyzes the social and personal data of the volunteers (to the extent these are available), the characteristics of the task and performs a personalized ranking of the volunteers. Finally, the Social Explanation component further analyzes the list of the volunteers and aims at providing arguments to the requestor about the acceptability of each volunteer with relation to the task at hand. The explanation is performed via a knowledge-based methodology that relies on rules to provide explanations and the reasons about the acceptance of a given volunteer for the user's task.

This round of design and implementation that is reported in this deliverable is dedicated to the integration of diversity into the three basic components. The design and the fine-tuning of the components will be an ongoing procedure and they will be constantly expanded with the availability of social interaction data from the next WeNet pilots, so that the resulting implementations can be fine-tuned, trained and tested on real WeNet data.

2.1 Diversity Calculation Metrics

Entropy is a widely used measure of diversity and measures the amount to which a (usually finite) set of entities is *unpredictable* where by unpredictable we mean that it is as hard as possible to guess what a randomly chosen entity from that set will be. To begin with, let X be a categorical variable with a finite domain $dom(X) = \{x_1, x_2, \dots, x_n\}$. Assume now that we have at our disposal a sample $S = \{s_1, s_2, \dots, s_k\}$ of values of X. In order to measure diversity, one may use the so-called *Shannon Entropy,* $E(S)$, defined as follows:

$$E(S) \coloneqq -\sum_{i=1}^{n} p_i \ln p_i = \ln \frac{1}{\prod_{i=1}^{n} p_i^{p_i}},$$

where $p_i = \frac{k_i}{k}$ denotes the relative frequency of the i −th value of X, x_i, in the given sample S. As the sample becomes more diversified, in the sense that it is more difficult to predict what the value of a randomly drawn instance from S will be, Shannon Entropy approaches it maximum value, $\ln n$, while as the result of such draws is more predictable, Shannon Entropy vanishes.

While the above are well defined for one dimensional categorical data, there might be a difficulty generalizing the above for multidimensional data. Below we shall present a way to do so. Consider a set $S = \{e_1, e_2, \dots, e_N\}$ of entities described by some categorical variables $X_1, X_2, \dots X_M$, which all have finite domains of cardinality $d_i, i = 1,2, \dots, M$. Let also $p_{i,k}$ denote the relative frequency with which the i −th value of X_k appears in S for $i = 1,2, \dots, d_k$ and $k = 1,2, \dots, M$. Then, one may define the diversity of S to be:

$$E(S) \coloneqq -\frac{1}{M} \sum_{k=1}^{M} \sum_{i=1}^{d_k} p_{i,k} \ln p_{i,k}.$$

The above is the mean of the entropies of all variables that appear in S.

A generalization of the above definition of “multidimensional” diversity could be the following one:

$$E_w(S) \coloneqq -\sum_{k=1}^{M} w_k \sum_{i=1}^{d_k} p_{i,k} \ln p_{i,k},$$

where $w_k, k = 1,2 \dots, M$ are non-negative weights such that $w_1 + w_2 + \cdots w_M = 1$. The intuition behind the above more general definition of multidimensional diversity is that in certain scenarios there might be attributes that are more important in measuring diversity than others. For instance, assuming that our entities are volunteers within a WeNet task – say, to organize a social dinner – it might be more important that our guests are diversified in terms of their preferred cuisines than in terms of the means of transportation they usually use. So, by introducing significance weights as above, one may control the importance of each of the available attributes and their contribution to the overall diversity score for the sample S.

Lastly, in case that X_k have domains of different cardinalities, which naturally affects the maximum values of their entropies, one might need to normalize all entropies to $[0,1]$ so the weighted multidimensional entropy becomes:

$$E_w(S) = -\sum_{k=1}^{M} \frac{w_k}{\ln d_k} \sum_{i=1}^{d_k} p_{i,k} \ln p_{i,k}.$$

Interestingly, one may also utilize entropy to measure diversity in cases where data are described by numerical values. Say, for instance that the domain of a variable X is the closed interval $dom(X) = [0,1]$. Then, one may split the variable’s domain into a finite number, let N, of classes, $C_i, i = 1,2, \dots, N$ – usually, of the same length – and calculate entropy as described above based on the relative frequency of each class C_i, let p_i, for $i = 1,2, \dots, N$. So, in a

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sample S of M values of a continuous numerical variable X, splitting $dom(X)$ into N classes, let C_i, and defining p_i as follows:

$$p_i := \frac{\#\{x \in S : x \in C_i\}}{M},$$

allows us to compute the diversity of S as follows:

$$E(S) = -\sum_{k=1}^{N} p_k \ln p_k.$$

The above is actually a discrete form of the definition of entropy for continuous variables:

$$E := -\int_{dom(X)} f(x) \ln f(x) dx,$$

where $f(x)$ is the probability density function of a continuous variable X determining its *probability distribution*[1]*.* Given that, evidently, the thinner the classes one chooses, the more accurate the resulting measurement of entropy is. Nevertheless, it is also important, when it comes to finite samples, for the classes to be semantically coherent.

3. SOCIAL RELATIONSHIPS

In this section, we present the way that tie strength is initiated by utilizing existing social information in Facebook, the way that it is constantly updated by using users interaction within WeNet and the way that social relationship diversity is specified and is utilized.

3.1 TIE STRENGTH SPECIFICATION

The Social Relationships component focuses on tie strength, that is the weight of friendship and measures the extent that user A is friend to user B. The weight of a friendship between two users is calculated based on the analysis of the interaction between them and includes, with certain weight of significance, main communication and interaction parameters. In determining the weight of a friendship, one must be aware that a friendship is not necessarily a reflexive relationship, so it is possible that user A considers user B a better friend than user A is considered a friend by user B. The goal is to recognize and estimate the weight of the relationship between users by analyzing their interactions and their accounts. The existing binary connection, which describes whether someone is connected (e.g. they are friends) with someone else or not (0 or 1), can become more detailed with a weight that represents the extent that someone is connected to someone else. Thus, we are building an implicit social network over an explicit social network. The formulated implicit social network is described with a directed weighted graph.

Tie strength is the main concept that measures the value which is placed by individuals on their relationships referring to the general sense of closeness with another individual [2] . In this context, social relationships are measured with the currency of the tie strength [3] . In

[1] Actually, the above discretization process is an approximation of the integral used to define continuous entropy by the corresponding *histogram* which is a maximum likelihood estimator of the probability distribution of X.

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this context, two types of ties are specified, strong ties and weak. In general, when the sense of closeness between two individuals is strong, a strong tie is defined and, in the same regard, when it is weak, a weak tie is defined [2] . Strong ties are considered to exist with people one trusts and their social circles highly overlap. Weak ties are mainly considered the acquaintances.

Measuring and predicting tie strength, and moreover, understanding the factors that drive tie strength, has been an expanding area of interest in social sciences, with increasing utility in the analysis of social networks [Mattie al., 2018]. Analyzing and predicting tie strength in social networks can lead to new insights into human social behavior and assist in designing novel user-centric services [Arnaboldi et al., 2013]. So, the analysis of the social relationships and the accurate specification of the tie strength is highly desired.

3.1.1 Dimensions of Interactions and Tie Strength

Tie strength constitutes a factor of high importance in the analysis of social networks and it is considered to be a complex factor that is hard to accurately estimate. The main reason for this is that tie strength is a multidimensional factor where different forms and levels of interaction need to be considered. Tie strength is highlighted to have many dimensions and different manifestations. Granovetter in his landmark paper on The Strength of ties specified four main dimensions for tie strength [2] . These dimensions are the time spent connecting and interacting with others, the emotional intimacy, the intensity and the reciprocal services. After that, three additional dimensions were proposed and the list of dimensions was extended with the proposal of the emotional support [20] the social distance and the structural topology of the social network [19] . Each dimension captures different elements of the social relationships.

The **time** dimension captures the duration and the frequency of the communication. In general, the more frequent and higher the interaction between a pair of individuals is, the stronger the sentiment of friendship and tie people feel. Strong tie is bound up with the constant and frequent communication and the amount of time can promote other dimensions too [18]

The **intensity** dimension represents the recognition of entities producing emotions that affect the cognition of others. It is relative to the absolute strength and individuals with highly intensive relationships are expected to spend more time with each other [22] .

The **Intimacy** concerns the affection between two individuals and acts as a sense of security and reliance. It is stated that intimacy relationships are willing to talk with open mind and demonstrate great support and recognition. It necessitates considerably more commitment and presumably a greater amount of positive affect between each other [23] .

The **reciprocal services** dimension represents the different forms of communication and the services utilized in interaction. An important parameter to develop a relationship is revenue that can be measured by the cost and the profit including energy, time emotion, and others. Social networks can reduce the cost of the social activities [18] . Strong ties can easily share the information and the resources they possess and also they can provide access to information circulating in their dense network. So, strong tie includes more reciprocity services in exchanges [2] .

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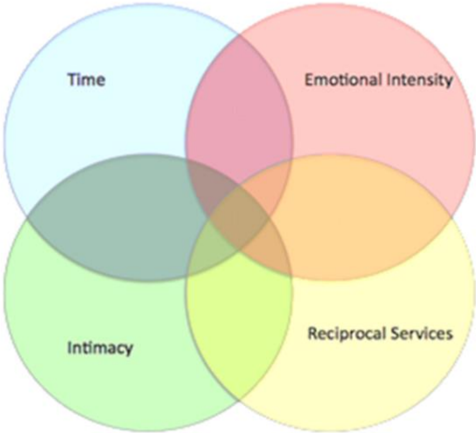

Figure 2: Overlap of the four main dimensions.

The **emotional support** dimension represents a tie on an emotional level and concerns cases of discussions and advice offering on personal and family problems, something that can indicate a strong tie between the users [3] . The dimension refers to providing messages that involve emotional content, re-assuring that the one is valuable and care about. Strong ties provide powerful emotional support that unites to face challenges and overcome crises.

The **structural dimension** represents factors such as the topology of the social network and social circles of the users in it [Xiang et al., 2010]. Strong ties and more likely to connect similar people and similar individuals tend and are more likely to cluster together. So, given that strong ties connect individual A to B and also to C, then it is very likely that C and B will develop a friendship once they meet [2] .

The **social distance** is also highlighted to influence tie strength and factors like gender, race, socioeconomic status, education and political views and affiliation and can affect the tie strength development between individuals. Research studies have indicated that strong ties are more common between individuals of the same age, interests and who share certain life activities [17]

3.1.2 Predictive Variables for Tie Strength

The dimensions have facilitated the definition and the quantification of possible factors and predictive variables of tie strength [15] . These variables derive from the social information in the networks that relate to the profiles of individuals as well as to the interaction with their peers and which will be used as predictors of tie strength between two individuals. Table 1 categorizes the predictive variables used in research works in the literature. The predictive variables are mapped into the seven dimensions of the tie strength. Given that different social networks provide their users with different means of interaction, some variables generalize to any network, while some other may be specific to a number of social networks. For example, photo tags variables and check-in denoting that individuals appear together in photos. User social profiles and interaction activities with their peers in a social network need to be analyzed in order to identify relative variables that can be quantified and be used in order to infer tie strength between individuals.

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Friendship is shown as a one-way connection from user A to user B, where user A is the ego-user, and user B is in the network friend of user A. The weight of friendship between user A and user B is not necessarily equal in both ways. The friendship weight is calculated based on a set of interaction parameters between the two users.

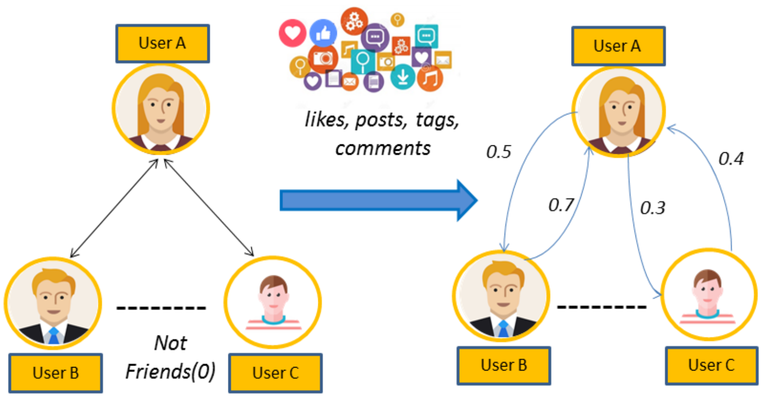

Figure 3: Weighted relationships and tie strength

In the dimensions of time, time since first communication measures the length of the connection while the time since last communication captures the recency. The frequency is a proxy for the volume of the interaction between two individuals.

In the dimension of intensity, exact communication aspects and messages are measured like the number of messages exchanged, the posts, comments, likes. The variables of this dimension rely heavily on the characteristics and the communication means of each social network.

In the intimacy dimension, intimacy words measure the topics of the messages exchanged while the relationship status captures specific types of relationships that may be denoted by the users such as married with each other, family members, etc. Common appearances in photos is another measurement of the intimacy counting photographs that the two individuals appear together and the common check-ins measures places that they have been together.

In the dimension of reciprocal services, common applications measure the services and the applications that both the user and the friend share. The same stands for the links exchanged where URLs passed between two users can be indicative of the reciprocal services both use.

In the dimension of structural topology, variables capture aspects of the network structure and the groups that the individuals belong to. So, the common groups variable measures the groups that the two individuals belong to, while the overlapping networks capture the social circles, organizations and networks like universities and companies that both individuals are members. Mutual friends can also indicate clues for tie strength and having mutual friends can foster relationship development [21] .

In the dimension of the emotional support, deep analysis of text messages and interaction of the individuals aims to specify emotional support indicators and predictive variables like positive emotional words and negative emotional words. Dictionaries and linguistic resources

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like LIWC can provide indicative information about the categories of the words and the context messages.

Dimension	Description
Time	Time since first communication Time since last communication Frequency of communication
Intensity	Communication aspects with friend Messages-comments exchanged Likes
Intimacy	Relationship status Appearances together in photos Common check-ins Intimacy words in the communication
Reciprocal Services	Common applications Links exchanged by wall posts
Structural Topology	Common groups Mutual friends
Emotional Support	Specification of emotional context and emotional words - positive and negative contexts
Social Distance	Age difference Occupation difference Education difference Language difference

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In the social distance dimension, variables measure the age difference, the education discipline and level of the individuals, the political view and the occupation status. The identity information of the profiles are used to measure the social distance of the individuals [17]

3.1.3 Initialization of Tie Strength with Facebook App

For the initialization of the tie strength prior information about the WeNet participants as found in their Facebook profiles, is utilized with the aim to face the cold-start problem when initializing their WeNet social contexts. In this regard, a web application was designed and developed that offers access to Facebook data in a secure way and also complies with ethical and personal protection protocols.

A web application has been formulated to facilitate the collection of information about users from their Facebook accounts. The user can access the app via a browser and login to their social profile. Initially the user is prompted to login to their WeNet profile account using their credentials. The social data are accessed on user's consent and the procedure is secure and complies with ethical and personal protection protocols.

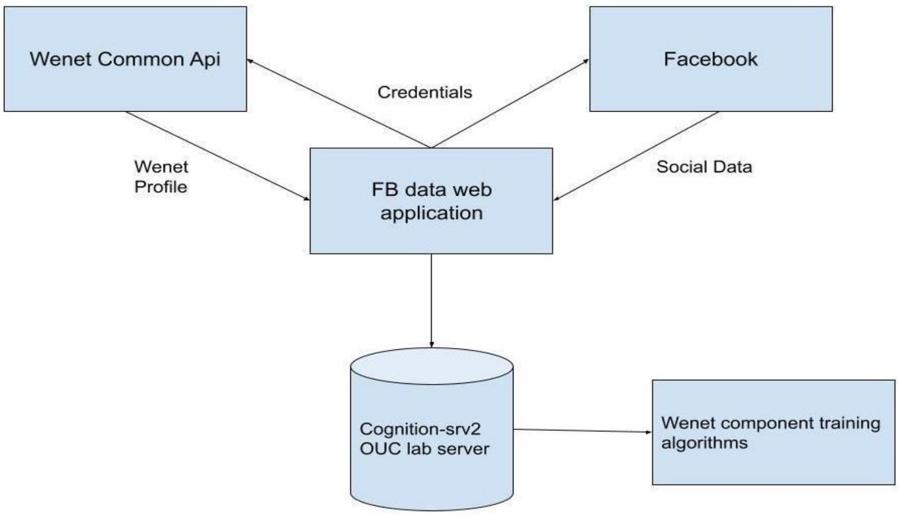

Figure 3. The overall architecture of the Facebook Application

For this interconnection to happen, we have created the OUC WeNet app ouc-social-dev. Using this app we can have access to WeNet from a third party application (Facebook data app). The WeNet profile of the user is retrieved and then they will be able to login to their Facebook profile. For the second interface to happen we use the OUC Facebook app wenet_test_1. The Facebook profile of the user is loaded along with their social data. What follows is saving a copy of this information to the lab server and also sending one to the WeNet platform. The role of the commons API is important here as it serves as an access point for the data to flow in the WeNet platform from an outside source. The data collected belong to the following categories:

Personal information

- Facebook ID
- email address

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- date of birth
- age range
- gender
- home town

Friends

- retrieval of the user's friend

First we can get all the information about the friends of the ego user, that is, who they are, and how many mutual friends there are.

Wall feed

- Posts and links published by the user and others on the profile wall.

These include the post message, date, who posted, whether it is check-in or includes others (possible personal contact), as well as number of reactions

The WeNet platform offers public access to their ecosystem through the WeNet Common API. This API is designed to be the access point from third party applications.

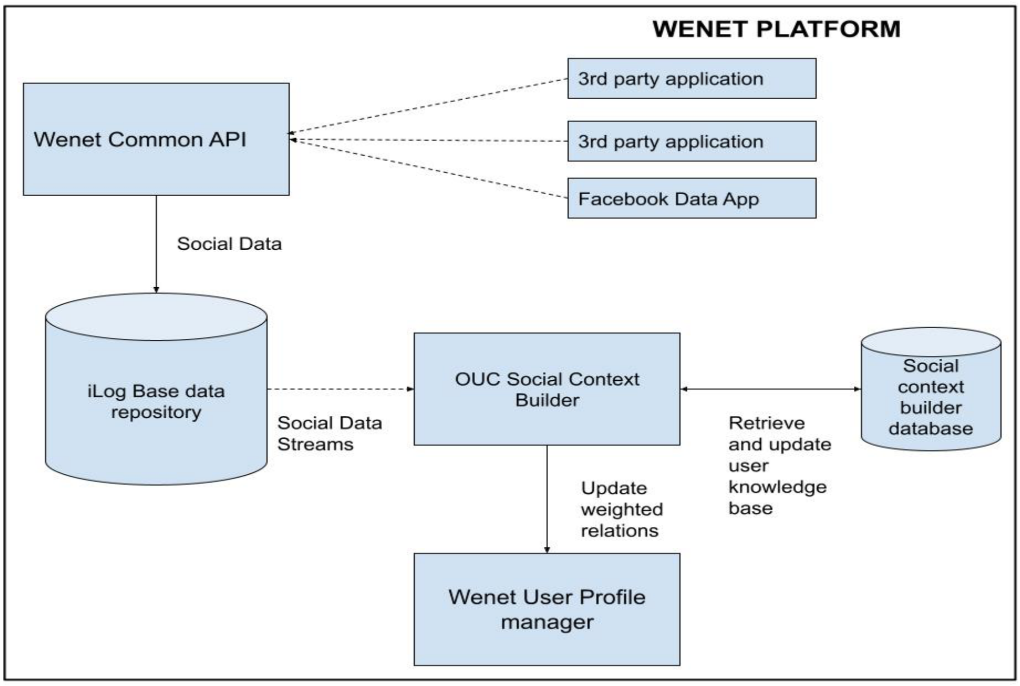

Figure 4. The flow of data within WeNet Platform

As part of the WeNet hub we have created our own WeNet app named ouc-social-dev. This app enables us to connect to the platform and either retrieve or inject data to WeNet.

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Figure 5. Interconnection between WeNet and Facebook

The Facebook data app uses ouc-social-dev to share the logged-in user data to WeNet, enabling to create the social relations of the platform's users. Facebook gives access to their rich API through their software development kit (SDK). For this purpose we created the Facebook OUC app *wenet_test_1.* Using this application we enable the user to login with their Facebook account by pressing a dedicated FB button. Additionally, wenet_test_1 provides access to the user's data in order to improve the user experience using our web application. The OUC app wenet_test_1 gives access to the fields of social profile information, friend list, social events and wall feed using the Facebook API V8.00

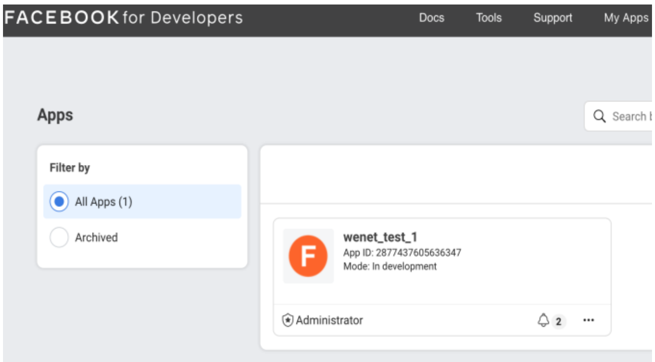


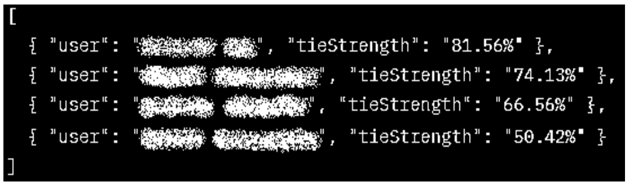
Figure 6:. The application on Facebook for Developers

After the collection of the data, the calculation of the tie strength between the users is made. The tie strength is modeled as a linear combination of the interaction parameters on the different dimensions between two users. We model a continuum instead of a discrete scale for tie strength according to Mark Granovetter who conjectured that tie strength is continuous and also because applications can round a continuous model's predictions to discrete levels (such as strong tie, weak tie and so on) as appropriate [3] .

$$s_i = a + \beta R_i + \varepsilon_i$$

where s_i represents the tie strength of the i^{th} friend of the user R_i represents the vector of the interaction variables and ε represents the error term.

For the purpose of the study, we created and utilized a synthetic dataset that consisted of 35 users and generated interactions between them as well as the annotated tie strength. A linear regression approach was implemented to model the tie strengths of the users. We analyzed the model and it fitted the data very well. The reported mean absolute error was 0.0982 on a continuous 0-1. So, on average the model is able to predict tie strength within almost one-tenth of its true value.



```
[
  { "user": "[redacted]", "tieStrength": "81.56%" },
  { "user": "[redacted]", "tieStrength": "74.13%" },
  { "user": "[redacted]", "tieStrength": "66.56%" },
  { "user": "[redacted]", "tieStrength": "50.42%" }
]
```


Figure 7. Example of calculated tie strength

3.1.4 Update of Tie Strength with interaction within WeNet

The interaction and the metrics to update the friendship weight of the users based on their interaction in WeNet platform are specified. The main types of interaction of the users in the context of a task are the following:

1. A potential volunteer accepting/rejecting to volunteer to a user's task.
2. A task user accepting/rejecting one of the volunteers.
3. A task user rating an accepted volunteer after the task.
4. A volunteer (who participated in the task) rating the task user after the task.

The analysis of these interaction types could provide indicative information to update the friendship weight between two users, who are the task creator and a potential volunteer.

1. A potential volunteer accepting/rejecting to volunteer.

The analysis of this type of interaction assists in specifying metrics like the acceptances of a specific, potential invited volunteer (e.g. Alice) towards to the tasks of a particular task creator (e.g. Bob)

$$Volunteer\_intentions = \frac{acceptances\ to\ participate\ to\ the\ tasks\ of\ a\ specific\ user}{total\ invitations\ to\ participate\ to\ the\ tasks\ of\ a\ specific\ user}$$

Let's suppose that Bob has created a set of tasks and suppose that Alice has been reached and expressed her interest to participate in n tasks of Bob's. Now let's suppose that Alice has accepted total p invitations in Bob's tasks, where $p \leq n$. The volunteer_intentions metric will be:

$$volunteer\_intentions = \frac{p}{n}$$

2. A task user accepting/rejecting one of the volunteers.

The analysis of this type of interaction assists in specifying metrics like the acceptances of a particular potential volunteer by a task creator in the context of the tasks he/has created in WeNet platform.

$$acceptances\_of\_volunteer\_intention = \frac{acceptances\ of\ a\ potential\ volunteer\ by\ the\ task\ creator}{total\ expressions\ of\ interest\ the\ potential\ volunteer\ to\ participate\ in\ the\ tasks\ of\ the\ task\_creator}$$

Let's suppose that in Bob's tasks, Alice was reached and she had accepted to participate in p tasks. After that, Bob accepted Alice in $k \leq p$ tasks. So, Bob towards Alice has:

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$$acceptances\_of\_a\_specific\_volunteer\_intention = \frac{k}{p}$$

3. A task user rating an accepted volunteer after the task.

After a task is over, the rating of the task creator is important in assessing his/her attitude towards a specific accepted volunteer.
Let's suppose that k tasks of Bob's have taken place and that Alice participated in them. Bob has rated Alice in each one of the k tasks. The rates of the task creator towards the specific volunteer will be:

$$Avg\_Rating\_of\_Volunteer = \frac{total\_rating\_score}{k}$$

4. A volunteer (who participated in the task) rating the task user after the task.

In addition, the rating of the task creator is important in assessing the experience and the attitude he/she has towards the task creator.
Let's suppose that k tasks of Bob's have taken place and that Alice participated in them. Alice has rated Bob in each one of the k tasks. The rates of the volunteer towards the task creator will be:

$$Avg\_Rating\_of\_task\_user = \frac{total\_rating\_score}{k}$$

The interactions will assist in updating the tie strength weight between the task creator and the volunteer.

The weight of the tie strength between two users is calculated based on the interaction between them within WeNet platform. The tie strength weight between two users is not necessarily a reflexive relationship, so it is possible that user A considers user B a better friend than user A is considered a friend by user B. So, between two users, two friendship weight S are to be calculated.

In this regard, the aforementioned types of interaction of users in the context of a task will assist in updating the friendship weight between the task user and a given volunteer.

User interactions "1" (A potential volunteer accepting/rejecting to volunteer) and "4" (a volunteer who participated in the task rating the task user after the task) will assist in updating the tie strength that the potential volunteer has towards the task user. So, the tie strength of the two users is updated as follows:

$$\begin{aligned} tie\_strength_{volunteer \to taskuser} &= tie\_strength + Volunteer\_intentions * W_1 + Avg\_Rating\_of\_task\_user \\ &* W_2 \end{aligned}$$

where $W_1$and W_2represent the weights that the volunteer intentions metric and the ranking of the task user by the volunteer have in the update process.

On the other hand, user interactions "2" (A task user accepting/rejecting one of the volunteers) and "3" (a task user rating an accepted volunteer after the task) will be used in updating the tie strength that the task user has towards a specific volunteer.

$$tie\_strength_{taskuser \to volunteer} = tie\_strengt + acceptances\_of\_volunteer\_intention * W_3 + Avg\_Rating\_of\_Volunteer * W_4$$

where $W_3$and W_4represent the weights that the task creator's acceptance of the particular volunteer and the ranking of the volunteer by the task creator have in the update process. In the experimental procedure and the case studies the update procedure report quite satisfactory performance and the weights will be fine-tuned in the context of the pilotings with the use of real interaction data

3.2 Diversity in Social Relationships

The specification of the tie strength is a main way for measuring social relationships and for assessing the quality of the relationship between two individuals. Several diversity aspects of users social relationships can be measured. Diversity in the social relationship component is calculated as a mean to provide indicative information about i) the diversity of the interactions between a user and his/her friends, ii) the diversity of the set of friends (list of users) with whom a specific user has interacted, iii) the diversity in the tie strength of a user with his friends / the list of users he interacts.

3.2.1 Interaction Diversity

First, the diversity of the interactions between two individuals can be assessed with respect to the seven dimensions of interactions. In this regard, the existence or not of interactions on each dimension is specified and the overall diversity is measured in terms of different ways and mediums of interaction. Example cases are illustrated in the next Table.

Table 1. Diversity of interactions.

	Dimensions of interaction							Tie Strength	Diversity of Interaction Dimensions
	Time	Intensity	Intimacy	Reciprocal Services	Structural	Emoti onal	Social		
User_1	x	x	x	x	x		x	0.88	0.86
User_2	x	x	x					0.75	0.43
User_3	x	x	x			x		0.72	0.57
User_4	x		x		x			0.59	0.46

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In the table, we illustrate for an example user and the dimensions of the communication and the interactions he/she has with a set of four other users. The diversity of the interaction the user has with each one of his friends is estimated with entropy and is illustrated in the last column.

In addition to the diversity of interaction the user has each of his friends, the overall diversity of interactions of the user with all his/her friends can be also is calculated. In the aforementioned short example case, the overall diversity of the interactions of the user with other users is specified to be 0.58. This provides meaningful information about the different types of interaction and the different medium-ways of interaction of a user with other users. A high diversity indicates that the user communicates and interacts with his peers in different ways and in different dimensions, while a low diversity indicates that the user prefers a narrow set of ways to interaction and to communicate with others users.

3.2.2 Diversity of the social relationships tie strength of the user

Another interesting aspect of diversity with respect to the social relationships concerns the diversity of the tie strength of a user with his friends or the list of users he interacts. In this regard, we can assess, of a given user, the diversity of the tie strengths he has with his friend list. An example cases are illustrated in next Table where for four users the tie strength they have with their friends are presented. Entropy is used for measuring diversity.

Table 2. Diversity of tie strength of the social relationships of users

	User_1	User_2	User_3	User_4	User_5	User_6	User_7	User_8	Diversity of tie strengths of the relationships
Bob	0.88	0.72	0.10	0.05	0.85	0.99	0.95	0.65	**0.49**
Alice	0.95	0.90	0.95	0.88	0.87	0.95	0.99	0.89	**0.33**
Plato	0.10	0.35	0.55	0.95	0.85	0.65	0.55	0.50	**0.61**
John	0.45	0.35	0.10	0.35	0.15	0.55	0.05	0.10	**0.58**

The diversity of the social relationships of a user in terms of tie strength indicates how different tie strengths with the friend list are. In the example scenario, we see that Bob's relationships have a tie strength diversity that is measured to be 0.49. Alice's relationships

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have a tie strength diversity that is measured to be 0.33 while Plato's relationships have 0.61 diversity. A low diversity indicates that the user has a narrow set of tie strength relationships with other users while a high diversity indicates that the friend list of the user consists of different types of friends, from close friends to users who barely knows. This is also an indicator of how easily a user can add other users to his friend list. For example, Alice has a friend list that consists of users with whom she has high tie strength and strong tie, in contrast to Plato where his friend list consists of both close friends (high tie strength), acquaintances (low tie strength) and friends that lie between them (medium tie strength) and thus has a high diversity of 0.61.

It is worth emphasizing again that the emphasis is on the use of external data (to the WeNet platform), to the extent that those are made available with the consent of the user and following proper GDPR-compliant procedures. Nonetheless, it can be easily seen that the same ideas described above will be used during WeNet pilot studies and when interaction data will be available. In the same way that a "like" of one user by another is taken into account in computing their tie strength, so can the rating of a volunteer that has helped a user within the WeNet platform. We will focus on this part of the learning process as we transition from Task T3.2 to task T3.3, and as it becomes clear what regularities we will be able to observe in actual WeNet interaction data from the WeNet pilot on M35.

4. SOCIAL PREFERENCES

The Social Preferences component is responsible for ranking volunteers with respect to a specific task that a user poses. The component takes as input the list of volunteers that the procedures developed in the context of WP5 have specified and after that, performs a personalized ranking of the users and implements a knowledge-based methodology that utilizes rules to perform the user ranking.

In this section, we will present and discuss our abstract methodology for social ranking. In general, the presented approach is quite abstract and capable of performing ranking for a wide range of applications. Moreover, we will also discuss how our methodology can be adapted in order to allow for diversity-aware ranking, according to several parameters. The way in which diversity is introduced remains agnostic of the way in which diversity itself is measured, which apparently allows for flexibility when it comes to diversity estimation – we will present and discuss a concrete methodology for measuring diversity in terms of several parameters in section 5.

The rest of this section is structured as follows: (i) in 4.1 we present a method for preference elicitation which will serve as the basis for our ranking methodology – ignoring diversity; (ii) in 4.2 we present our ranking methodology as well as a concrete way in which diversity can be introduced into the ranking process.

4.1 A PREFERENCE ELICITATION METHODOLOGY

One of the main purposes of WeNet is to allow for diversity-aware suggestions. The majority of ranking methodologies in the literature do not directly address such subtleties and are mostly oriented towards utility/similarity ranking methodologies. Moreover, WeNet's interaction protocol combines several features addressed by many existing ranking

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methodologies separately, which would make the adoption of an already existing ranking methodology inefficient and, probably, problematic, in terms of efficiency. As a result, we designed a novel diversity-aware ranking methodology that allows for diversity to play a significant role, on condition that a user wishes so, while at the same time aligns properly with WeNet's structure.

So, in this subsection we present our methodology for entity ranking. To begin with, we assume that all entities are represented as vectors on some d-dimensional Euclidean space - i.e. $\mathbb{R}^d$. Then, given this representation, we propose a geometric approach which captures a user's ranking preferences with respect to these attributes by having access only to the user's first choice.

The rest of this subsection is structured as follows: (i) in 4.1.1 we present the problem that our methodology addresses; (ii) in 4.1.2 we present the methodology itself alongside with some examples and; (iv) in 4.1.3 we make some remarks regarding our methodology.

4.1.1 Setting the problem

Entity ranking is an important process for several applications. However, in several scenarios, while it is mandatory to provide an as much as possible accurate list of ranked suggestions to an end user according to their preferences, the only available feedback is the user's first choice, usually interpreted as the entity that is ranked first according to their own personal criteria. Given that imbalance between the received input and the required output, we propose a methodology that, given a user's first choice among a list of N entities, iteratively captures the user's ranking preferences.

Furthermore, we make two key assumptions within the purposes of this work:

1. That each entity is represented as a vector on some d-dimensional Euclidean space - i.e. $\mathbb{R}^d$. This implies that all their attributes should be represented using numerical values.
2. That each user has some optimal entity that would be the best fit for that specific scenario. This, in contrast to the previous assumption, is not a strict one in the sense that, as we shall discuss below, it suffices for the user to have some set of entities that would be considered as most fitting for a certain scenario.

As far as the first assumption is concerned, while it restricts us from using categorical representations of entities, we considered that the benefit of using purely analytical methods in our ranking process was worth it. Regarding our second assumption, it is plausible to expect that each user should have some rough view - be it implicit or explicit - on how an optimal entity in some scenario should be like[2].

4.1.2 Ranking Methodology

Our ranking methodology relies on the generalization of a simple geometric idea. Suppose we have two points, let a and b, on the plane, as shown in Figure 8. Now let us draw the median of the segment ab, which is represented as m. Observe that the median splits the plane into two half-planes, let H_1 and H_2 represent the two half-planes. Each of the half-

[2] We shall address any issues regarding diversity in the next subsection, 3.2.

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planes contains the median as well as exactly one of a, b. Moreover, each of the half-planes contains, apart from the median itself, all the points of the plane that lie closer to a (b, respectively) than b (a, respectively). Actually, this is a characterization of a half-plane determined by the median of two points which can be well generalized into abstract normed spaces[3]. This generalization is captured by the following lemma:

Lemma 2.1. Let $a, b, c \in \mathbb{R}^d$. Then:

$$\|c - a\| < \|b - a\| \Leftrightarrow (c - a) \cdot (b - a) < (c - b) \cdot (a - b).$$

The above lemma actually provides an equivalent way of saying that point c is closer to a than b by using their angular distance with respect to a third point, namely c. The above lemma can be utilized in order to prove the following proposition:

Proposition 2.1. Let $a, b, c \in \mathbb{R}^d$ be three pairwise distinct points on a d-dimensional Euclidean space. Denote also by H_L, H_R the following two half-spaces:

$$H_L = \frac{a + b}{2} + \{x \in \mathbb{R}^d : x \cdot (b - a) \leq 0\}$$
$$H_R = \frac{a + b}{2} + \{x \in \mathbb{R}^d : x \cdot (b - a) \geq 0\}$$

Then, the following equivalence holds:

$$\|c - a\| \leq \|c - b\| \Leftrightarrow a, c \in H_L.$$

Actually, Proposition 2.1, captures in a more formal manner our intuition as described above – i.e. a point lying closer to a than b should lie in the same half-space that is determined by a and the median of the segment [a,b]. Now, consider the following scenario, where two entities, let a and b, are presented to a user. Suppose also that the user prefers a over b. Under our assumption that the user ranks any entities presented to them by their distance from an implicit optimal entity, then the above proposition allows us to ignore the half-space determined by the median of [a,b] and b. Repeatedly doing so in any other occasion the user is requested to rank two or more entities, we expect to gradually restrict ourselves to a relatively small area, surrounding the user's implicitly optimal entity. So, our preference elicitation algorithm could be described as follows:

1. Initialize p_0 at $0_{\mathbb{R}^d}$ and let $K_0 = K$ – where K is a convex and compact subset of $\mathbb{R}^d$ within which all the entities that will be presented to the user live[4].

2. For $T = 0,1, \ldots$ repeat:

    a) Present a list of n entities to the user, let $(v_1, v_2, \ldots, v_n)$.

    b) Receive the user's ranking on them, let $\left(v_{\sigma^{-1}(1)}, v_{\sigma^{-1}(2)}, \ldots, v_{\sigma^{-1}(n)}\right)$, where $\sigma \in S_n$. S_n denotes the set of all permutations of $\{1,2, \ldots, n\}$.

    c) Let $a = v_{\sigma^{-1}(1)}$ and $b = v_{\sigma^{-1}(2)}$ and let $K_{T+1} = K_T \cap H_a$, where $H_a = \frac{a+b}{2} + \{x \in \mathbb{R}^d : x \cdot (b - a) \leq 0\}$.

    d) Let $p_{T+1} = c(K_{T+1})$.

[3] For the purposes of our work, we shall restrict ourselves to the usual finite-dimensional Euclidean space, $\mathbb{R}^d$.

[4] Namely, the most common case is that of K being a d –dimensional rectangle, i.e. $K = \prod_{i=1}^{d} [a_i, b_i]$.

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In the above, $c(A)$, where $A \subseteq V$ is a convex and compact subset of V, denotes the centroid of A and p_T are our estimations of the user's implicit optimal model. Intuitively, the above algorithm separates the attribute space at each step into two convex and compact subsets:

1. one containing the user's implicit model, p as well as their most preferred entity from the ones presented;

2. the set-theoretic supplement of the above.

Iteratively, we consider the intersection of all the emerging half-spaces, which yields at each iteration a convex polytope, let P_i such that is decreasing with respect to set inclusion and $p \in \cap_{i=1}^{\infty} P_i$. At each iteration, we use as an approximation of p the centroid of the corresponding polytope, $c(P_i)$.

As far as centroid computation is concerned, we adopted a simple grid-based methodology. Namely, we initially construct a grid with step $\varepsilon > 0$ on each dimension of V — in our case $V = \mathbb{R}^d$ and $\cdot$ is the usual dot product on $\mathbb{R}^d$ — and we consider the arithmetic mean of all the points included in P_i to be $c(P_i)$. As we proceed, given than $P_{i+1} \subseteq P_i$, we maintain in our grid only these points that are contained in P_i so as to reduce space and time complexity.

To clarify the above, consider the scenario shown in Figure 1. There, the user is presented with eight (8) entities – denoted by the light cyan points – and is requested to choose (at least) one of them as their preferred one – denoted by a light crimson border. Using the user's choice, let c represent choices, we can restrict ourselves in an area containing it as well as the hypothetical implicit optimal entity of the user. To begin with, we choose some non-chosen entity, let v_1 represent such an entity, and we draw the median of the segment $[c, v_1]$. As shown in Figure 9, the user's optimal entity could lie anywhere inside the colored area but nowhere outside it. So, by only considering one single option, we have considerably restricted our search space.

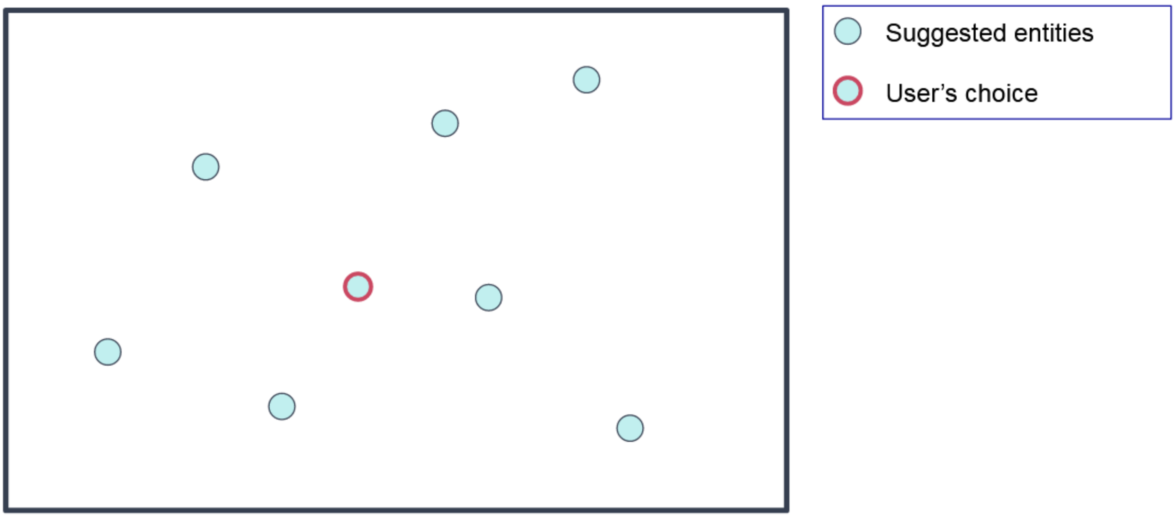

Figure 8 : A SET OF 8 ENTITIES DESCRIBED BY TWO ATTRIBUTES. THE HIGHLIGHTED POINT DENOTES THE USER'S CHOICE AMONG THESE ENTITIES.

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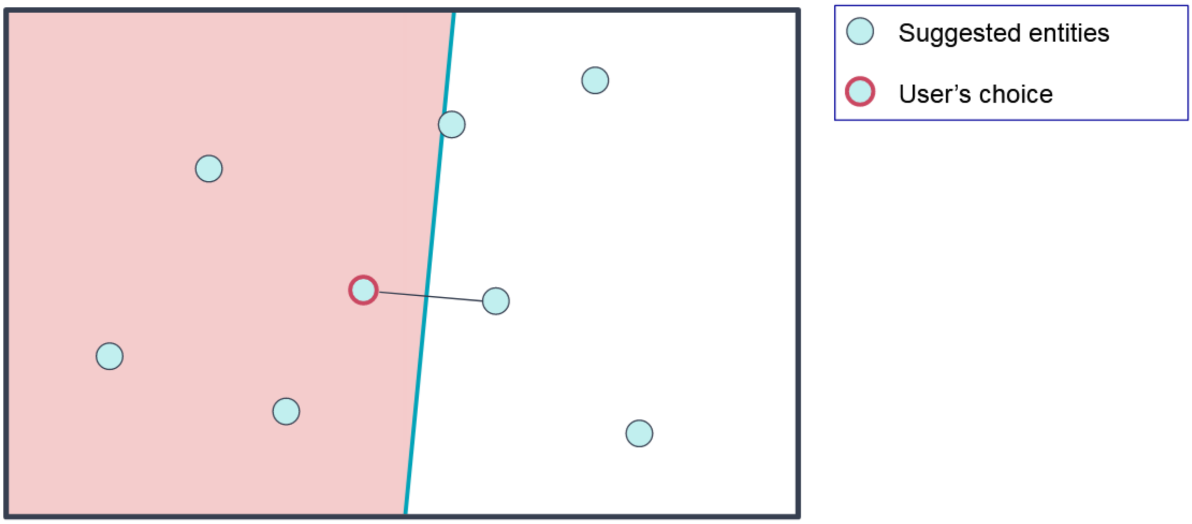

Figure 9: USING THE USER'S CHOICE AS WELL AS ANOTHER ENTITY THAT HAS NOT BEEN PREFERRED BY THE USER, WE CAN INFER THAT THE RIGHT (UNCOLORED) PART OF THE PLANE IS OF NO INTEREST, SINCE THE USER'S IMPLICIT OPTIMAL MODEL SHOULD LIE ON THE LEFT PART OF THE PLANE.

In a similar manner, we choose another non-chosen entity – Figure 3. Again, drawing the corresponding median and by restricting ourselves to the half-plane that contains the user's choice, we obtain a significantly smaller area in which we expect our user's implicit model to lie. We can make one more step, which, as shown in Figure 4, leads to an even more restricted area within whose boundaries our user's optimal entity should lie.

Having processed in a similar manner the rest of the non-chosen entities, we end up with a convex and compact subset of the plane, let A. Now, as we shall further analyze in the next subsection, our ranking will be based on measuring the distances of the barycenter $c(A)$ from all the other presented entities.

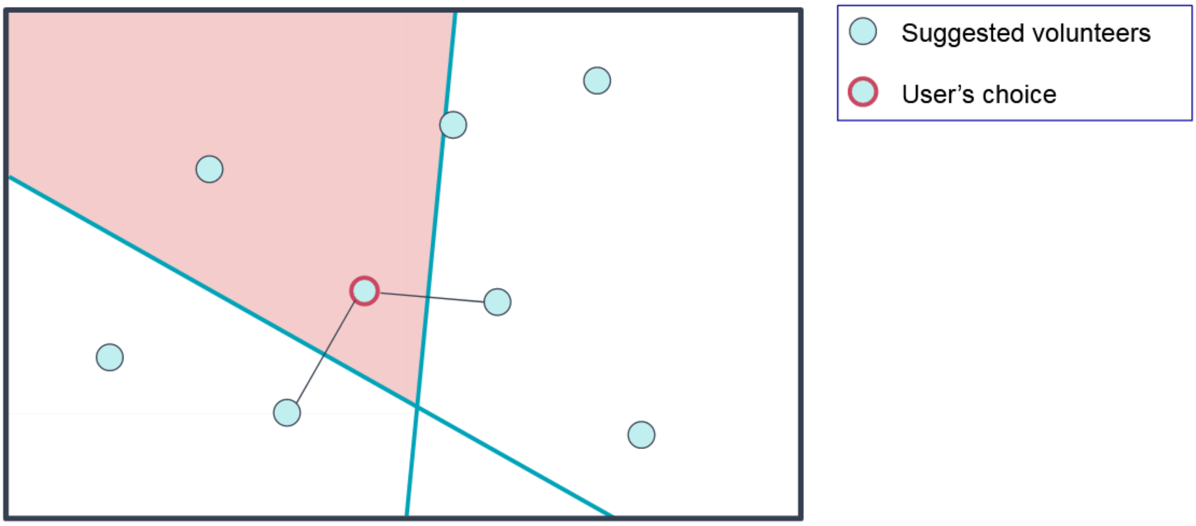

Figure 10: PROCEEDING IN A SIMILAR MANNER, WE CAN FURTHER RESTRICT OUR SEARCH SPACE BY DRAWING ANOTHER MEDIAN BETWEEN OUR USER'S CHOICE AND ANOTHER ENTITY.

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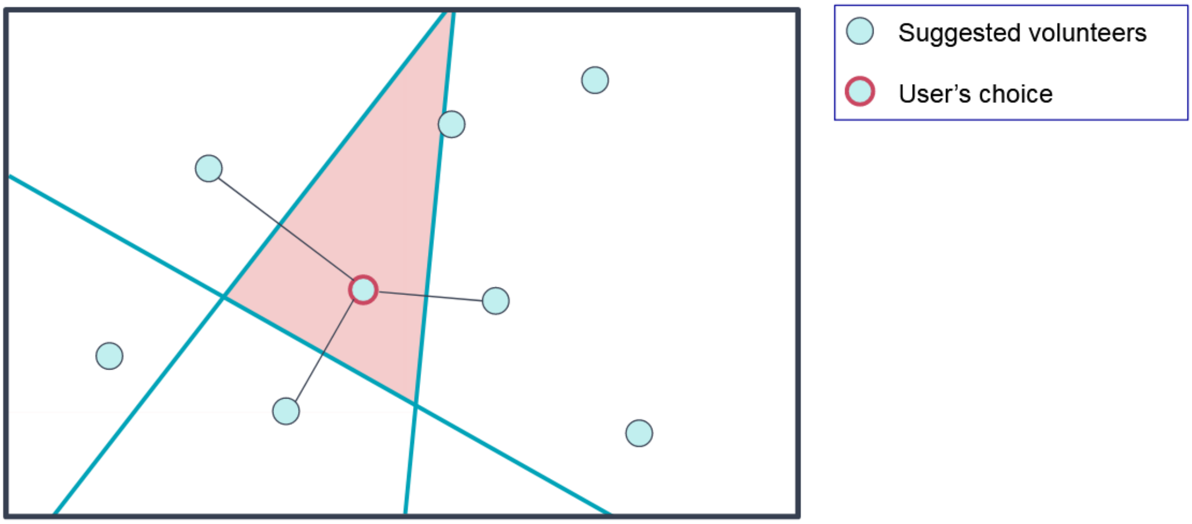

Figure 11: As one may observe, as the iterative cutting process proceeds, one obtains a significantly smaller area of interest, especially when compared to the initial search space.

4.1.3 Remarks

As we discussed in the first paragraphs of this section, our methodology is designed so as to address the issue of providing a full entity ranking according to the preferences of a user based solely on the user's first choice - which, as discussed, is interpreted as their most preferred entity from the one's presented. However, the above methodology is also capable of handling richer input from the user's part. That is, assuming that the user provides e.g. their three (3) most preferred choices, ordered by descending preference, then again one could use the user's first choice as described above while the other two could also be used in a similar manner. This way, one expects faster convergence given the fact that more hyperplanes and, hence, more cuts, are expected to be made at each iteration[5].

Another crucial part that should be addressed is the extent to which our key assumption of the existence of a single implicit model of preference is valid. In case a user is found to rank entities according to more than one such models, then alterations are needed to be made to our methodology in order to capture such subtleties. One way to do so would be to change the metric used in our methodology. For instance, using the usual 2-norm we silently assume that all attributes are of an equal importance when it comes to ranking entities, which may not be the case for all users. For instance, one user may systematically consider some certain dimension, say, x_3 more important when ranking entities in a specific scenario. Given our assumptions, such subtleties should be captured by our metric since according to this and our estimation of the user's implicit model we rank any presented entities. So, our metric failing to capture the user's preferences appropriately means that there is a high chance that our results will mostly be erroneous.

To avoid the above, one may introduce a weighted variant of the Euclidean metric. That is, instead of defining $d_2 : \mathbb{R}^d \times \mathbb{R}^d \to [0, +\infty)$ as:

[5] Nevertheless, one should always take into account the computational cost of computing a cut, given that it depends on the complexity of the polytope at hand, which, in general. is increasing after each iteration.

$$d_2(x,y) = \left(\sum_{k=1}^{d} |x_k - y_k|^2 \right)^{\frac{1}{2}},$$

one may define $d_{w,2}: \mathbb{R}^d \times \mathbb{R}^d \to [0,+\infty)$ as follows:

$$d_{w,2}(x,y) = \left(\sum_{\{k=1\}}^{d} w_k |x_k - y_k|^2 \right)^{\frac{1}{2}},$$

where $w_1, w_2, \ldots, w_d$ are non-negative weights such that $\sum_{k=1}^{d} w_k = 1$. In this way, one allows for the used metric to be more expressive and, thus, capture more efficiently subtleties as the ones described above.

Another point one should take care of is the metric that is used during both learning as well as ranking – evidently, for reasons of consistency, it should be the same. Given that the above results hold for any metric that is induced by an inner product on $\mathbb{R}^d$, our methodology could utilize several well-established metrics such as the usual Euclidean metric or any weighted variant of it[6]. Which metric should in general be used remains, yet, an open question that needs to be addressed based on evaluation on real user interactions data.

4.2 Diversity in Social Preference

In this section, we present an abstract ranking methodology based on the above preference elicitation algorithm. The structure of this section is as follows: (i) in 4.2.1 we present our ranking methodology and the rationale behind it; (iii) in 4.2.2 we introduce an abstract framework in which two distinct ranking methodologies can be blended, which allows for diversity to be taken into account within the ranking process described in 4.2.1.

4.2.1 Ranking methodology

Having presented a preference elicitation method, we shall now discuss how entity ranking is being conducted based on the knowledge accumulated through the above methodology. Before this, we should highlight once again that, as with preference elicitation, we work under the same assumptions – i.e. that each entity is represented as a real vector and that each user has a certain implicit model per scenario, according to which they choose which entity they prefer among others in terms of proximity to that model.

Given the above assumptions, our ranking methodology is quite simple. Given the estimation p_T of a user's implicit model at some time T we rank all the presented entities by ascending distance from p_T. That is, the closer an entity lies to p_T the higher we decide to rank it among others. Note that the metric used for ranking purposes is the same as the one used during the learning phase – otherwise, one might obtain inconsistent results.

[6] Observe at this point that our formalization, when restricted to finite –dimensional spaces, can be expressed in ways independent of the existence of an inner product, which means that one may use any norm they which on $\mathbb{R}^d$.

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To facilitate the extension of the above ranking methodology in a diversity aware manner – for more, see 3.3 – we will also introduce a ranking score. Namely, if e is an entity and p is an estimation of a user's implicit model then we define e's ranking/fitness score, $r(e)$ to be:

$$r(e) \coloneqq 1 - \frac{d(e,p)}{\mathrm{diam}K},$$

Where K is a convex and compact subset of $\mathbb{R}^d$, d is a metric defined on K and $\mathrm{diam}K$ is the diameter of K – i.e. the maximum distance two points in K may have. As one may observe, $r(e) \in [0,1]$ while at the same time the closer e lies to p the closer $r(e)$ is to 1. Consequently, high fitness scores for a certain entity imply that the entity is close to our estimation of the user's implicit optimal entity. In general, one may define $r(e)$ as:

$$r(e) = f\left(\frac{d(e,p)}{\mathrm{diam}K}\right),$$

where $f: [0,1] \to [0,1]$ is any decreasing bijection – in our case, $f(x) = 1 - x$.

4.2.2 Introducing diversity

In 4.2.1 we have described a methodology according to which one may rank entities based on the preference elicitation method presented in 4.1. Moreover, we have defined a fitness ranking score, r, which indicates the extent to which an entity is an appropriate suggestion for some user's criteria – the higher the value of r is the more adequate the entity. Assume now that, apart from fitness, we also have some other criterion according to which we can rank entities. Let $r': [0,1] \to [0,1]$ be a ranking score function for that criterion, similarly to r. Then, we may mix these two score functions and determine a new ranking function, let r_λ, for some $\lambda \in [0,1]$, as follows:

$$r_\lambda = \lambda r' + (1 - \lambda) r.$$

Thus, r_λ is a ranking score function where our new ranking criterion measured by r' is taken into account at a rate of λ while the rest accounts for fitness – i.e. r. For instance, for $\lambda = 0.5$ fitness and r' are considered of equal importance when ranking while for $\lambda < 0.5$ fitness is considered more important than r'. Observe how in the above we may also allow both functions to take values on any closed interval of real numbers. Regarding our choices, of great interest could also be the range $[-1, 1]$ (other than $[0, 1]$) where the negative values are interpreted as *deterring factors* when it comes to suggestions under a certain criterion.

So, choosing r' such that it measures the score of a ranking process based on *diversity*, we can extend our ranking methodology as presented in 4.2.1 so as to include diversity of the suggested entities as one of the suggestion criteria. In following, we present an abstract way to determine r'.

Assume that $div: P(K) \to [0,1]$ is a function that measures the diversity of sets of entities from K – where K is defined as in 4.2.1 to be the compact convex set where all our entities live. To determine a ranking score function we do not need any more information about div so, as discussed above, the methodology we shall present here remains agnostic of the way in which diversity is measured. Now, for any $\emptyset \neq A \in P(K)$ and for any $e \in A$ we define the *marginal diversity contribution* of e in $A, mdc(e, A)$, to be:

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$$mdc(e, A) \coloneqq div(A) - div(A \setminus \{e\}).$$

That is, the marginal diversity contribution of an entity e in a non-empty set of entities A is the increment or decrement of diversity brought to A by including e into it. As one may observe, $mdc(\cdot,\cdot)$ may well be positive or negative. Indeed, in a set where all entities are more or less similar, it is expected that a quite diverse entity will contribute positively in the sets entropy while in set of quite diverse entities, introducing one that is similar to some of the already included is expected to reduce the sets entropy. In order to use $mdc(\cdot,\cdot)$ as a ranking score function we need to first normalize it, introducing *normalized marginal diversity contribution* of e in A, $mdc_N(e, A)$ determined as:

$$mdc_N(e, A) \coloneqq \frac{mdc(e, A)}{\sum_{x \in A} mdc(x, A)}.$$

The above normalized value of $mdc(\cdot,\cdot)$ takes values on $[-1,1]$. As discussed above, this implies that our methodology of ranking by diversity actually penalizes entities which contribute negatively to overall diversity. So, using $mdc_N(\cdot,\cdot)$ as our diversity ranking score we can define a total ranking score as:

$$\lambda mdc_N + (1 - \lambda) r,$$

for some value of $\lambda \in [0,1]$ – for more on the computation of λ consult section 6.

5. SOCIAL EXPLANATIONS

The Social Explanations component is responsible for providing arguments to the user about the acceptability of each volunteer. It utilizes PRUDENS and the Machine Coaching [14] Cycle to provide explanations and the reasons on why a given volunteer (identified by WP5) for the requestor's task should eventually be accepted by the requestor to help with the task. It is worth noting that the explanations in question are not explanations of why a certain volunteer was proposed in the first place (by WP5). Rather, we are interested in a post-filtering step where the user is aided to confirm which, among those volunteers, will actually be involved in the task and interact with the requestor. Accordingly, the requestor is able to question the explanations that are provided, and coach the component towards learning to offer personalized explanations to the requestor (which might have little to do with the reasons that WP5 chose to return those volunteers in the first place).

In this section, we present our social explanations component. The overall architecture of the social explanations component has not been severely altered when compared to the version presented in the D3.1 deliverable. However, we shall discuss and present here ways in which our methodology is capable of taking into account diversity when it comes to explanations.

5.1. LEARNING AND EXPLAINING

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In this subsection, we shall briefly present our explanation mechanism. Namely: (i) in 5.1.1 we present Machine Coaching as described in [14] (ii) in 5.1.2 we present the language of Machine Coaching; (iii) in 5.1.3. we present a short example so as to clarify the way in which our methodology is intended to work and; (iv) in 4.1.4 we present how Machine Coaching is capable of capturing diversity aware criteria on condition that they are included within a user's preferences.

5.1.1. Machine Coaching

Our main tool for producing explanations is PRUDENS, a computational tool that implements Machine Coaching as described in [14] . Machine Coaching is based on the following learning cycle:

1. An agent starts with an initial prioritized Knowledge Base (KB), about some certain scenario - possibly initially empty.
2. Then, a certain set of facts is provided to the agent, based on which the agent draws any inferences it can, respecting the rules' priorities - this output may possibly be empty.
3. The user is presented with both the outcome of the inference process as well as the argument that internally has led the agent to that outcome. At this point, the user may either approve the outcome as well as the backing argument or reject any of them - or both.
4. In case the user rejects the above, they are allowed, if they wish to, to provide counter-argumentation which is integrated by the agent to its already existing knowledge.
5. The above steps are being repeated until the agent has learned the user's theory at an acceptable level.

The above process is quite generic since it works in any context on the condition that any related knowledge is expressible in terms of if-then rules. A specification of the above process in the context of WeNet may be seen in Figure 12, where the basic proposed workflow in terms of explanations is presented. The workflow is as follows:

1. At first, the agent receives the profile of a certain volunteer that has been proposed as eligible for suggestion.
2. Using the existing knowledge base, K, the agent decides whether that volunteer should be suggested to the user as an appropriate choice or not.
3. In case the volunteer is not suggested by the agent, then the agent waits for the next volunteer to enter the pipeline or terminates the process.
4. In case the volunteer is adequate for suggestion, the agent presents them to the user alongside with the corresponding argument.
5. The user, now, decides whether they wish to accept the agent's suggestion as well as the corresponding explanation presented.
    a. In case they do so, the agent either waits for the next volunteer or terminates the process.

In case the user rejects the suggestion and/or the corresponding explanation, then the agent asks for some counter-argumentation from the part of the user. Using that feedback, the agent updates its knowledge and waits for the next volunteer or terminates the process.

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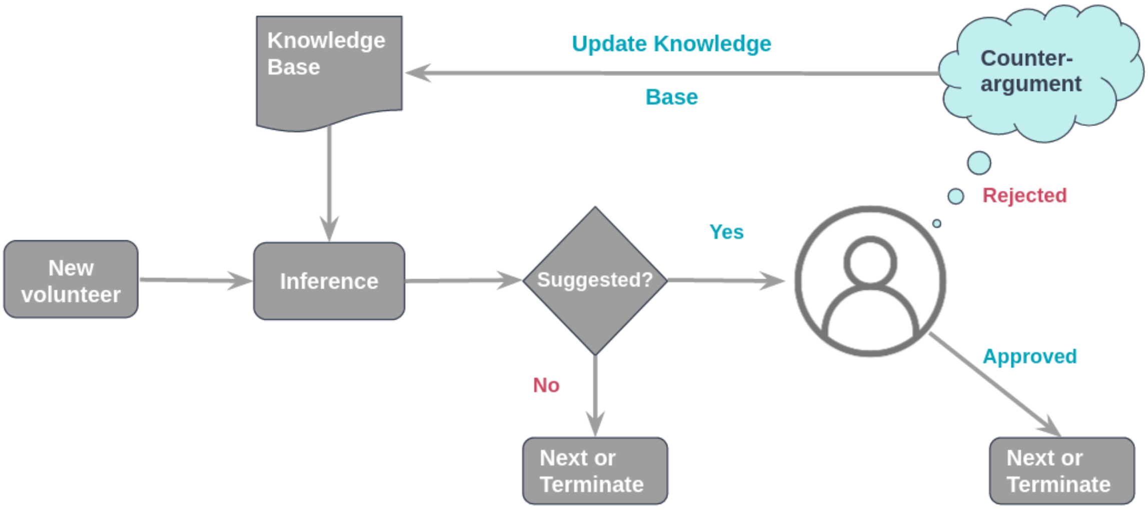

Figure 12: The machine coaching learning cycle. Whenever a new volunteer arrives, PRUDENS assesses their eligibility for suggestions and acts accordingly. Then, the end-user either accepts or rejects the suggestion, alongside some corresponding explanation.

5.1.2. A language for Machine Coaching

As one may realize, in order to allow for a dialectical human-machine interaction, one needs a common language through which both parties will communicate. In this section we shall present in short the language used from PRUDENS in order to represent knowledge obtained by the end-user.

To begin with, PRUDENS's language is a first-order language, containing the following:

- Symbols for **constants** which represent entities of our universe and are denoted by strings starting with a lower-case letter – e.g. alice, bob, dog.
- Symbols for **variables** which serve as placeholders for constants and are denoted by strings starting with an upper-case letter – X, Y, User.
- Symbols for **predicates** which represent relations between entities of our universe and, as constants, are denoted by a string starting with a lower-case letter and followed by a comma-separated arguments list enclosed in parentheses – e.g. friendOf(X, bob), likes(alice, pizza), enjoys(User, Activity).
- A logical **negation** symbol, -, which is interpreted as classical logical negation. It is important to stress at this point the fact that PRUDENS's language, unlike e.g. prolog, does not work under a Closed World Assumption (CWA). This means that lack of knowledge about the truth state of some predicate p in some context does not imply for PRUDENS that p is not true under certain circumstances – which would be the case under a CWA.
- A symbol for **equality**, denoted by ?=(·,·) and which is always interpreted as "the first argument is the same entity as (or unifies with) the second entity". A generalization of ?=(·,·), namely ?in(·,·) allows for the second argument to be a list of constants, thus facilitating faster computation and less lengthy rules and knowledge bases.
- A built-in mathematical operator for **comparison**, ?<(·,·), which allows to efficiently compare numerical constants – for instance, ?<(1,3) is true while ?<(X,3) is true *on condition that* X unifies with some numerical constant c such that c<3.

Using the above language, one may define the following:

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- **Literals** are either predicates (positive literals) or negated predicates (negative literals) – e.g. siblings(X,Y), -siblings(alice, bob). Two literals that differ only in terms of their sign – i.e. the one is positive while the other is negative – are said to be *conflicting*.
- **Rules** are triplets of the form (name, body, head) where:
  - *Name* is a string consisting of letters, digits and underscores.
  - *Body* is a list of pairwise non-conflicting literals that are interpreted as the rule's hypotheses.
  - *Head* is a single literal that is interpreted as the rule's inference given the rule's body.

  Two rules are said to be *conflicting* when their heads are conflicting literals (see above).
- A **prioritized knowledge base** or, simply, a **knowledge base**, is a set of rules alongside with a priority relation defined over pairs of conflicting rules.
- A **context** is a set of pair-wise non-conflicting literals which contain no variables. A context is intended to be interpreted as a set of facts about some specific situation.

The above are all used so as to internally represent knowledge regarding a user's preferences and heuristics about certain scenarios.

5.1.3. A simple example of Machine Coaching

Before proceeding with the rest of this section, regarding diversity, we shall at first present a small example of Machine Coaching as a learning methodology. Consider a user, say Bob, who would like to organize a social dinner at his home and asks for help regarding who to invite to this social gathering from an agent with the following simple knowledge base:

R1 :: friend(X) implies suggest(X);

Assume now that an old friend of Bob, Alice, who is abroad at the moment, is suggested from the agent – since, as we said, she is one of Bob's friends. On seeing this, Bob rejects the suggestion from the agent, providing the following counter-argument:

"When a friend of mine is abroad, do not suggest them!"

Given this counter argument, the agent updates its knowledge base so as to adhere to the new knowledge it has received, leading to the following knowledge base:

R1 :: friend(X) implies suggest(X);

R2 :: friend(X), abroad(X) implies –suggest(X);

R2 > R1

So, from now on, any time the agent is presented with a volunteer who is not at home, it will not suggest them. The above process is presented in Figure 6.

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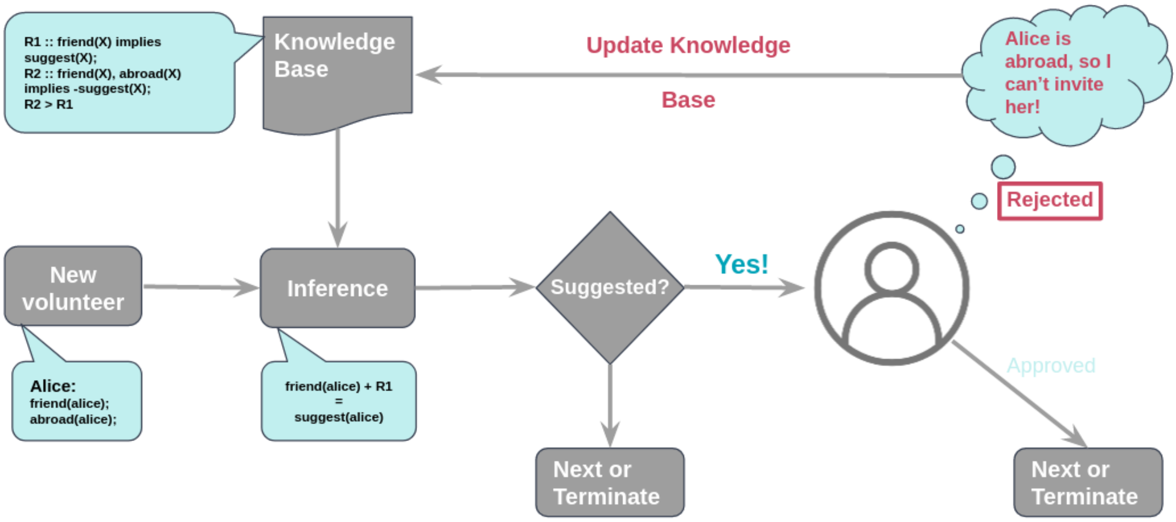

Figure 13:An example of Machine Coaching. Here, PRUDENS's suggestion was found to be missing critical context by the user, who rejected it, providing accordingly reasoning for their actions which led to PRUDENS refine its knowledge base.

5.2. Capturing Diversity with Machine Coaching

As one may observe, the above framework is quite generic. In this subsection we will show how using Machine Coaching one can iteratively capture any diversity aware criteria found in the user's knowledge. It is important to stress at this point, prior to presenting examples of diversity aware preference elicitation, that diversity – as well as any concept – may be captured through via Machine Coaching *on condition that* it is also present in the user's theory and can be expressed in PRUDENS's language – as we shall see, the latter should not bother us, in general. So, our methodology cannot introduce diversity into a user's preferences should they not wish to, while, as we shall demonstrate, it is capable of capturing any diversity-aware preferences as per the user's will. Given that, we will present some examples to help us demonstrate the above.

Consider a user, say Alice, a teacher, who wishes to have some musicians visit her school and talk to her class's students about music and the instruments they play. Evidently, she would prefer that the musicians she is going to invite all play different instruments. In other words, Alice needs high diversity in terms of the instruments played by each musician she will be suggested. The above desired behavior could be expressed through the following rule:

Div1 :: plays(X,I), suggested(Y), plays(Y,I), -?=(Y,I) implies –suggest(X);

Accordingly, Div1 should be of higher priority than any other rule that suggests a musician so as to effectively cancel out any argument in favor of the inclusion of a musician that may play the same instrument as some of the already suggested ones. Of course, in more complex scenarios one may need more than a single rule in order to describe their preference effectively.

We shall now present a more complex example in order to further demonstrate how Machine Coaching is capable of capturing a user's diversity aware preferences – always on condition that the user's preferences themselves are diversity aware. For this purpose, let us consider the following scenario: A WeNet user, Alice, wishes to start a new task she has never

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launched before, namely, to organize a social dinner. Since she has never run a task like this before, she is prompted to a dialog in which she is requested to provide key information regarding her preferences regarding that task. Namely, let us assume that the following dialogue takes place between Alice and a chatbot:

- (Chatbot) Would you like me to suggest you volunteers somehow related to you?
- (Alice) Yes, I would prefer you to suggest me only close friends of mine.
- (Chatbot) Would you like them to have some special skill(s)?
- (Alice) Yes, I would like them to be good at cooking.
- (Chatbot) Would you like them to possess anything special/specific to this task?
- (Alice) No, not in particular.
- (Chatbot) Would you like me to take into account anything else?
- (Alice) No, I’m fine!

The above dialog leads to the chatbot create the following three rules, which constitute the initial knowledge base according to which users will be filtered out:

Rule_1 :: friends(X, alice, high), has_skill(X, cooking, good) implies suggest(X);

Rule_2 :: friends(X, alice, Y), ?in(Y, [medium, low]) implies –suggest(X);

Now, given the above knowledge base as well as the users shown in Table 3 – where, for reasons of simplicity we omit profile data irrelevant to our example – we see that the volunteers suggested by our agent are users 1,2,3,4,6 and 8.

Table 3. Ten volunteers and their attributes regarding Alice's social dinner.

User ID	Attributes
1	friends(1, alice, high), has_skill(1, cooking, good), cooking(1, italian), …
2	friends(2, alice, high), has_skill(2, cooking, good), cooking(2, italian), …
3	friends(3, alice, high), has_skill(3, cooking, good), cooking(3, italian), …
4	friends(4, alice, high), has_skill(4, cooking, good), cooking(4, indian), …
5	friends(5, alice, medium), has_skill(5, cooking, good), cooking(5, chinese), …
6	friends(6, alice, high), has_skill(6, cooking, good), cooking(6, italian), …
7	friends(7, alice, low), has_skill(7, cooking, good), cooking(7, greek), …
8	friends(8, alice, high), has_skill(8, cooking, good), cooking(8, italian), …
9	friends(9, alice, medium), has_skill(9, cooking, good), cooking(9, french), …
10	friends(10, alice, high), has_skill(10, cooking, medium), cooking(10, mexican), …

As we see, the suggested volunteers are all but for user 4 good at cooking the same cuisine. On seeing that, Alice realizes that she would like to include some more diversity on the upcoming dinner, so she informs the chatbot accordingly:

- (Alice) Take care for my suggestions so as to include no more than one cook per cuisine. Also, in case a volunteer cooks a different cuisine than the rest of the suggested volunteers at a good level, suggest them, on condition that they are at least somehow related to me
- (Chatbot) Fine!

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The above may be translated into PRUDENS's language as follows[7],[8]:

Rule_4 :: suggest(X), cooking(X, Y), cooking(Z, Y) -?=(X, Z) implies –suggest(Z);

Rule_5 :: cooking(X, Z), suggest(U), cooking(U, Z) implies –suggest(X);

Rule_6 :: friends(X, alice, Y), ?in(Y, [medium, high]), has_skill(X, cooking, good) implies suggest(X);

So, given the above Alice is presented with the volunteers 1, 4, 5 and 9 which are apparently more diverse in terms of the cuisines they are capable of cooking.

Of course there is plenty of room for more sophistication in the above, since ties between volunteers who cook the same cuisine are resolved based solely on their order of appearance in the user list. The needed sophistication – e.g. preferring volunteers who have other characteristics that are considered fitting for Alice for this task – may be provided by further coaching the agent in future – or this – learning cycles.

6. CASE STUDIES

In the context of the case study, we demonstrate the functionality of the three components and the methodologies in various scenarios and case studies. Below we discuss the characteristics of the scenario, the data used and we explain the functionality of the components. In the scenarios, we measure diversity using the entropy metrics presented above.

6.1. Diversity among suggested volunteers

In this first scenario, we consider a set of volunteers that will be presented to a user for some certain task and present a way through which one may assess their diversity, as discussed above. To begin with, assume we have the set of volunteers shown in the next Table.

Table 4. A set of five volunteers described by some materials they own as well as by their Big Five personality traits.

ID	Materials	Meanings (Big Five - OCEAN[9])
1	"car"	(0.8, 0.6, 0.3, 0.5, 0.2)
2	"car", "bike"	(0.7, 0.6, 0.8, 0.5, 0.6)
3	"motorcycle"	(0.6, 0.5, 0.9, 0.5, 0.2)
4	None	(0.2, 0.4, 0.1, 0.4, 0.5)
5	"motorcycle", "car"	(0.9, 0.6, 0.5, 0.6, 0.4)

As one may observe, in Table 4 we present only a small part of a WeNet user's profile, mostly for reasons of clarity. We will use entropy to measure diversity in the above sample,

[7] For the purposes of this presentation, we will not delve into more details about the natural-language-to-first-order-logic translation process.
[8] Rule priorities are implicitly determined by the order of their appearance in the above lists. That is, the higher a rule is displayed, the higher its priority over conflicting rules is.
[9] OCEAN stands for Openness to Experience, Conscientiousness, Extraversion, Agreeableness, Neuroticism, i.e. the five factors that are described by the "Big Five" personality traits model.

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since thus we can handle sufficiently well and in a uniform manner both categorical data – i.e. “Materials” – as well as numerical ones – i.e. “Meanings”.

To begin with, we compute the diversity in terms of each variable of our dataset.

In terms of materials, diversity is computed as declared in 2.1 using entropy. To begin with, we have at our disposal four categories – namely, “car”, “bike”, “motorcycle” and “None” – distributed as shown[10] in next table. The entropy of the above data equals 1.28 for a maximum entropy value of 1.39.

Table 5. Distribution of the materials of each volunteer.

Category	Car	Bike	Motorcycle	None
Frequency	3/7	1/7	1/7	1/7

In terms of “Meanings”, we see that this variable is a vector of real numbers in $[0,1]$. So, we shall use the multidimensional version of diversity that we have presented in 2.1 after splitting $[0,1]$ into three classes[11] of equal length, 0.33. The relative frequencies for each class and each personal trait are shown in next Table.

Table 6. Distribution of the Big Five traits of the five presented volunteers.

Class	O	C	E	A	N
[0,0.33)	1/5	0	2/5	0	2/5
[0.33,0.66)	1/5	2/5	1/5	5/5	3/5
[0.66,1]	3/5	3/5	2/5	0	0

Now, given the above data, we compute the diversity in terms of entropy for each for the five variables, as shown in the next Table.

Table 7. Diversity per personal trait across the presented set of five volunteers.

Personality trait	Diversity
Openness	0.95
Conscientiousness	0.67
Extraversion	1.05
Agreeableness	0.00
Neuroticism	0.67

The maximum diversity for the above case, where we have three classes, is 1.10. Now, assuming that all traits are of equal importance we obtain an overall diversity for the “Meanings” variable equal to 0.67 out of a theoretically maximum value of 1.10.

[10] Whether one includes the option “None” as a separate category or not depends on how it may be interpreted in each context. In our example we chose to include it, interpreting it as a volunteer who has no means of transportation and possibly moves around using e.g. public transport.

[11] The number of classes here was chosen arbitrarily, yet it is dependent on the number of volunteers one has at hand. Supposing, say, that we had at our disposal 20 or more volunteers

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Having computed the diversity of each of our variables separately, it remains to combine them using two significance weights, w_1, w_2. Namely, our sample's total diversity, $E(V)$ will be:

$$E(V) = \frac{1.28}{1.39}w_1 + \frac{0.67}{1.10}w_2.$$

Now, the values of the two weights may vary depending on the exact scenario. For instance, in case we do care to attract people that are inherently diverse but we do not care about the materials – in this scenario, their means of transportation – they have at their disposal, then it would be natural to demand that $w_2 > w_1$. On the contrary, there might be scenarios in which we would like to have a more diverse sample of volunteers in terms of the means they prefer to use – for instance, we might have just moved to a new town and would like to hear from several people about the most efficient way to move around.

6.2 Diversity among answers

Another aspect in terms of which it would be useful to measure diversity is among the answers returned by volunteers on a task creator's request. Let us consider the scenario where a question asked by a user – i.e. the task creator – has four possible answers, let A, B, C and D. Let us also consider that twenty (20) volunteers have responded, as shown in next table.

Table 8. Responses from 20 volunteers on a hypothetical multiple choice question.

Answer	Frequency
A	6
B	2
C	9
D	3
Total	**20**

Given the above data, we may compute the diversity with respect to the provided answers which is equal to 1.235 for a maximum value of 1.386 – so, a normalized 0.891 diversity score.

Moreover, based on the above one may rank volunteers based on their contribution in the diversity of the answer set. For instance, let as consider two volunteers, Alice and Bob who have answered B and C respectively in the above question. Then, removing Alice from the set of volunteers leads to a new set of answers as shown in next table.

Table 9. Answer distribution after removing Alice.

Answer	Frequency
A	6
B	1
C	9
D	3
Total	**19**

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Removing Alice, the answer set now has a diversity of 1.164 for a maximum value of 1.386, leading to a relative diversity score of 0.840. On the contrary, removing Bob from the volunteers set leads to an answer set as the one shown in next Table.

Table 10. Answer distribution after removing Bob.

Answer	Frequency
A	6
B	2
C	8
D	3
Total	**19**

The above answer set corresponds to a total diversity of 1.257 for a maximum value of 1.386, which means that it has a relative diversity score of 0.906.

As one may observe, omitting Alice from our volunteers set leads to a reduction in relative diversity by $0.840 - 0.891 = -0.051$ which was expected, since Alice had provided one of the scarcest answers in our answer set and, naturally, including one less instance of it would make our set of answers more predictable – and hence, less diverse.

On the contrary, removing Bob from our volunteer set let to our answer sets diversity increase by $0.906 - 0.891 = +0.015$. Again, this was expected since Bob's answer was one which was apparently provided by most of the requested volunteers, so removing him from the volunteer set would make the answer set less predictable and, hence, more diverse. Taking into account all of the above, one may say that in terms of diversity Alice should be ranked higher than Bob, since Alice's contribution in the answer set diversity is larger than that of Bob.

6.3. Diversity with respect to tie strength

Another attribute that may be interesting to track in terms of diversity would be the distribution of tie strength between the volunteers has chosen for a certain task historically and the user themselves. To do so, apart from other typical statistical metrics, such as mean value or standard deviation, we can also compute the diversity of the user's choices with respect to tie strength. In next Table, we present a user's choices as far as tie strength with their chosen volunteers is concerned across five similar tasks.

Table 11. Tie strengths between a user and five suggested volunteers.

Task	Tie strengths of chosen volunteers
1	0.94, 0.92, 0.88, 0.86, 0.85, 0.85, 0.84, 0.79
2	0.96, 0.89, 0.88, 0.85, 0.82, 0.80, 0.79, 0.79, 0.76, 0.75
3	0.91, 0.85, 0.84, 0.80, 0.76, 0.76, 0.76, 0.75
4	0.93, 0.88, 0.86, 0.86, 0.84, 0.83, 0.80, 0.77, 0.76
5	0.91, 0.90, 0.88, 0.87, 0.84, 0.83, 0.81, 0.78, 0.75, 0.75

We may compute the diversity of the above as we have already presented, by splitting our observations into classes. We choose to split [0,1] – i.e. the range over which tie strength

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may take values – into 20 classes of the same length, 0.05. Using the relative frequencies, f_k, of each class we can compute the normalized tie strength diversity for each task using:

$$E = -\frac{1}{\ln 20}\sum_{k=1}^{20} f_k \ln f_k.$$

In the next Table, we present for each task the corresponding relative frequencies[12] as well as the corresponding diversity value.

Table 12. Relative frequency and diversity per task.

Class	Relative Frequency				
	Task 1	Task 2	Task 3	Task 4	Task 5
[0,75,0.80)	0.1250	0.4000	0.5000	0.2222	0.3000
[0.80,0.85)	0.1250	0.2000	0.2500	0.3333	0.3000
[0.85,0.90)	0.5000	0.3000	0.1250	0.3333	0.2000
[0.90, 0.95)	0.2500	0.0000	0.1250	0.1111	0.2000
[0.95,1.00)	0.0000	0.1000	0.0000	0.0000	0.0000
Diversity	**0.4049**	**0.4272**	**0.4049**	**0.4375**	**0.4560**

As one may observe, the diversity with respect to tie strength is relatively low, which was expected since all the observations are within a quarter of tie strength's range – i.e. [0.75,1.00). Consequently, there are at least 15 classes in each task that are not represented, leading to the above low values of diversity.

Using the above data one may also compute the total diversity across all five tasks – the corresponding results are shown in the next table.

Table 13. Relative frequencies of tie strength classes.

Class	Relative frequency
[0.75, 0.80)	0.3111
[0.80,0.85)	0.2444
[0.85,0.90)	0.2889
[0.90,0.95)	0.1333
[0.95,1.00)	0.0222
Diversity	**0.4738**

6.4. Ranking by diversity

Building up on the previous scenario we have presented, we shall demonstrate how one may rank volunteers based on diversity using entropy, as above. To begin with, assume that we have received answers from 20 distinct volunteers, with user IDs ranging from 1 to 20, as show in the next table.

[12] We have restricted ourselves to classes that are non-empty for at least one of our tasks.

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Table 14. The answers of 20 volunteers on a hypothetical multiple choice question.

Answer	Frequency	Volunteer IDs
A	6	5, 6, 8, 11, 13, 20
B	2	17, 19
C	9	1, 2, 3, 4, 7, 10, 12, 16, 18
D	3	9, 14, 15
Total	**20**	**-**

Let us also assume that the user has requested to rank the above volunteers with respect to diversity regarding their answers only. In next Table we see the diversity contribution for each of the four types of answers.

Table 15. Diversity contribution of each answer.

Diversity Contribution	+0.009	+0.051	-0.015	+0.031
Answer	A	B	C	D

So, any user providing an answer like B would be ranked higher in terms of diversity than any other user, since they contribute the most in the answer set's diversity. So, a ranking of the above users, with unbroken ties, would be:

17=19>9=14=15>5=6=8=11=13=20>1=2=3=4=7=10=12=16=18.

As one may observe, the above methodology, while it ranks volunteers with respect to their contribution in terms of diversity of the overall set of suggested volunteers, is not adequate for group suggestion. Yet, should our intention be to suggest a *group* of volunteers with maximal diversity, since entropy is maximized on the condition that all categories are of the same cardinality, one may merely suggest one volunteer from each category – i.e., in our example, this would mean suggesting four volunteers – possibly ranking them internally in terms of diversity contribution.

6.5. A full ranking example

Finally, we shall present a full ranking example. To begin with, assume that we have a user, say Alice, who creates a task and asks for some advice. Let us also assume that Alice has not explicitly stated the amount to which diversity should contribute to the final ranking outcome, which means that we should rely on historical data from previous similar tasks. For this purpose, assume that we have access to four similar past tasks, as shown in the next Table.

Table 16. Historical data of Alice.

Task id	1	2	3	4
Diversity ratio	0.42	0.35	0.38	0.41

So, based on the above – which indicates as discussed in 4.2.2 the amount to which Alice wanted diversity to play a role in previous similar tasks – we compute an average diversity ratio, λ, equal to $\lambda = 0.39$. So, this is the extent to which diversity should be taken into

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account in our ranking. Now, let us also assume that we have five (5) presented volunteers, as shown in next Table, described only by the their Big Five personality traits, for reasons of clarity.

Table 17. Five volunteers who have shown up for Alice's task.

ID	Meanings (Big Five - OCEAN)
1	(0.8, 0.6, 0.3, 0.5, 0.2)
2	(0.7, 0.6, 0.8, 0.5, 0.6)
3	(0.6, 0.5, 0.9, 0.5, 0.2)
4	(0.2, 0.4, 0.1, 0.4, 0.5)
5	(0.9, 0.6, 0.5, 0.6, 0.4)

Now, assuming that we have a previous model for Alice from tasks similar to these that indicate that she prefers users with the following distribution of Big Five:

$$p_0 = (0.50, 0.45, 0.63, 0.38, 0.49).$$

Further assuming that Alice has provided no preference over the user's attributes – e.g. that she would prefer more extrovert users – we assume that they all account matter the same, so we use an unweighted Euclidean metric. In Table 16 we present the distances of these volunteers from our implicit model of Alice's optimal volunteer for that task.

Table 18. Distance of volunteers from Alice's estimated optimal choice.

User ID	1	2	3	4	5
Distance from model	0.5656	0.3434	0.4288	0.6115	0.5059

Now, as one may observe, the volunteers presented in Table 18 are the same – with respect to their Big Five attributes – as the ones presented in Table 5. Using the results from Table 8, we present in the next Table the normalized diversity values for each of the OCEAN attributes.

Table 19. Normalized diversity for each of the Big Five personality traits.

Personality trait	Diversity
Openness	0.8636
Conscientiousness	0.6091
Extraversion	0.9545
Agreeableness	0.00
Neuroticism	0.6091

As above, assuming no particular preference on some specific attribute in terms of diversity, we obtain an average diversity score of 0.6101. Now, as described above, we calculate the diversity contribution of each of the volunteers in the above set, as shown in the next Table.

Table 20. Each volunteer's diversity contribution.

User ID	1	2	3	4	5
Diversity contribution	+0.0268	+0.0030	+0.1137	+0.0899	+0.0611

Normalizing the above data, we obtain our normalized diversity contributions, as shown in the next Table.

Table 21. Normalized diversity contributions.

User ID	1	2	3	4	5
Diversity contribution	0.0910	0.0102	0.3861	0.3053	0.2075

Lastly, inverting the distances shown in Table 19 and computing the λ –weighted average of them alongside with diversity contribution from Table 22, we obtain our final ranking scores as shown in the next Table.

Table 22. Total ranking score of each volunteer.

User ID	1	2	3	4	5
Ranking score	0.3005	0.4045	0.4990	0.3561	0.5210

So, based on the above, our final ranking will be:

3>2>5>4>1.

On the above we did not take into account the diversity of the answers. To do so, we could, as we have demonstrated above, take into account a weighted mean of the diversity scores of both the volunteer's Big Five attributes as well as the diversity contribution of each of the corresponding answers they have provided. For instance, let us consider a possible distribution of answers as the one show in next Table

Table 23. The answers of the users.

User ID	1	2	3	4	5
Answer	C	C	A	A	B

Assuming that diversity with respect to answers is of equal importance as diversity with respect to answers, we can compute total diversity as their arithmetic mean. Since normalized answer diversity equals 0.9602, we have a total normalized diversity of 0.7852. In Table 24, we present the normalized answer diversity contribution of each volunteer, their normalized total diversity score as well as their overall ranking score.

Table 24. Ranking after taking into account answer diversity.

User ID	1	2	3	4	5
Answer Diversity Contribution	0.0359	0.0359	0.0359	0.0359	0.8564
Total Diversity Contribution	0.0635	0.0231	0.2110	0.1706	0.5320
Ranking score	0.2897	0.4095	0.4307	0.3035	0.5089

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Taking into account the above leads to the following ranking:

5>3>2>4>1.

As one may observe, taking into account the answers of the volunteers at a significant rate – namely, taking into account the *diversity* of their answers – led to a formerly averagely ranked volunteer, namely volunteer 5, to be ranked as the most appropriate. Of course, this was a result of that volunteer's highly diverse answer as well as the fact that diversity was taken into account at a significant rate – and, especially, answer diversity was considered equally important as diversity regarding personality traits. In cases like the above, were a volunteer has some unique feature – e.g. they are the only who have answered C, as above – then our methodology of diversity assessment seems quite adequate, provided that it is within the user's desires to allow for such distinguished volunteers to be ranked high into our suggestions list.

6.6 Historical data on diversity awareness

Having the above data at our disposal and in order to raise diversity awareness not only in terms of how our mechanisms function but also in terms of informing the user about their choices and how diverse they have been, we could present them with diversity-related historical data. Namely, given a certain task – or, when possible, a certain group of similar tasks – we could inform the user as per their wish about the proportion of diversity included in each of their past selections. For instance, assuming that in 8 past tasks diversity significance for a certain user is demonstrated by the data displayed in Table 25, then we could present them with a plot like in Figure 14, where diversity significance and its evolution with time for that certain (group of) task(s) is shown.

Table 25. DIversity significance for a certain user and task.

Task	1	2	3	4	5	6	7	8
Diversity significance	0.56	0.57	0.49	0.42	0.43	0.38	0.29	0.33

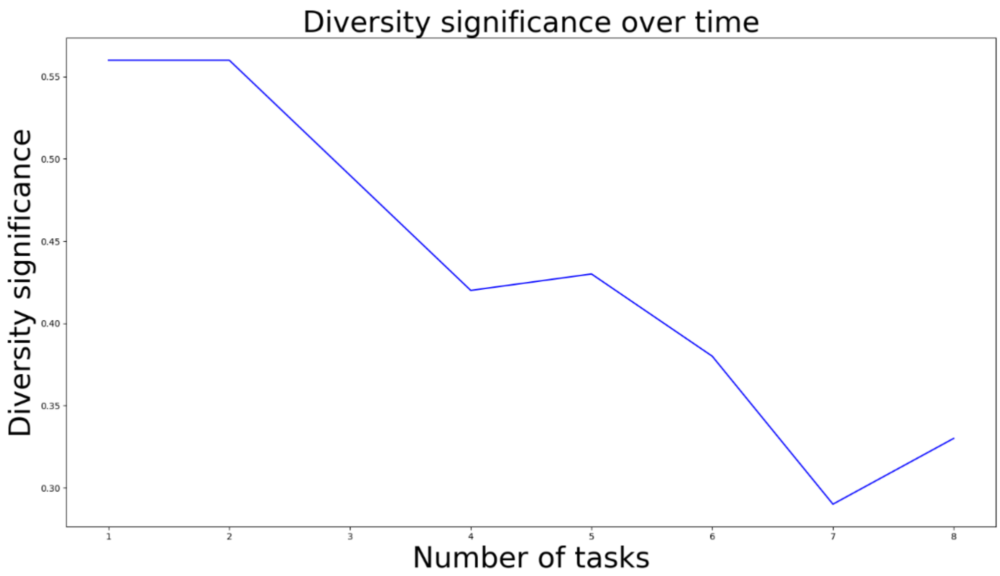

Figure 14: DIVERSITY SIGNIFICANCE OVER TIME ACROSS SIMILAR TASKS

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6.7 Friend recommendation

The above process, as presented, is a generic process that can allow for entity ranking taking into account both user preferences as well as diversity in terms of the attributes of the suggested entities. While the scenarios we have presented above all refer to a user being presented adequate volunteers regarding a task they have initiated, we can also utilize the very same process for other diversity-aware suggestion tasks that are not necessarily initiated by the user. A notable example could be a friend suggestion functionality within the scope of WeNet. That is, our task is to suggest to a user a ranked list of other users – not volunteers in this context – that we consider as appropriate to include in their list of friends/social network. As with diversity-aware volunteer suggestion, our methodology is capable of taking into account both fitness as well as diversity-aware criteria when making such suggestions/rankings.

For instance, let us consider, for reasons of simplicity the same five volunteers that we have already used in our previous examples. Also, let us assume that in terms of friend suggestion, our model for a user's preferences is given by:

$$p_0 = (0.65, 0.62, 0.74, 0.44, 0.51).$$

In Table 26, we summarize their Big Five traits, their distance of each of these five volunteers from our user, their normalized diversity contribution – computed as above – as well as their total ranking score – we assume that previous interactions have yielded a diversity significant coefficient $\lambda = 0.43$.

Using the data shown in the next Table we obtain the following ranking:

3>5>2>4>1.

This means that we could suggest the above five (5) users in the above order as potential friends.

Table 26. Ranking friend suggestions.

User ID	OCEAN	Distance from model	Diversity contribution	Total ranking score
1	(0.8, 0.6, 0.3, 0.5, 0.2)	0.2515	0.0910	0.4658
2	(0.7, 0.6, 0.8, 0.5, 0.6)	0.0603	0.0102	0.5400
3	(0.6, 0.5, 0.9, 0.5, 0.2)	0.1686	0.3861	0.6399
4	(0.2, 0.4, 0.1, 0.4, 0.5)	0.3639	0.3053	0.4939
5	(0.9, 0.6, 0.5, 0.6, 0.4)	0.1779	0.2075	0.5578

7. CONCLUSIONS AND NEXT STEPS

The deliverable has as main aim to present the diversity-aware social context builder and analyze the functionality of the three components it comprises. The emphasis is on the integration of diversity into the functionality of the three components. The components have discrete and complementary functionalities and aim to assist in delivering more accurate and diversity-aware procedures to the users and enhance their overall experience into the WeNet. The deliverable also presents the methodology used to determine the diversity and illustrates a set of case studies that showcase the functionality of the components. The

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further extension of the functionality of the components is an ongoing process that will continue and ultimately be finalized in M48. This round of design and implementation that is reported in the deliverable was meant to lead to diversity-aware procedures and specify the context of their deployment into the WeNet platform.

The next steps concern the actual use and fine-tune of the diversity-aware components with real data during the pilot studies. Specifically, pilot studies will facilitate the collection of real data and evaluate the developed components, using appropriately chosen metrics of performance, in the context of the pilot trials run in WP7 in the next months. Also, an aim will be to measure the benefits of diversity-awareness when dealing with social relations, social preferences and social explanations in the WeNet platform. The performance will be evaluated and the functionality of the methods will be constantly improved to accommodate for any newly observed features that will emerge from the case study.

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