Second International Conference on Computational Intelligence in Data Science (ICCIDS-2019)

TaskDo: A Daily Task Recommender System

Dr. Mohammad Amin Kuhail
Assistant Professor
School of Computing and Engineering
University of Missouri – Kansas City
kuhailm@umkc.edu

Nikhil Sai Santosh Gurram
Graduate Student
School of Computing and Engineering
University of Missouri – Kansas City
ng3qn@mail.umkc.edu

***Abstract*—Many individuals like working professionals, students, and house makers often find lack of time and time management as problems forsuccessful task accomplishment. One of the key reasons for failure in task accomplishment is inefficient planning of the tasks. There are many task management and to-do-list applications, but most of them do not advise on optimal task management and guidance for optimal performance. This problem has driven us to contribute a task recommender system which suggests a specific type of tasks to users based on their history of tasks and various factors at that specific time. This system not only suggests a specific type of task for the user but also collects feedback from the user to make the recommender system learn on how to provide useful recommendations thus making the users time much productive.**

Keywords—Data Analysis, Correlation Analysis, Data Science, Recommender Systems

I. Introduction

Striving to be productive remains a challenge for many workers, professionals and students alike. Various researches and surveys state that 70% of employees work beyond scheduled time and on weekends; more than half cited "self-imposed pressure" as the reason [1]. The survey, conducted by Greenfield Online [2], found that nearly half of college students (47 percent) feel their high school did not prepare them with the organizational skills required to do well in college and 54 percent felt they would get better grades if they "got organized and stayed organized."To recover from these sorts of problems, spending time organizing daily tasks would be helpful. Research says thatfor every hour of planning, 3 to 4 hours are saved from redundancy, waiting for information, not being prepared and poorly managed tasks [3]. With new age advancements in information technology, we have many applications which focus on time and task management. Task and time management tools such as Todoist [4] and Wunderlist [5] allow users to add and track tasks. However, these tools do not have a mechanism for suggesting tasks to be done at a specific time. Hence, users are left on their own to plan their daily schedule. Further, these tools have implemented some visual analytics to help users to understand their productivity, and how it changes over time.

Driven by the importance of time and task management, and lack of the tools which suggest a specific task for a specific time, we are inspired by the research question: “Based on the user’s history of completed tasks, can we recommend certain task types to be done at certain days of The week and times of day to increase a user’s productivity?”. To answer this question, we contribute TaskDo, a task recommender system which suggests a specific task to be done on certain days of the week and/or at certain times of the day. In generating the recommendations, the system relies upon the history of a user’s task completion. For example, since the system has observed that Adam tends to complete his chores at a shorter time on weekends in the morning, the system will recommend to Adam that he does his chores in the morning on weekends. This is a simple case, but it illustrates the point of the system learning about user’s habits of task completion and suggesting what is believed to best the best time for a specific type of task. Our initial thought is that the recommendations of task types will be affected by many variables such as day of the week, time of day, whether the task is done indoors or outdoors, whether the task is intellectual or physical, and so on.

II. Related Work

A. Task Management Applications

Many task and time management tools allow users to manage their tasks and times. These tools operate based on the simple idea of allowing users to add tasks, set due dates to them, and complete them when they can. However, these tools do not assist users in planning their daily or weekly schedule with tasks that users may be able to complete to increase productivity. There are some popular task management applications such as Wunderlist [5] which focuses on the

978-1-5386-9471-8/19/$31.00 ©2019 IEEE

organization of tasks into folders, hosting communication for tasks which involve multiple people, adding remainders, setting due dates and related notifications and so on. There is one more popular application called Todoist [4] which has most of the functions of Wunderlist, and it has additional features like organizing tasks into separate projects, and tracking user's productivity with help of various types of visual analytics which demonstrate task progress, task completion and pending tasks with help of bar graphs, pie charts and so on. However, these tools do not recommend users suitable type of tasks for a specific day and time. Timeful [6] was an application that aimed at understanding users' habits and schedules by asking users how often and when they want to do things. The system then assists users with planning their schedule. The idea seems promising, but the application is currently unavailable, which makes it hard to evaluate the accuracy of the application.

B. Recommender Systems

Recommender systems are used to filter out user relevant data from the enormous amount of data based on the ranking of recommendations. Using recommender systems can be beneficial for both producers and consumers because they filter out a massive amount of irrelevant data which might use extra resources with no productivity. There are two main types of recommender systems used in most of the applications, the generic definitions for them are

- Collaborative Filtering: Collaborative filtering recommends items by identifying other users with a similar taste.
- Content-BasedFiltering: Content-based filtering recommends items based on the user profile, it does not consider other users. [7]

Martínez, A. B., Arias, J. P., Vilas, A. F., Duque, J. G., & Nores, M. L have designed a system which recommends T.V shows for the users using both contents based and collaborative filtering. They have implemented a hybrid model using both the techniques because to avoid the cold start problem (no recommendations when starting off) which is caused by collaborative filtering and to avoid the over-specialization problem (showing only very few items from the user profile) caused by content-based filtering. [8]

Bagher, R. C., Hassanpour, H., & Mashayekhi, H have defined a model to estimate user personal interests by using collaborative filtering. They have implemented profile matching and latent factors as two main approaches for modeling the user. They have built this using a Bayesian non-parametric model, which provides a framework for constructing an evolutionary model. [9]

III. Design

TaskDo is an application which provides recommendations for a specific user for a specific day of the week and specific time of the day based on the user's previous task performance history. In the process of constructing this task recommender system, we found out that there are various dependent and independent modules. In order to explain this, the design of TaskDo can be divided into following subsystems that are shown in figure 1.

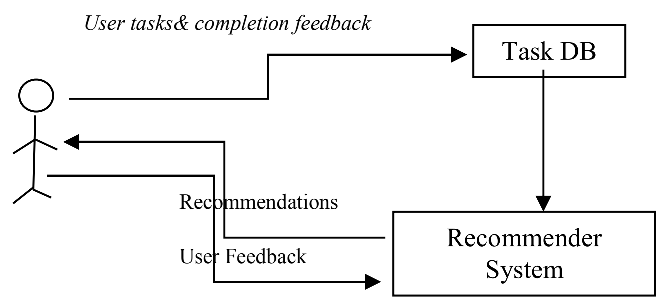


Figure 1. System Architecture

Fig.1 shows the system architecture for TaskDo, task recommender system. Firstly, users provide their tasks and related variables (will be explained in detail intask preferences and user feedback) into the system for some period of time. Later, after the completion of the task, the system will ask the user to record feedback on task completion satisfaction. Eventually, after recording many numbers of tasks for a certain period, the recommender system starts giving recommendations for example, if the user records successful completion of chores on Monday early mornings frequently and if the same user fails to successfully complete other types of tasks on Monday early mornings, the recommender system will recommend the user to perform chores over other task types on a Monday early morning. Once when the recommendations are provided to the user, the recommender system collects feedback on whether the provided recommendations were helpful or not and later, the system again provides the recommendations based on the updated feedback.

978-1-5386-9471-8/19/$31.00 ©2019 IEEE

A. *Task Preferences and user feedback*

During the process of building this system, we recognized that there isa wide range of tasks and we need to organize the user's tasks into different categories. Firstly, we narrowed down the scope of the tasks and divided all the tasks into the following categories listed in Table 1.

Table 1. Task Type table

Task Example	Task Type
Studying, Reading, Homework, etc.	Intellectual
House Maintenance, Gardening, etc.	Physical
Prayers, Meditation, etc.	Spiritual
Swimming, Jogging, Workout, etc.	Fitness & Health
Kids, Parents, Friends, etc.	Social
Groceries, Sending Mails, Shopping, etc.	Errands
Cooking, Cleaning, Laundry, etc.	Chores

Later, we discovered that there are some dependent variables which can influence on user's productivity such as Day type(Sunday, Monday, Tuesday, etc.), Time of the day(Early Morning, Morning, Afternoon, Evening, Night and Mid Night). When a user enters his task into the system, he is also required to enter all the subcategories for the dependent variables regarding that specific task. After the task is completed (or the time allocated for the task is completed) the system collects Task Completion Satisfaction Rating from the user regarding task completion. This feedback is collected from the user in the means of categorical 1 to 5 rating system as (1-Very Low Task Completion Satisfaction, 2-Low Task Completion Satisfaction, 3-Medium Task Completion Satisfaction, 4-High Task Completion Satisfaction, 5-Very High Task Completion Satisfaction). Eventually, after some amount of time each user has their Database in the system (Task DB) which contains all his tasks with feedback and the recommender system provides recommendations based on the tasks and feedback recorded in Task DB, hence making it a Content-Based Recommender System. The problem that we faced in developing a recommender system is that we do not have the task DB of specific user pre-recorded with us in order to develop and evaluate the recommendations. For this reason, we simulated a database such that a permutation and combination of each task type with each day, day type that is possible.

IV. METHODOLOGY

Whenever a user enters a task, its dependent variables and task completion satisfaction rating into the recommender system, it is stored into the Task DB as an input similar to a row in Table 2. For example, If a user performs Intellectual task on a Monday early morning, and if the same user records Very High Task Completion Satisfaction rating, it will be entered into TaskDB as first row in Table 2.

Table 2. Sample TaskDB table

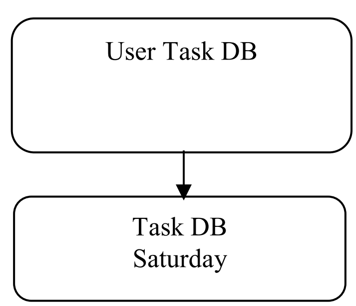
Time of the day	Type of the Day	Task Category	Task completion Satisfaction Rating
Early Morning	Monday	Intellectual	5
Afternoon	Tuesday	Physical	3
Evening	Sunday	Spiritual	4

After recording all tasks into the system in away mentioned above, the two most successful type of tasks is recommendedconcerning the type of the day and time of the day as a weekly plan.The sample weekly plan is shown in the Table 3.

Table 3. Weekly plan

	Early Morning	Morning	Afternoon	Evening	Night	Midnight
Saturday	1. intellectual 2. fitness	1. physical 2. intellectual	1. physical 2. chores	1. social 2. errands	1. fitness 2. intellectual	
Sunday	1. Spiritual 2. errands	1. chores 2. errands	1. Spiritual 2. physical		1. chores	1. fitness 2. physical
Monday	1. fitness 2. intellectual	1. intellectual	1. fitness 2. chores	1. social 2. fitness	1. social 2. Spiritual	1. intellectual 2. chores
Tuesday		1. errands 2. fitness	1. chores 2. social	1. fitness 2. social	1. intellectual 2. physical	1. errands 2. Spiritual
Wednesday	1. physical 2. intellectual	1. intellectual 2. errands	1. intellectual 2. physical	1. chores 2. physical	1. physical 2. fitness	1. social 2. errands
Thursday	1. errands 2. intellectual		1. errands 2. Spiritual		1. physical 2. chores	1. physical
Friday	1. fitness 2. intellectual	1. chores 2. fitness	1. chores 2. Spiritual	1. intellectual 2. Spiritual	1. social 2. Spiritual	1. chores 2. physical

To generate these type of weekly plan recommendations shown in Table 3, the Task DB is drilled down to create the recommendations. For example, if the system needs to recommend the two most successful tasks for Saturday early morning, the system drills down the whole user Task DB into required portion as shown in Figure 2.



978-1-5386-9471-8/19/$31.00 ©2019 IEEE

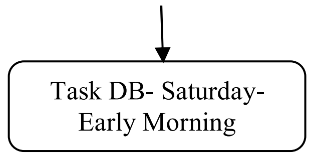


Figure 2 – TaskDBDrill-down

After drilling down data as shown in Figure 2 according to day and the time of the day, internally in our recommender system, we encode the values of Task Category and Task Completion Satisfaction Rating into binary categorical variables as shown in Figure 3

Time of the day	Type of the Day	Task Category	Task Completion Satisfaction Rating
Early Morning	Saturday	Intellectual	5

Task Category							Task completion Feedback				
Intellectual	Physical	Spiritual	Fitness	Social	Errands	Chores	Very low	Low	Medium	High	Very High
1	0	0	0	0	0	0	0	0	0	0	1

Figure 3. Binary Encoding

Once the system does the binary encoding shown in figure 3, it calculates the correlation between Task types (Intellectual, Physical, etc.) and Task Completion Satisfaction Rating categories (1, 2, 3, etc.). For example correlation between Intellectual task type and very low Task Completion Satisfaction Rating, Intellectual task type and low Task Completion Satisfaction Rating etc. for all task types are calculated.For this correlation analysis, we used the Phi correlation coefficient to calculate correlation coefficient between both of these binary variables.After, performing the correlation analysis, the correlation table looks likeTable4.

	Intellectual	chores	social	errands	fitness	physical	Spiritual
Very Low	0.193463	-0.17436	0.210183	-0.0406	-0.00717	-0.14092	-0.0406
Low	0.193463	-0.00717	-0.14092	-0.0406	0.193463	-0.17436	0.210183
Medium	-0.14092	-0.00717	-0.14092	-0.0406	0.193463	-0.17436	0.210183
High	-0.0406	-0.00717	-0.14092	-0.0406	0.193463	-0.17436	0.210183
Very High	-0.0406	-0.00717	0.210183	0.210183	0.193463	-0.17436	0.210183

Table 4. Correlation Table

So, the final recommendations into the weekly plan are given by calculating the rank score of each task type as shown below:

Rank Score for each task type = 2(Correlation of very high Task Completion Satisfaction Rating vs. Task Type) + 1*(Correlation of high Task Completion Satisfaction Rating vs. Task Type) + 0*(correlation of medium Task Completion Satisfaction Rating vs. Task Type) - 1*(Correlation of low Task Completion Satisfaction Rating vs. Task Type) - 2*(Correlation of very low Task Completion Satisfaction Rating vs. Task Type)*

After calculating the rank score for each task type, the two highest positively rank scored task types will be provided as recommendations into a weekly plan for every type of the day and time of the day combination as shown in Table 3. The pseudocode for this entire process is written below;

Import Task DB
For all Type of the day values:
  For all Time of the day values:

- *Drilldown TaskDB as shown in figure2*
- *Apply binary encoding to all values in the Drilled Task DB*
- *Calculate the Phi correlation between theTask typecategories and Task Completion Satisfaction Rating categories*
- *Calculate a rank score for each task types with the formula given above*
- *Return two best task types with highest positive rank score into the weekly plan for selected Type of the day and Time of the day*

V. FUTURE WORK

Since the data that we are using currently is simulated by ourselves to perform validation over the developed system, the system may not be the best fit yet with real-world data. For this reason, we want to anonymously collect data from 20 different volunteers for over two months to get a real-world task dataset. After getting this dataset, we want to perform the same correlation analysis and provide recommendations back to the user regardingthe weekly plan and check whether the users are satisfied with the provided weekly plan or there are any adjustments that need to be done to the system based on the user's feedback on provided recommendations.We also found some dependent variables such as Weather, Task location, Task Duration,etc. which may influence the productivity of the tasks. In the future, we also

978-1-5386-9471-8/19/$31.00 ©2019 IEEE

want to take them into account and perform the correlation analysis before providing the recommendations. Moreover, since most the data that we are using to provide recommendations is categorical, we also want to use Machine Learning classification algorithms such as Bayesian classifiers, cluster analysis, decision trees,and Artificial Neural Networks to provide better task recommendations to the user.

REFERENCES

[1] "Time Management Statistics." Key Organization Systems. Accessed December 3, 2018.

[2] Wires, RP News. "College Students Struggle with Organizational Skills." Reliable Plant. November 15, 2006. Accessed December 03, 2018.

[3] "Organizing & Time Management Statistics." Simply Productive. April 23,2014. Accessed December 03, 2018.

[4] "Todoist – The Best To Do List App & Task Manager." Todoist. Accessed December 03, 2018

[5] "To-do List, Reminders, Errands - App of the Year!" Wunderlist. Accessed December 03, 2018.

[6] Etherington, Darrell. "Google Acquires Timeful To Bring Smart Scheduling To Google Apps." TechCrunch. May 04, 2015. Accessed December 03, 2018.

[7] Isinkaye, F. Et Al. "Recommendation Systems: Principles, Methods and Evaluation." NeuroImage. August 20, 2015. Accessed December 03, 2018.

[8] Martinez, Ana Belen Barragans, Jose J. Pazos Arias, Ana Fernandez Vilas, Jorge Garcia Duque, and Martin Lopez Nores. "What's on TV Tonight? An Efficient and Effective Personalized Recommender System of TV Programs." An Introduction to Biometric Recognition - IEEE Journals & Magazine. April 17, 2009. Accessed December 03, 2018.

[9] Bagher, R. C, Hassanpour, H., and Mashayekhi, H. "User Trends Modeling for a Content-based Recommender System." NeuroImage. June 13, 2017. Accessed December 03, 2018.

978-1-5386-9471-8/19/$31.00 ©2019 IEEE