# *Machine Learning for Task Recommendation during Disasters*

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*The success of a disaster relief effort depends strongly on the recruitment, organization, and collaboration of the volunteers. Much time and energy is spent registering volunteers and assigning tasks to them based on their skills as well as available resources. If this process could make use of modern technology and be automated, then more time could be spent doing meaningful and urgent work. To better match these volunteers with tasks that they are likely to prefer and complete successfully, we propose a recommender system that connects user-provided data with the needs of disaster relief organizers. The Cayenne Team's system will use volunteers' input to shape recommendations for future task assignments.*

## Introduction

This note explores the various ways machine-learning algorithms help with disaster relief efforts. The methods described here and those used in the Cayenne Team's project solution (Figure 1) involve the concept of recommender systems. This idea will be combined with a more efficient signup and communication system to better organize disaster relief.

A recommender system matches users with tasks based on their mutual compatibility. Profiles are created for both tasks and users, which are then matched based on preference ratings. Users have preferences for certain tasks, and those preferences must be teased out of the data. To do thi,s there must be some sort of consistency in the definition of tasks and users to be able to match aspects of both. Users will have to be defined somewhat like tasks and vice versa. By assigning tasks based on computed fits rather than random delegations, we will ensure that users are more likely to complete their tasks and feel more rewarded since they will most likely be matched with a task they would have chosen.

The second and crucial part of a recommender system is the ability to learn from experience. The system recommends future tasks based on users' success—in terms of completion and satisfaction—with tasks. As a user completes tasks, the system will learn and be able to recommend future options in a more informed manner. The key to enabling this system is to use a

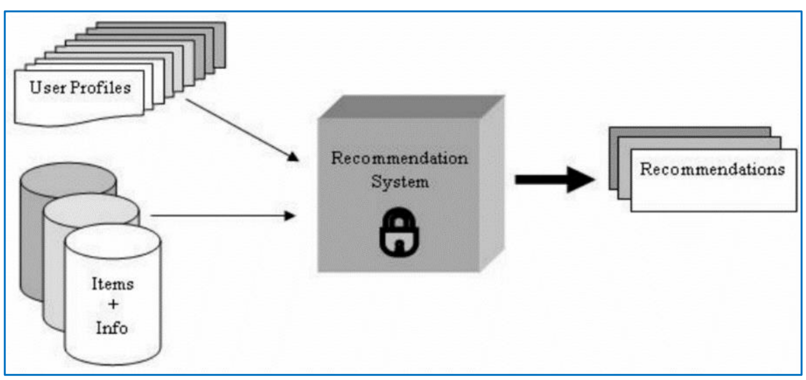


*Figure 1. Cayenne Team's Recommender system.*

*machine-learning* algorithm as opposed to a simple *matching* algorithm.

Machine-learning algorithms are ubiquitous in today's content driven online universe. From targeted ads, to online shopping, online dating, Netflix, and more, everything uses your current experiences to recommend content for the future. A simple example are the page clicks used to track your web habits and your ratings of certain products, such as movies on Netflix, to recommend similar ones you might not find otherwise.

## Theory / Background

Machine-learning involves a class of computer algorithms which able to 'learn' from their own computational experience and improve their performance for future iterations. A computer program is said to 'learn' from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E (Mitchell, 1997).

The field of machine learning has gained much traction and become much more mathematical in its approach for a more scientifically accurate result. The field stems mainly from research in pattern recognition and is now used in a wide variety of software solutions. One popular branch of the greater machine-learning field is that of recommender systems, which uses big data analysis to learn from past models to predict future occurrences. In the context of the Cayenne Team's project, a predictive model for future task assignments is built so that it learns from past predictions.

Recommender systems help solve the classic paradox of choice, where users have too much choice, making them feel overwhelmed, yet simultaneously feel they have no options. A recommender system helps filter out the options to leave the user with a more limited but tailored subset of choices. Users on Netflix, for example, will lose interest in choosing a DVD title after 60 to 90 seconds of searching (Gomez-Uribe & Hunt, 2015). The risk that Netflix faces is in losing those customers who cannot find an appealing title within a limited timeframe. This risk also exists for our project. Volunteers will be given the choice of several tasks and if they do not find one that they would be willing to volunteer for in a limited amount of time, they might abandon our system. Therefore, our system must ensure that the users will find their preference within the first few screens they view. In our case, a bigger risk is that users will volunteer for tasks that they may be unsuited for, thus hurting the efficiency of the overall relief effort. And these mismatched users may be disinclined to volunteer in the future if their experience was an unpleasant one.

The objective of our system is to offer potential volunteers a more enjoyable volunteering experience. Because relief efforts depend heavily on the goodwill of volunteers, we must ensure that they find the experience rewarding so that they are inclined to volunteer in the future. The recommender system will help target volunteers with tasks that they will enjoy and complete successfully. It will learn from the user's experience and only improve its recommendations. By presenting users with options they are most likely to choose, we are freeing up critical time previously wasted choosing a task that now can be spent on performing a task. We are also more likely to assign volunteers to tasks they will complete successfully, contributing to the success of the overall relief effort.

The entire system will help improve communication and streamline the sometimes labor intensive process of volunteering. The benefits of this system can be measured in the time it will save volunteers in signing up, along with the intangibles of volunteer morale. This is an exciting field of research because it combines an established concept of machine learning with a new and untested platform: volunteering.

### *Sample Systems and Further Work*

An interesting extension to this research and a current hot topic in machine-learning is the analysis of social media for use in disaster scenarios. Many papers on this topic have been published and systems even deployed during disaster relief efforts with the goal of determining needs based on Tweets. One article discusses the use of a machine learning system in Nepal to classify tweets and use them to map the needs of the victims across the country (Meier, 2015). This approach could be incorporated into our system as an extension of our predictive algorithm. Because disasters are subject to change, this could help our algorithm adjust to the needs of the victims in real-time. After completing their initial assigned tasks, volunteers could then be re-allocated to other tasks as determined by the Tweet mining system.

Another article (Huang & Xiao, 2015) discusses the use of Tweet mining to determine the stages of a disaster. It discusses the idea that a disaster goes through four stages (mitigation, preparedness, emergency response, and recovery) and suggests that analyzing tweets could help classify a disaster's current stage.

## Conclusion

The Cayenne Team believes that we will see the classification of a system as a "machine-learning algorithm" disappear over time as it becomes more deeply understood and engrained into our software solutions. These applications closely resemble a human approach to problem solving. Machine-earning helps us make sense of the chaotic nature of human communication and as opposed to making humans adhere to what is understandable by a machine it makes the machine adhere to us. This will only become more prevalent and even essential in any system so that solutions may become increasingly simple to use.

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