## Weather Sensitive Smart Stylist <br> By Alex Bukovac

## INTRODUCTION

According to Bill Cunningham, "fashion is the armor to survive the reality of everyday life". To some, the worst part of their day is waking up and having to pick out their outfit. There are a few things to consider: the temperature, the percent humidity, the type of weather and the time of the year/season. It can be difficult to contemplate all these aspects when you just wake up. However, what if there was a program that recommended an outfit in your wardrobe based on the weather that day?

This study delves into creating a rule-based relationship between weather and clothing. The rules created as a baseline for the general user was deduced by surveying a group of 100 people. Once the general rules were established, we wanted to explore the possibility of adapting to a specific user. To create a "smart stylist" and enhance user experienced, we asked the user about the recommended outfit choice to learn and adjust with machine learning. This adaptive rule-based system was inspired by Haosha Wang's paper titled "Machine Fashion: An Artificial Intelligence Based Clothing Fashion Stylist". In this study, the user input their style preferences and the program recommended an outfit for them. Yet, we wanted to take a different approach by asking for the user's thoughts post-recommendation.

## METHODS

Two separate approaches needed to be taken in order to solve the original problem of recommending an outfit for the user.

## Approach 1 Abstract

The first approach required developing a rule-based system to generate outfit recommendations. To begin, my rule-based system takes in weather data for the user's current location using weather undergrounds API. It also takes in closet data which includes every item in the user's closet, with categorizations and scales such as material, color, brand, etc. For the closet input, I used items from my own closet. The rule-based system generates a complete recommendation for the user including shoes, pants, top, etc. The initial rules were generated by taking a survey of one hundred people, asking at what temperature they would wear shorts, sweaters, boots, etc. The generated recommendation was shown to the user. If the user responded that they weren't going to wear the outfit, their reasoning for not wearing it was collected and stored. I used SQL to store all the recommendations as well as the user's responses. This process was repeated 100 times to have a base set of recommendations for the machine to learn from.


Approach 1 Diagram

## WEATHER RETRIEVAL

For using today's weather, we ask the user to input the city and state they will be wearing the outfit in. Using this information, we make a call to the Weather Underground. Weather Underground's API gives reliable global coverage. We request the temperature in degrees Fahrenheit, type of weather (rain, snow, etc.) and the date.

## RULE-BASED SYSTEM

In order to give a complete outfit recommendation, we created a rule-based system that pairs items based on the weather. The baseline rules were based off of a survey taken by 101 people evaluating at what temperature they would wear certain items. For example, a survey taker would answer at what temperature they would wear shorts or open-toed shoes. After these temperature rules were created, the next layer of constructing a full outfit needed to be accomplished. To do so we made sure that dresses weren't paired with pants, shoes weren't paired with other shoes, etc. Basically, we made sure the outfit was fully put together and was not conflicting. -See survey below-

After the recommendation was given to the user, the user responded about whether or not they wore it and if they didn't, why? The outfit and the user's response to the outfit was saved in a SQL table.

Q1
At what temperature do you like to wear shorts/bare your legs?


Q2
At what temperature do you like to wear long sleeves/a sweater
Answered: 100 Skipped: 0


Q3
At what temperature do you like to wear flip-flops/open toed shoes?
Answered: 100 Skipped: 0


Q4
At what temperature do you like to wear a coat
Answered: 100 Skipped: 0


## Q5

At what temperature do you like to wear boots
Answered: 100 Skipped: 0


The second approach required machine learning to generate customized user experience. The assumptions of weather and closet data remained the same. As well as the rule-based system recommending an outfit for the user, but this time the recommendation is not immediately shown to the user. It is fed into the case-based reasoning step. Those 100 stored recommendations from the previous approach are also fed into case-based reasoning step too.

Case based reasoning compares the current recommendation with the previously recommended outfits. It uses the difference of squares to compare the outfits. Once it finds the most closely related outfit, it checks the user's previous response to the outfit. If the user said no previously, the system will generate a new rec, but if they previously said yes, it is shown to the user.

The other side of "machine learning" in this research is the adjustment of the temperature profile. Early in this presentation when I talked about the rules created based on the survey results, these rules are changed based on when the user responds that they were too hot or too cold in an outfit.

The user interface from approach 1 remained the same. However, this new approach is cyclical system because SQL database of recommendations and user's responses continues to get added to (meaning it is constantly learning)


Approach 2 Diagram

## CASE-BASED REASONING

After having a full recommendation and the user's response in a database, we decided to implement a machine learning aspect. Since we already had previous recommendations, we chose case-based reasoning. In our scenario, the recommendation is generated using the rulebased system and then that recommendation is compared with all the previously recommended outfits. Using the difference of squares, the outfits are compared and evaluated. Then we look closer at the previous recommendation that is most similar to the current recommendation. If the user previously said yes, we will show the recommendation to the user and store their response. If the user previously said no, we will rerun the system to give a new recommendation. If the user has previously said no to 3 of the created recommendations, the system will automatically show the third one in order to get more data about the user's preferences.

## USER INTERFACE

Although I didn't have the chance to create an app for this program, I did create an HTML interface. I received assistance from Alana Wimer, Connecticut College, to design mockups of the ideal mobile application.


Mockup of mobile app for research

## CONCLUSION

Overall, the two approaches taken allowed us to achieve our goal of generating a recommendation for the user. We successfully incorporated the user's style and temperature preferences. In future developments, we play to take into account the timing of outfits (not recommending the same outfit twice in a week). We also plan to incorporate season and occasion as an attribute of the clothing items

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