MACHINE FASHION:

AN ARTIFICIAL INTELLIGENCE BASED CLOTHING FASHION STYLIST

by

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(Under the Direction of Khaled Rasheed)

ABSTRACT

"Clothes make the man," said Mark Twain. This work presents a survey study and an application as our answer to "Can an AI machine be a fashion stylist?" This study expounds upon the focus of earlier studies and summarizes previously employed AI techniques in the fashion domain. In addition, we provide a tool for the community: Style-Me. Style-Me is a machine learning application that recommends fashion looks. More specifically, Style-Me learns user preferences through the usage of Multilayer Perceptron model. The system scores user's customized style looks based on fashion trends and users' personal style history. Although much remains to be done, our study demonstrates that an AI machine can be a fashion stylist.

INDEX WORDS: Machine Learning, Clothing Fashion, Artificial Neural Network, Adaptive Rule-Based System

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DEDICATION

To my parents, Qin Xu and Zhiyi Wang, with love.

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# CHAPTER 1

# INTRODUCTION

Human creativity as one of the major challenges for the AI domain has captured the world's attention for years. Artist Harold Cohen's AI artist program, "AARON", was the first profound connection between AI and human creativity and has been in continual development since its creation in 1937 (Cohen, 1995). "JAPE" (Joke Analysis and Production Engine), is another example of an AI imitating human creativity. In this case, computer program generates punning riddles modeling human humor (Binsted, 1996). Among all of these domains of human creativity, the fashion industry's unpredictable irrationality, individual uniqueness and cultural dependence make human fashion behavior modeling one of the biggest challenges in this area (Boden, 1998). Moreover, according to a survey done by OfficeTeam, the 93% out of more than 1000 senior managers at companies with 20 or more employees responded that clothing choice affects an employee's chance of promotion (OfficeTeam, 2007). However, keeping track of fashion sense requires significant time and effort, which leads some people to seek help from a professional stylist. Hiring personal stylists can be expensive and not always accessible. This study discusses whether an Artificial Intelligence system could be the new fashion stylist and how to implement such a system. There are many benefits associated with using AI programs as the future stylist. There are many benefits associated with using computer programs as future stylists. They could process large amounts of data faster when learning a user's style and memorizing users' feedback. AI stylist programs can also store descriptions of user's items and help users be more organized and efficient.

Our contribution is two-folds: a survey study of earlier related studies and an AI-based model "Style-Me". In the Chapter 2, the survey study explores AI methods in the clothing fashion domains. Three major components of a full styling task are identified and earlier projects' relevant fashion theories and employed AI methods are summarized. In the Chapter 3, we present the essence of Style-Me and the major AI techniques that have been implemented. In this version, we created a manageable database which contains 32 dresses and 20 shoes for 4 different events, encode a standard style rules engine, generate more than 500 looks and rank them by a final score in descending order. The score indicates how fashionable each look is based on users' feedback. The learning component trains an Artificial Neural Network (ANN) to learn users' personal preferences and adjust the final score. Moreover, the system provides a feature that allows users to customize a fashion look. This feature provides a shopping guide to inform users' purchase plans. On the front-end of the Style-Me system, users initialize Style-Me by taking a fashion personality quiz. The User Interface (UI) design of Style-Me follows minimalistic and intuitional style, which gives users a smooth experience. There are five sub-sections in Chapter 3: 3.3 System Overview; 3.4 Data Preparation and Preprocessing; 3.5 User Interface Design; 3.6 Machine Learning Approaches; 3.7 Summary and Future Work. Generally, a full product level system requires the large amount of data and takes significant time to build. Chapter 4 summarizes several interesting works we hope to perform in the future.

# CHAPTER 2

# ARTIFICIAL INTELLIGENCE IN CLOTHING FASHION [1]

[1] Haosha Wang, Khaled Rasheed Accepted by *International Conference on Artificial Intelligence 2014*. Reprinted here with permission of publisher.

## 2.1 ABSTRACT

"Clothes make the man," said Mark Twain. This article presents a survey of the literature on Artificial Intelligence applications to clothing fashion. An AI-based stylist model is proposed based on fundamental fashion theory and the early work of AI in fashion. This study examines three essential components of a complete styling task as well as previously launched applications and earlier research work. Additionally, the implementation and performance of Neural Networks, Genetic Algorithms, Support Vector Machines and other AI methods used in the fashion domain are discussed in detail. This article explores the focus of previous studies and provides a general overview of the usage of AI techniques in the fashion domain.

## 2.2 INTRODUCTION

There might be a moral argument about whether people should be judged by their apparel. In practice however, few people would consider a person in baggy jeans walking into their first meetings seriously. Dressing properly brings a big ROI (Return of Investment). According to a survey done by OfficeTeam, 93% out of more than 1000 senior managers at companies with 20 or more employees responded that clothing choice affects an employee's chances of promotion (OfficeTeam, 2007). However, keeping track of fashion sense requires significant time and effort, which leads some people to seek help from a professional stylist. Personal stylists can be expensive though and cannot be with clients all the time. This study discusses whether an Artificial Intelligence based computer program could be the new fashion consultant and how it might be executed. There are many benefits associated with using computer programs as future stylists. They could process large amounts of data faster when learning a user's style and memorizing users' feedback. AI stylist programs can also store descriptions of user's items and help users be more organized and efficient.

The goal of this survey study is to explore AI methods in the clothing fashion domain. In the second section, three major components of a full styling task are identified. The third section is a summary of earlier projects and relevant fashion theory. In the methodology section, earlier works in AI implementation and their solutions to each major problem are explored. The last section is a discussion.

### 2.2.1 RELATED AI-TECHNOLOGIES

Every fashion clothing styling task which is completed has 7 steps: picking a theme, deciding on a primary color, mixing and matching clothing pieces, selecting accessories, model or client fitting and finally hair styling and make up.

An AI based computer program focused on modeling centers on solving the following questions:

1. How to represent garments computationally?
2. How to model human stylist behavior?
3. How to detect, track and forecast fashion trends?

Popular AI methods used previously include Fuzzy Logic, Genetic Algorithms, Neural Networks, Decision Trees, Bayesian Networks and Knowledge Based Systems and their variations. This section will briefly outline these AI methods.

A *Bayesian Network* is a probabilistic model that represents variables and their conditional dependencies (Russell & Norvig, 2009). They have been used to infer relationships between previous fashion trends and future trends.

*Fuzzy logic* is an approach that utilizes uncertainty and approximate reasoning (Eberhart & Shi, 2007). It represents truthfulness and falsehood with degrees and works closer to human brain because it outputs a straightforward like or dislike.

Using *Artificial Neural Networks (ANNs)* is a learning method inspired by animal nervous systems. An ANN maps input to a target output by adjusting weights (Eberhart & Shi, 2007). This method works well for modeling complex styling tasks with multiple features.

*Knowledge-Based Systems* are programs that represent knowledge and solve complex problems by reasoning on how knowledge artifacts are related or not related (Eberhart & Shi, 2007). They are used to show the relationships between features in fashion styling.

*Decision Trees* are tree-structured graphs that represent attributes as internal nodes and outcomes as branches (Kokol, Verlic, & Krizmaric, 2006). They are widely used in human decision-making models.

*Genetic Algorithms (GAs)* are search techniques that look for approximate or exact solutions to optimization problems. They are guided by a fitness function. Interactive Genetic Algorithms (IGAs) have been used in earlier studies aimed at achieving real-time interaction. The biggest difference between IGAs and regular GAs is that instead of using a fitness function, IGAs assign a fitness value to each individual (Tokumaru, Muranaka, & Imanish, 2003).

## 2.3 CONTEMPORARY APPLICATION

### 2.3.1 RESEARCH DESIGN OF THIS STUDY

In this study, the AI-based fashion applications and articles are classified based on the fundamental definition of fashion. Fashion is a major part of people's daily lives and the fashion market itself is quite large. In the next two sections, current popular computer applications and prior research from the last decade are summarized.

### 2.3.2 POPULAR APPLICATIONS

There are four major types of applications as shown in Table 1. *Internet Based Human Stylist Consultant Services* put the communication between clients and stylists on the Internet. They improve the flexibility and accessibility of styling work. *Virtual Fitting Systems* fill one of the major gaps between e-commerce and retail stores. The third type of application is *Recommender System Implementations in E-commerce*; for example Amazon recommends new items based on users' browsing histories**.** The last type is *Online Fashion Communities*, such as Polyvore, which provide a platform for people to share, gain and communicate fashion inspiration and shopping information online.

### 2.3.3 EARLIER RESEARCH PROJECTS

Conceptually, fashion can be defined as a two dimensional concept, an object and a behavior process. The form of a "fashion object" can be a specific product or innovative

Table 1: Popular Fashion Applications List

*All sites listed above were visited on April 15$^{th}$, 2014

| Business Model | Name | Website URL* |
|---|---|---|
| **Human Stylist Internet-Based Consultant Services** | | |
| Recommend new items to mix and match with user's existing items | Topshelf | http://www.topshelfclothes.com/ |
| | MyPrivateStylist | http://www.myprivatestylist.com/ |
| Exclusive, high reputation and experienced stylists offer service to their members | KeatonRow | https://keatonrow.com/ |
| | Style-MeASAP | http://Style-Measap.com/ |
| Human stylists style male customers within clothing collections | TrunkClub | http://www.trunkclub.com/ |
| **Virtual fitting system** | | |
| Customized virtual avatars for virtual clothes fitting experiences with clothing imagery | Glamstorm | http://glamstorm.com/en |
| | CovetFashion | http://www.covetfashion.com/ |
| | ChroMirror | (Cheng, Ouhyoung, Chung, Chu, Yu, & Chuang, 2008) |
| **Recommender system in e-commerce sites** | | |
| Recommend items based on user' activities and browsing records | Amazon | http://www.amazon.com/ |
| Recommend new trendy clothing items and search for relevant clothing items based on user's | Google Shopping | http://www.google.com/shopping |

| | | |
|---|---|---|
| search queries | | |
| Pushes sale information based on user's preferences | Shop It To Me | http://www.shopittome.com/ |
| **Online fashion community** | | |
| Platforms for users to create, share and look for fashion inspiration | Polyvore | http://www.polyvore.com/cgi/home |
| | Lyst | http://www.lyst.com/ |
| | StyledOn | http://styledon.com/ |

specific product or innovative technical features or new membership services. While "fashion process" is a process through which a "fashion object" emerges from its creation to public presentation, trendsetter adapting, majority acceptance/rejection, and replacement of newer object and merge of next trend (Sproles, 1979).

The major focus of this study is to find solutions for the three target problems stated in Section 2.2. Among the three problems, the first one, garment representation focuses on fashion object. The third one, detection, tracking and forecasting of fashion trend are about fashion process. While the second one, modeling human stylist behavior is a mixture of both.

2.3.4 AI TECHNIQUES ON "FASHION OBJECT"

Back in 2000, Genetic Algorithms were used in a fashion design assistant system (Kim & Cho, 2000). Clothing color styling model was proposed in the Virtual Stylist Project in (Tokumaru, Muranaka, & Imanish, 2003). Decision Trees with Genetic Algorithms were used to model individual's clothing in (Kokol, Verlic, & Krizmaric, 2006). Researchers implemented Category Learning and Neural Networks in an intelligent clothing shopping assistant system in 2008 (Cheng & Liu, 2008). Computer Vision techniques with Support Vector Machine (SVM) classifiers were used to discover the semantic correlations between attributes in (Chen, Gallagher, & Girod, 2012).

2.3.5 AI TECHNIQUES ON "FASHION PROCESS"

Previous studies tried to understand, detect and predict fashion trends and fashion cycles from both the perspectives of theory and application. Two earlier studies focused on predicting clothing color fashion trends. Mello's team developed an expert system that assists the stylist with the proposal of new color trends. Their system implemented a Bayesian Network model stylist proposing process (Mello, Storari, & Valli, 2008). Yu's team compared different AI

Table 2: AI in Fashion Projects List

| Year | Title | Reference |
|---|---|---|
| **Garment Representation – Fashion Object** | | |
| 2000 | Application of Interactive Genetic Algorithm to Fashion Design | (Kim & Cho, 2000) |
| 2012 | Describing Clothing by Semantic Attributes | (Chen, Gallagher, & Girod, 2012) |
| **Human Stylist Behavior Model – Fashion Objects & Fashion Process** | | |
| 2003 | Virtual Stylist Project – Examination of Adapting Clothing Search System to User's Subjectivity with Interactive Genetic Algorithms | (Tokumaru, Muranaka, & Imanish, 2003) |
| 2006 | Modeling Teens Clothing Fashion Preferences using Machine Learning | (Kokol, Verlic, & Krizmaric, 2006) |
| 2008 | An Intelligent Clothes Search System Based on Fashion Styles | (Cheng & Liu, 2008) |
| 2008 | Mobile Fashion Advisor – A Novel Application in Ubiquitous Society | (Cheng & Liu, 2008) |
| **Fashion Trend Detection, Track and Forecasting- Fashion Process** | | |
| 2010 | Application of Machine Learning Techniques For the Forecasting of Fashion Trends | (Mello, Storari, & Valli, 2008) |
| 2012 | An Empirical Study of Intelligent Expert Systems on | (Yu, Hui, & Choi, 2012) |

| | | |
|---|---|---|
| | Forecasting of Fashion Color Trend | |
| 2012 | Understanding Cyclic Trends in Social Choices | (Sarma, Gollapudi, Panigraphy, & Zhang, 2012) |

models for predicting fashion color trends with an expert system (Yu, Hui, & Choi, 2012). There are many interesting models of fashion trends. One model on simplified general fashion cycles was of specific interest. This model has three major factors: base utility, social influence and user boredom (Sarma, Gollapudi, Panigraphy, & Zhang, 2012).

## 2.4 AI METHODS IN FASHION

### 2.4.1 GARMENT REPRESENTATION

Garments can be described by a set of features as shown in Figure 1. Different pieces have their own unique features. The most basic features are Color, Shape, Print and Fabric (Material). Computer Vision techniques are able to automatically recognize the first three. Color is initially represented in a RGB (Red, Green and Blue) model and converted into an HSI (Hue, Saturation and Intense) model for further computation (Tokumaru, Muranaka, & Imanish, 2003) (Cheng & Liu, 2008). The Outline can easily be extracted with Computer Vision techniques and the print of a garment can be considered in its loudness. The loudness in this case is the frequency of color changes in the garment and the changes in locality on this garment. Fabric is the trickiest one. Even humans would have difficulties recognizing a fabric just by looking at it.

One possible solution for tricky attributes like "fabric" is inspired by the computer vision research project in 2012. They researched stylistic semantic correlations between clothing attributes. For example, Mark Zuckerberg's dressing style contains attributes like "gray/brown" and "t-shirt/outwear". They applied Support Vector Machine classifiers on single attributes to determine how useful these attributes would be in prediction. Then, the system makes predictions based on inference of different attributes' mutual dependency relations in a Conditional Random Field (Chen, Gallagher, & Girod, 2012). With a similar model, systems One possible solution for tricky attributes like "fabric" is inspired by the computer vision

research project in 2012. They researched stylistic semantic correlations between clothing attributes. For example, Mark Zuckerberg's dressing style contains attributes like “gray/brown” and “t-shirt/outwear”. They applied Support Vector Machine classifiers on single attributes to determine how useful these attributes would be in prediction. Then, the system makes predictions based on inference of different attributes' mutual dependency relations in a Conditional Random Field (Chen, Gallagher, & Girod, 2012). With a similar model, systems could learn correlations between attributes and fill in missing values. For instance, a formal dress has a high possibility of being made of silk. Casual style white t-shirts are likely to be made of cotton.

### 2.4.2 COMPUTATIONAL STYLING TASK

#### 2.4.2.1 COLOR HARMONY EVALUATION

Color is the very first step in a fashion styling task. In previous research, Matsuda's Color Coordination (MCC) has been used to evaluate the harmony rate between colors (Tokumaru, Muranaka, & Imanish, 2003; Cheng & Liu, 2008). Yutaka Matsuda who had investigated color schemes of female clothes and dress through a questionnaire for 9 years proposed MCC. In MCC there are 80 color schemes (8 hue types and 10 tone types) and a color scheme is harmonious if there are many samples in the system. Each individual has a unique style preference. An ideal intelligent style system should be able to adapt from a standard color scheme to a specific user's personal preference instantaneously. One working solution is to make static color schemes more dynamic.

In VSP, they added linguistic labels (“neutral, “a little”, “slightly”, “fairly”, “very” and “extremely”) on the color scheme and linguistic labels are presented as fuzzy sets respectively. Their system adapts itself to a user's preference during its interaction with the user. They also


Figure 1: Describing garments with attributes *

*Websites are visited on April 30$^{th}$, 2014

implemented an Interactive Genetic Algorithm so that the system is able to do so in real time. There are three different types of nodes in their IGA: the parameters of four basic senses, the weight of four senses and fuzzy rules. The system displays some dress patterns based on its knowledge and the user rates the similarity to her clothing sensation from 1 to 5. Highly rated individuals are used to generate the next generation individuals (Tokumaru, Muranaka, &

Imanish, 2003). The experimental results confirmed that IGA optimized the system and the system was able to adapt itself to specific user preferences.

2.4.2.2 SHAPE, PRINTS AND FABRIC STYLING

Identifying shape, print and fabric is the second step in the fashion styling task. Style principles of these attributes are changing all the time. For instance, one of the standard style rules for prints is to wear only one pattern piece at a time. However, in the 2014 spring season, wearing two patterns with similar shades and detailing became very trendy. Moreover, it heavily depends on individual preference. Women with a classic style will not follow this new trend. Many other features also affect the styling task, such as occasion and cultural background. In this scenario, a stylist looks at a number of features from different categories and tries to classify items based on their experience and fashion sense. A Neural Network model is a good approach for a problem like this. In a previous study, an ALCOVE (Attention Learning Covering map) model based on NN was implemented in a clothing match system (Cheng & Liu, 2008). It converted garment physical attributes into garment sensation space in a fuzzy set (Table 3). Four garment sensations are input nodes of the NN. In Cheng and Liu's project, training data were

Table 3: Garment Physical Attributes and their garment sensation

| Major Physical Attributes | Garment Sensation |
|---|---|
| Color | Warm / Cold |
| Print | Cheeriness |
| Shape | Fitness |
| Fabric | Softness |

gathered through a questionnaire designed by a fashion stylist. Clothes were categorized into 10 different styles: Sexy, Modest, Sophisticated, Elegant, Luxuriant, Romantic, Girly, Masculine, Sporty and Casual. During training, the NN adjusted weights based on a given target output

Neural Network is a state-of-the-art model to classify items with numerous attributes into different classes. The drawback is that they are less interpretable. For instance, updated style rules would be a great data source to keep track of changes in fashion trends, but it is difficult to extract them out of a NN model.

Decision Trees, on the other hand, are very interpretable. Previous research has used Genetic Algorithms and Vector Decision Trees to model user clothing preferences and generated fashion rules (Kokol, Verlic, & Krizmaric, 2006). They implemented a GA in a tree structure where VDT's genotype and phenotype were the same. This actually sped up the fitness computation. The fitness function has 5 major components: average accuracy over all dimensions, accuracy of the whole vector, average performance of classifiers, the factor minimizing the overall fitness bonus score and a linear penalty to avoid overfitting. They trained the model with 60 initial trees with a mutation rate of 0.5%. The model had an accuracy of 85% after 1273 iterations and it showed that such model is able to handle this highly dynamic task (Kokol, Verlic, & Krizmaric, 2006).

### 2.4.3 FASHION TREND TRACKER

The ideal intelligent stylist program should be very sensitive to fashion trends. Fashion trend forecasting is the key to success in the fashion industry and always a bigger challenge than prediction of other fields. The biggest variable of it is human value. In the fashion process as shown in Figure 2, new trends get popular slowly before trendsetter adoption (Phase A), reaches to its peak of fast social majority acceptance (Phase B) and declines dramatically thereafter.

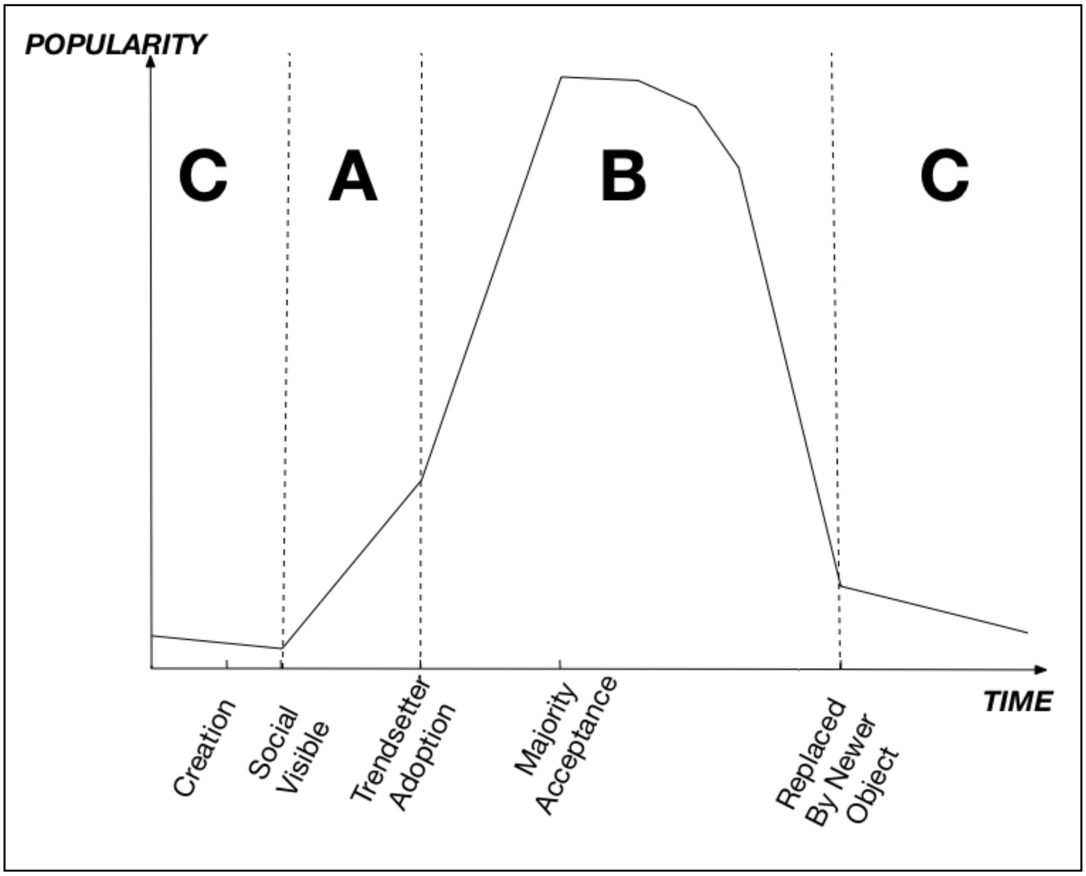


Figure 2: Fashion process or Fashion cycle

Two major reasons for the decline are: 1. Newer trends kick in; 2. People get bored with the trend after the peak. Generally, there are two types of fashion forecasting. The first one focuses on current fashion objects and it does predictions such as fashion color trends. Another type interests in a longer vision, for instance, black and white are never out of date regardless of season or occasion.

Some recent and relatively successful studies have attempted to predict fashion color trends with AI techniques. Dr. Mello and her team have implemented Knowledge Base Systems and Bayesian Networks (Mello, Storari, & Valli, 2008). They modeled a human stylist's new color trend proposal process with a Bayesian Network. Based on the knowledge of past and current color trends, BN classifiers classified color into binary target values, proposed or not proposed based on their probability. The human stylist then confirmed their application performance. In another study, researchers compared the performance of 5 models in fashion color prediction (Yu, Hui, & Choi, 2012) .The 5 models are the statistical models ARIMA (Autoregressive Integrated Moving Average), GM, GNNM (Grey Neural Network Model), Improved GM, ANN, ELM (Extreme Learning Machine). After the comparison, they proposed a hybrid GRA (Grey Relational Analysis)-ELM that achieved high accuracy and was less time consuming.

Researchers proposed a simplified fashion trend model taking three major factors into account: Base Utility, Boredom and Influence (Figure3).

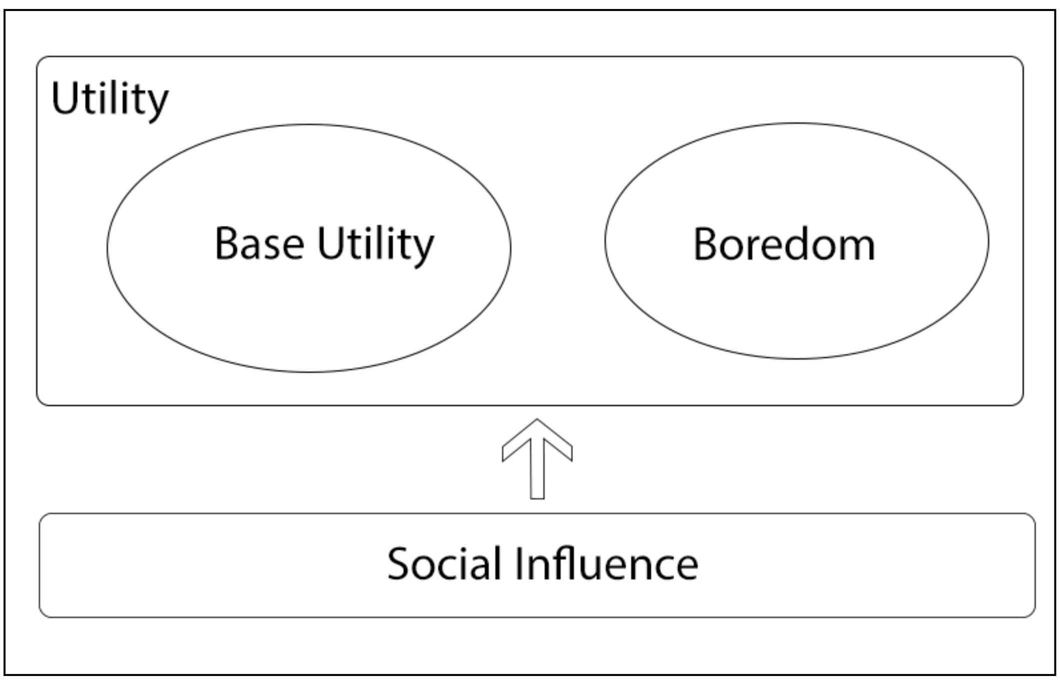


Figure 3: Simplified fashion process model

They modeled individual boredom as a "memory" factor of an object and the parameter of "memory" as the number of times using it in the past. With more times of use, more memories, higher boredom and less utility are left. The goal is to explore how to maximize the user's overall utility of an item. The fashion process is continuous and a solution to this problem is to compute the consumption cycle at a regular time (Sarma, Gollapudi, Panigraphy, & Zhang, 2012). They considered the fashion cycle as an NP-Hard problem and validated it with both a greedy algorithm and double greedy algorithm. In their experiment, they collected data including music, events and the boredom factors from Google Trend. Their experiment showed that a double greedy algorithm has better performance than a greedy algorithm in this model.

## 2.5 CONCLUDING REMARKS

AI based Stylist programs should consider the following three major components: (1) Visual Garment Representation, (2) Computational Styling and (3) Fashion Trend Tracking. This study has presented various ways to use AI techniques in a fashion stylist computational model.

For the first task, earlier works show that computer vision techniques can extract attribute information from an image and AI techniques such as semantic mapping give the program the ability to deal with tricky attributes, such as fabric. For cloth-piece styling, earlier researchers started off using Color Harmony Evaluation (Tokumaru, Muranaka, & Imanish, 2003) between garment pieces and then taking four basic attributes - color, outline, print and fabric - into consideration. Neural Networks with category learning techniques have been applied successfully (Cheng & Liu, 2008). However, a completed styling task requires more attributes, such as event, clothes, shoes, accessories, makeup and hairstyling. A stylist is also very personal. Earlier work used GAs and Decision Trees to model fashion personal preferences (Kokol, Verlic, & Krizmaric, 2006). Even though their study is not focused on a completed styling task, their model is a good example of a fashion personal preference model. Change is also central to fashion. Two research projects applied Bayesian Network Neural Networks and Knowledge Base Systems to fashion trend prediction (Mello, Storari, & Valli, 2008) (Yu, Hui, & Choi, 2012).

Their experiments indicate that hybrid models and Bayesian Networks both have good performance on predicting color trends in the next season.

Earlier work has shown that AI-based programs have the ability to execute a fashion styling task and fashion can be modeled with a simplified model. However, there is still much work to be done on AI based styling. Models in earlier studies are not comprehensive. For instance, styling task requires more features than color, fabric, shape and outline. Also fashion changes among different cultures and times. For instance, Asian fashion style is different from Parisian.

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# CHAPTER 3

# STYLE-ME

# -- A MACHINE LEARNING APPLICATION FASHION STYLIST [2]

[2] Haosha Wang, Khaled Rasheed To be submitted to The International Conference on Industrial, Engineer & Other Applications of Applied Intelligent Systems'15

## 3.1 ABSTRACT

"Style endures as it is renewed and evolved" according to the French fashion designer Gabrielle Chanel (Barry, 1965). In this study, we propose an AI based system called "Style-Me" as our answer to the question "Can an AI machine be a fashion stylist?" Style-Me is a machine learning application that recommends fashion looks. More specifically, Style-Me learns user preferences through the use of Artificial Neural Networks (ANN). The system scores user's customized style looks based on fashion trends and users' personal style history. Although much remains to be done, our implementation shows that an AI machine can be a fashion stylist.

## 3.2 INTRODUCTION

Human creativity as one of the major challenges for the AI domain has captured the world's attention for years. Artist Harold Cohen's AI artist program, "AARON", was the first profound connection between AI and human creativity and has been in continual development since its creation in 1937 (Cohen, 1995). "JAPE" (Joke Analysis and Production Engine), is another example of an AI imitating human creativity. In this case, computer program generates punning riddles modeling human humor (Binsted, 1996). Among all of these domains of human creativity, the fashion industry's unpredictable irrationality, individual uniqueness and cultural dependence make human fashion behavior modeling one of biggest challenges in this area (Boden, 1998). In a previous study (Wang & Rasheed, 2014), we compared and summarized earlier previous studies of using AI techniques in the fashion domain. It provides a foundation on the design and development of our system, which we call "Style-Me". Generally speaking, a full product level system requires a big amount of data and takes significant time to build. However, the aim of this work is to present the essence of Style-Me and the major AI techniques which have been implemented.

In this version, we created a manageable database which contains 32 dresses and 20 shoes for 4 different events, encode a standard style rules engine, generate more than 500 looks and rank them by a final score in descending order. The score indicates how fashionable each look is based on users' feedback. The learning component trains an Artificial Neural Network (ANN) to learn users' personal preferences and adjust the final score. Moreover, the system provides a feature that it allows users to customize a fashion look and then evaluates it. This feature provides a shopping guide to inform users' purchase plans. As mentioned in Chapter 2, the Mobile Fashion Advisor (MFA) system (Cheng & Liu, 2008) also targets assisting users shopping. The differences between MFA and Style-Me are, firstly that MFA only tells users whether this a new item could go with an existing item, while Style-Me provides a numeric evaluation for the users' references and secondly that Style-Me adapts to users' personal preferences, a feature not included in MFA. On the front-end of the Style-Me system, users initialize Style-Me by taking a fashion personality quiz and then agree with the quiz's result. The details of the quiz are described in the section 3.3. The User Interface (UI) design of Style-Me follows minimalistic and intuitional style, which gives users a smooth experience without instructions.

This chapter presents Style-Me in five sub-sections: 3.3 System Overview; 3.4 Data Preparation and Preprocessing; 3.5 Experiment; 3.6 Implementation and User Interface and 3.7 Summary and Future Work.

## 3.3 SYSTEM OVERVIEW

The Style-Me system comprises 5 major components for the fashion styling task. Figure 4 shows a schematic overview of the Style-Me architecture. The five major components include an Initialization program, Database, Style Engine, Learning Components and User Interface (UI). The main system is a Java Servlet application written in Java and HTML, which uses MySQL as the back-end and Apache Tomcat as the web server.

Users initialize the system by taking a fashion personality quiz, which contains 8 single choice questions and outputs 1 of 6 standard styles as the quiz result (Tables 4 & 5 and Appendix 1). For each style, the system has a set of default database and styling rules. For convenience in presentation the core content, we use a "Classic" style dataset in this paper. The database is a Relational Database and contains three tables ("clothing", "shoes" and "pairs") and a view ("pairsview"). View is a virtual table that stores queried data from different tables together and

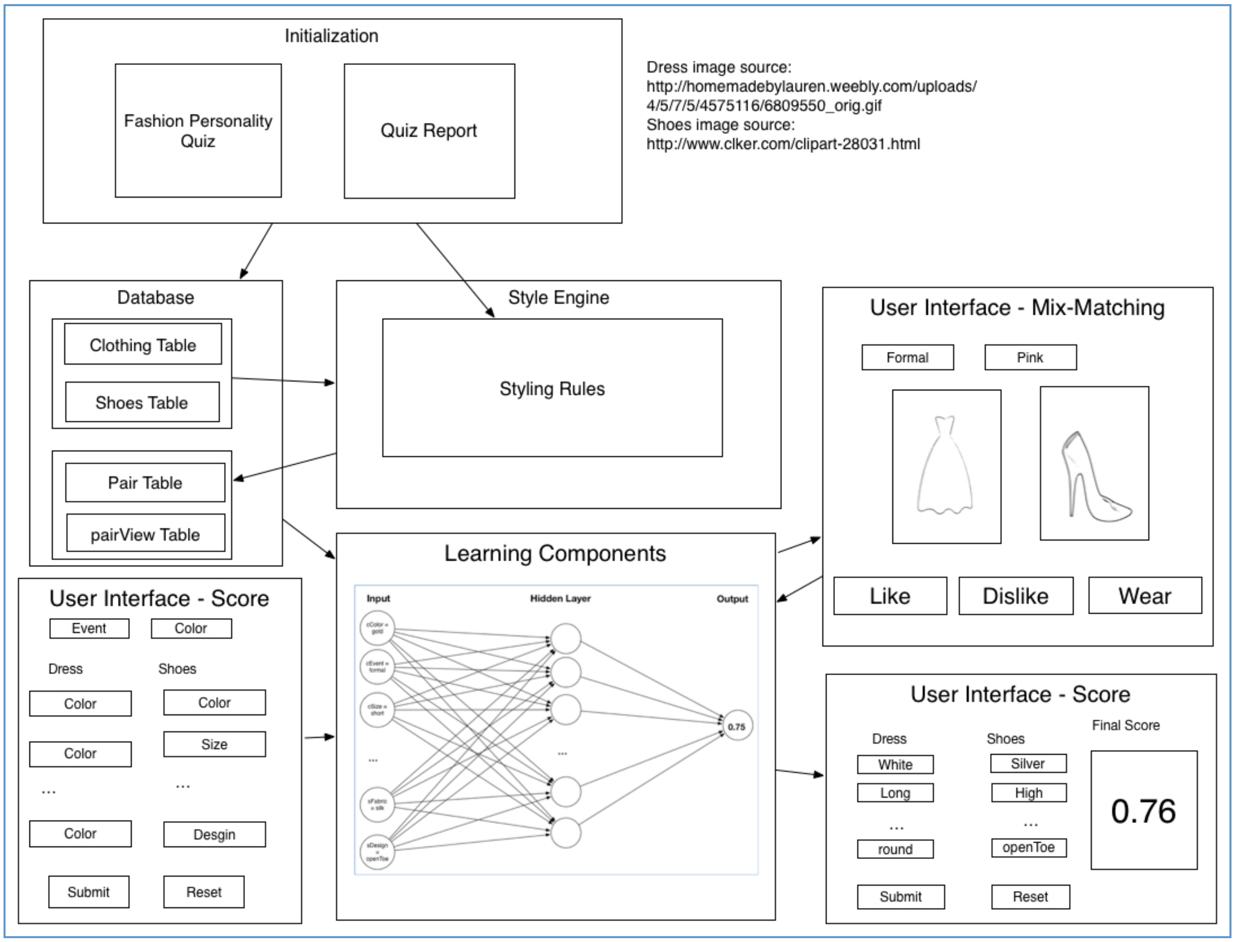


Figure 4: Style-Me Overview

details of the database are in Section 3.3. According to the style rules, the Style Engine pairs up dress and shoes, assigns initial scores on each pair and creates a "pairs" table in the database. The output of the Style Engine is an SQL Script that store in the Style-Me system so that users can start the program over by clicking "Reset System" button, avoiding the need to retake the quiz. The ANN model implemented in the Learning Components is a Multilayer perceptron model and we experimented the different models on WEKA (Waikato Environment for Knowledge Analysis), which is a Machine Learning algorithm collection and data-preprocessing tool for data mining experimental usage (Hall, Frank, Holmes, Pfahringer, Reutemann, & Witten, 2009). Details of our experiments are in Section 3.5. In Section 3.6, we demonstrate two major functions of Style-Me and the methodologies behind them. One is a recommender system that recommends users fashion looks and collects users' interactions. The other one is an evaluation system that evaluates users' customized looks with a score which assists users' shopping plans. There is still much that remains to be done and our model is not comprehensive enough for full product level use. We summarize and propose many interesting ideas for future work in Section 3.7.

Table 4 Fashion Personality Quiz (Partial). Completed version seen in Appendix 1

| Questions | Options |
|---|---|
| 1. What is your height? | A. Short; B. Moderate; C. Average; D.Tall |
| 2. What do your hands and feet look like? | A. Average; B.Narrow; C.Small; D.Large |
| … | … |

Table 5 Fashion Personality Quiz Report (Partial). Completed Version seen in Appendix 2

| Style | Report |
|---|---|
| Classic | Your fashion personality is **Classic**. A classic woman looks elegant and fashionable in **refined**, **well-tailored** and **simple lined** clothes. Flowing and soft fabric such as, **Chiffon**, **Silk** or **Soft Woolen** should be worn. Choose simple and balanced prints, such as **Soft Flowing Abstract**, **Hounds Tooth** and **Herringbone**. |
| … | … |

## 3.4 DATA PREPARATION AND PREPROCESSING

The purpose of the learning task is to predict a pair's score based on correlations between scores and items' attributes. We followed several steps preparing and preprocessing of the dataset. First of all, we collected 32 dresses and 20 shoes in typical standard style from various websites and designers' collections. Each clothes item has 13 attributes and each shoes item has 11 attributes as shown in Table 6 and 7.

We have collected 20 standard rules for the “Classic” database. Every rule interprets a relationship between pairs of attributes. The relationship is binary: “AND/OR” means “Positive” while “NOT” means “Negative”. The style engine matches pairs of attributes to styling rules and counts the number of matches as follows. Completed rules tables and relationship counts are shown in Table 8.

$$If\ relationship\ is\ postive, C_{Likes} + 1;\ C_{Dislike} + 0;$$

$$If\ relationship\ is\ negative, C_{Likes} + 0;\ C_{Dislike} + 1;$$

$$\boldsymbol{Score_{pair} = \frac{C_{Likes} - C_{Dislikes}}{C_{Likes} + C_{Dislikes} + 1}}$$

Boredom is one of the major factors in every fashion model (Sarma, Gollapudi, Panigraphy, & Zhang, 2012). In fashion styling for event, wearing the same looks several times is not fashionable. So, we add counts of “wear” in our model as a parameter of “boredom”. Currently, we assigned 0.03 to the “wear” weight, but the optimal value for the weight of the boredom factor is an interesting topic for future study. So, the popularity for each pair in recommender system is computed as:

$$Popularity = Score - 0.03 * C_{Wears}$$

The output of the Style Engine is the “pair” table that stores the pair data and pairs’ score as shown in Table 9. We also create a view table “pairsView”, which stores the essential data for Learning components and the Evaluation feature as shown. The “pairsView” table has 15 attributes and 640 instances as illustrated in Table 10.

Table 6 Attributes collection for Clothing;

* indicates that information of this attributes will change due to users' interactions

| Attributes | Type | Distinct | Unique | Values |
|---|---|---|---|---|
| ID | Numeric | 32 | 32 (100%) | {1,2, … ,32} |
| Color | Nominal | 11 | 4 (13%) | {gold, black, grey, nude, red, white, pink, yellow, blue, green, brown} |
| Event | Nominal | 4 | 0 (0%) | {cocktail, informal, formal, office} |
| Size | Nominal | 3 | 0 (0%) | {short, medium, long} |
| Shape | Nominal | 3 | 0 (0%) | {shift, sheath, gown} |
| Fabric | Nominal | 4 | 1 (3%) | {cotton, silk, polyester, leather} |
| Design | Nominal | 6 | 1 (3%) | {patchwork, solid, flora, sheer, lace, knit} |
| Sleeves | Nominal | 5 | 2 (6%) | {sleeveless, medium, cap, batwing, long} |
| Neckline | Nominal | 4 | 0 (0%) | {straight, v, round, asymmetric} |
| Likes | Numeric | 21* | 14 (44%)* | Numbers |
| Dislike | Numeric | 6* | 2 (3%)* | Numbers |
| Score | Numeric | 29* | 26 (81%)* | [-1,1] |
| Wears | Numeric | 1* | 0 (0%)* | Numbers |

Table 7 Attributes collection for Shoes;

* indicates that information of this attributes will change due to users' interactions

| Attributes | Type | Distinct | Unique | Values |
|---|---|---|---|---|
| ID | Numeric | 20 | 20 (100%) | {33,34, … ,52} |
| Color | Nominal | 8 | 5 (15%) | {purple, black, grey, nude, red, brown, white, yellow} |
| Event | Nominal | 2 | 0 (0%) | {day, evening} |
| Size | Nominal | 3 | 0 (0%) | {low, medium, high} |
| Shape | Nominal | 3 | 0 (0%) | {shift, sheath, gown} |
| Fabric | Nominal | 3 | 2 (10%) | {silk, leather, lace} |
| Design | Nominal | 5 | 2 (10%) | {pointedToe, openToe, roundToe, jeweled, leopard} |
| Likes | Numeric | 14* | 8 (40%)* | Numbers |
| Dislike | Numeric | 4* | 1 (5%)* | Numbers |
| Score | Numeric | 15* | 10 (50%)* | [-1,1] |

Table 8 Styling rules table

| Rule | Like | Dislike |
|---|---|---|
| "(shoes.color IN ('Red', 'Yellow', 'Blue', 'Green', 'Purple') AND clothing.color IN ('White', 'Brown', 'Nude', 'Pink')) ", | 1 | 0 |
| "(clothing.color IN ('Red', 'Yellow', 'Blue', 'Green') AND shoes.color IN ('Black', 'White', 'Gray', 'Brown')) ", | 1 | 0 |
| "((shoes.design = 'Opentoe') AND (NOT (shoes.event = 'Office' OR clothing.event = 'Office')) AND (NOT (clothing.design = 'V')) AND (clothing.size = 'Short')) ", | 0 | 1 |
| "((shoes.shape = 'Flats') AND NOT (clothing.event = 'Formal' OR clothing.event = 'Cocktail' OR shoes.event = 'Formal' OR shoes.event = 'Cocktail')) ", | 0 | 1 |
| … | … | … |

Table 9 Attributes Collection of Pairs

* indicates that information of this attributes will change due to users' interactions

| Attributes | Type | Distinct | Unique | Values |
|---|---|---|---|---|
| ID | Numeric | 20 | 20 (100%) | {32,33, … ,52} |
| Color | Nominal | 8 | 5 (15%) | {purple, black, grey, nude, red, brown, white, yellow} |
| Event | Nominal | 2 | 0 (0%) | {day, evening} |
| Size | Nominal | 3 | 0 (0%) | {low, medium, high} |
| Shape | Nominal | 3 | 0 (0%) | {shift, sheath, gown} |
| Fabric | Nominal | 3 | 2 (10%) | {silk, leather, lace} |
| Design | Nominal | 5 | 2 (10%) | {pointedToe, openToe, roundToe, jeweled, leopard} |
| Likes | Numeric | 14* | 8 (40%)* | Numbers |
| Dislike | Numeric | 4* | 1 (5%)* | Numbers |
| Score | Numeric | 15* | 10 (50%)* | [-1,1] |
| Wears | Numeric | 1* | 0 (0%)* | Numbers |

Table 10 Attributes of pairView table

| Attributes | Type | Distinct | Unique | Values |
|---|---|---|---|---|
| pScore | Numeric | 12 | - | [-1,1] |
| cColor | Nominal | 11 | 0 (0%) | {gold, black, gray, nude, red, white, pink, yellow, blue, borwn} |
| cEvent | Nominal | 4 | 0 (0%) | {cocktail, informal, formal, office} |
| cSize | Nominal | 3 | 0 (0%) | {short, medium, long} |
| cShape | Nominal | 3 | 0 (0%) | {shift, sheath, gown} |
| cFabric | Nominal | 4 | 0 (0%) | {cotton, silk, polyester, leather} |
| cDesign | Nominal | 6 | 0 (0%) | {patchwork, solid, floral, sheer, lace, knit} |
| cSleeves | Nominal | 5 | 0 (0%) | {sleeves, medium, cap, batwing, long} |
| cNeckline | Nominal | 4 | 0 (0%) | {straight, v, round, asymmetric} |
| sColor | Nominal | 8 | 0 (0%) | {purple, black, gray, nude, red, brown, white, yellow} |
| sEvent | Nominal | 2 | 0 (0%) | {evening, day} |
| sSize | Nominal | 3 | 0 (0%) | {medium, high, low} |
| sShape | Nominal | 3 | 0 (0%) | {pump, flats, boots} |
| sFabric | Nominal | 3 | 0 (0%) | {silk, leather, lace} |
| sDesign | Nominal | 5 | 0 (0%) | {pointedtoe, opentoe, roundtoe, jeweled, leopard} |

## 3.5 EXPERIMENT

WEKA is the abbreviation for Waikato Environment of Knowledge Analysis, a collection of Machine Learning algorithms and data preprocessing tools developed by the University of Waikato (Hall, Frank, Holmes, Pfahringer, Reutemann, & Witten, 2009). The learning task here is to predict the final score based on correlation with items' attributes. In order to find a suitable method and model for this task, we have run several experiments in WEKA.

### 3.5.1 Experiment 1: Classifier Comparison

In the first experiment, we test eight classifiers on the initial dataset with 10-fold cross validation. Here is a brief introduction of the methods have been used experiment. *SMOreg* is a regression model that implements a sequential minimal-optimization algorithm for learning (Shevade, Keerthi, Bhattacharyya, & Murthy, 2000). *RBFNetwork* is a normalized Gaussian radial basis function network that uses the K-means clustering algorithm to classify instances (Witten, Frank, & Hall, 2000). We also include two nearest-neighbor classifiers: the basic IBK and KStar, which KStar is an IBK with a generalized distance function (Witten, Frank, & Hall, 2000). There are two tree classifiers as well, *M5P*, which is a model tree learner to predict the value for a test instance and REPTree, a fast decision tree learner which builds a tree using information gain and variance and to prune the tree with reduced-error pruning (Witten, Frank, & Hall, 2000). Lastly, *Multilayer Perceptron (MLP),* a feedforward Artificial Neural Network model using a backpropagation algorithm to classify instances. The dataset of this experiment is the output of StyleEngine; we call it the initial dataset. The experimental results as shown in Figure 5. For the initial dataset, MLP achieves the highest correlation coefficient among all the other models.

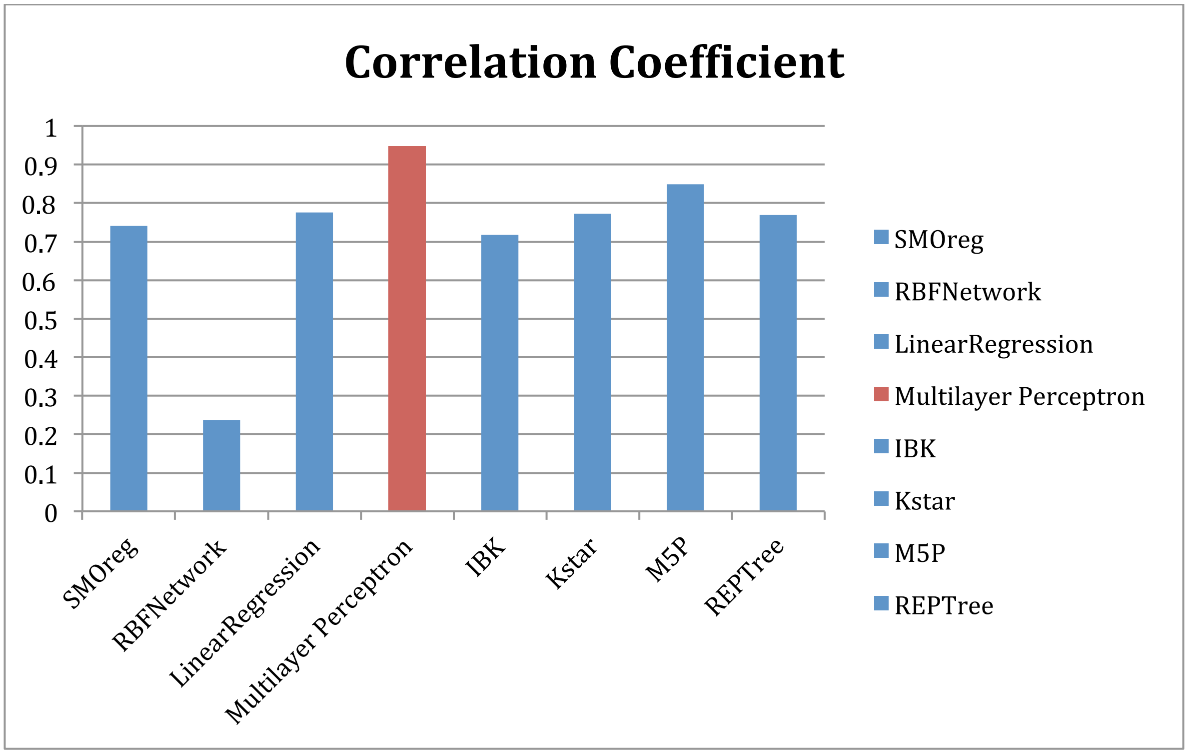


Figure 5: Correlation Coefficient of 8 different methods on initialized dataset

3.5.2 Experiment 2: Number of hidden unites and hidden layers

The second group of experiments is trying to decide the number of hidden layers and hidden units. We choose the MLP model that has the highest correlation coefficient in Experiment 1. The MLP with few hidden layer are proven as a universal approximator (Hornik, Stinchcombe, & White, 1989). Our experiment uses the initial dataset and test different units in one and two hidden layers respectively.

Firstly, we run experiment of the number of hidden units on one hidden layer with a 0.3 Learning rate and momentum term of 0.2 (*weka.classifier.functions.MultiplayerPerceptron –L 0.3, -M 0.2, -N 500, -V 0, -S 0 –E 20 –H *)*. Our experiment has tested the number of hidden unites from 3 to 50 (Table 11).

For single hidden layer model, 20 units achieve the highest correlation coefficient, 0.9496 and with hidden units ranging from 20 to 34 it has a very high correlation coefficient (average: 0.9472)

Table 11 Number of hidden units on one hidden layer

| Number of Hidden Units | Correlation Coefficient |
|---|---|
| 3 | 0.7578 |
| 5 | 0.8133 |
| 10 | 0.8894 |
| **20** | **0.9496** |
| 25 | 0.9477 |
| 30 | 0.9411 |
| 31 | 0.9479 |
| 32 | 0.9466 |
| 33 | 0.949 |
| 34 | 0.9486 |
| 35 | 0.932 |
| 40 | 0.9387 |
| 45 | 0.9277 |
| 50 | 0.9149 |

Secondly, we run an experiment of number of hidden units on two hidden layers with a 0.3 learning rate and momentum term of 0.2 (*weka.classifier.functions.MultiplayerPerceptron –L 0.3, -M 0.2, -N 500, -V 0, -S 0 –E 20 –H *).* Our experiment has tested the same hidden units on each layer from 3 units to 50 units for each layer (Table 12).

This experiment shows that two hidden layers with 35 hidden units on each layer achieve the highest correlation coefficient, 0.9616. With more hidden units, even the correlation coefficient increases but the time to build the model increases as well. So, we have decided to use single layers with 20 hidden units model in our implementation.

Table 12 Number of Hidden units on two hidden layers

| Number of Hidden Units | Correlation Coefficient |
|---|---|
| 3,3 | 0.8208 |
| 5,5 | 0.869 |
| 7,7 | 0.894 |
| 10,10 | 0.9169 |
| 15,15 | 0.9287 |
| 20,20 | 0.9403 |
| 25,25 | 0.9389 |
| 30,30 | 0.9525 |
| **35,35** | **0.9619** |
| 40,40 | 0.9492 |
| 50,50 | 0.9556 |

3.5.3 Experiment 3: Learning Rate

Learning rate is a decreasing function of time that determines the step size in the gradient descent search (Mitchell, 1997). When we learn to do something new, we are very inefficient at the beginning and our efficiency gets better with more practice. Learning rate is to mathematically measure this learning phenomenon and for a learning model, the lower learning rate is better (Witten, Frank, & Hall, 2000). We test the learning rate on one of the highest correlation coefficient models from the above experiment, one hidden layer with 20 hidden units and a momentum term of 0.2 (*weka.classifier.functions.MultiplayerPerceptron –L *, -M 0.2, -N 500, -V 0, -S 0 –E 20 –H 20).*

Table 13 Correlation Coefficient and learning rate

| Learning Rate | Correlation Coefficient |
|---|---|
| 0.1 | 0.9487 |
| 0.2 | 0.9466 |
| **0.3** | **0.9496** |
| 0.4 | 0.9267 |
| 0.5 | 0.8342 |
| 0.6 | 0.8015 |
| 0.7 | 0.7325 |
| 0.8 | 0.5732 |
| 0.9 | 0.3068 |

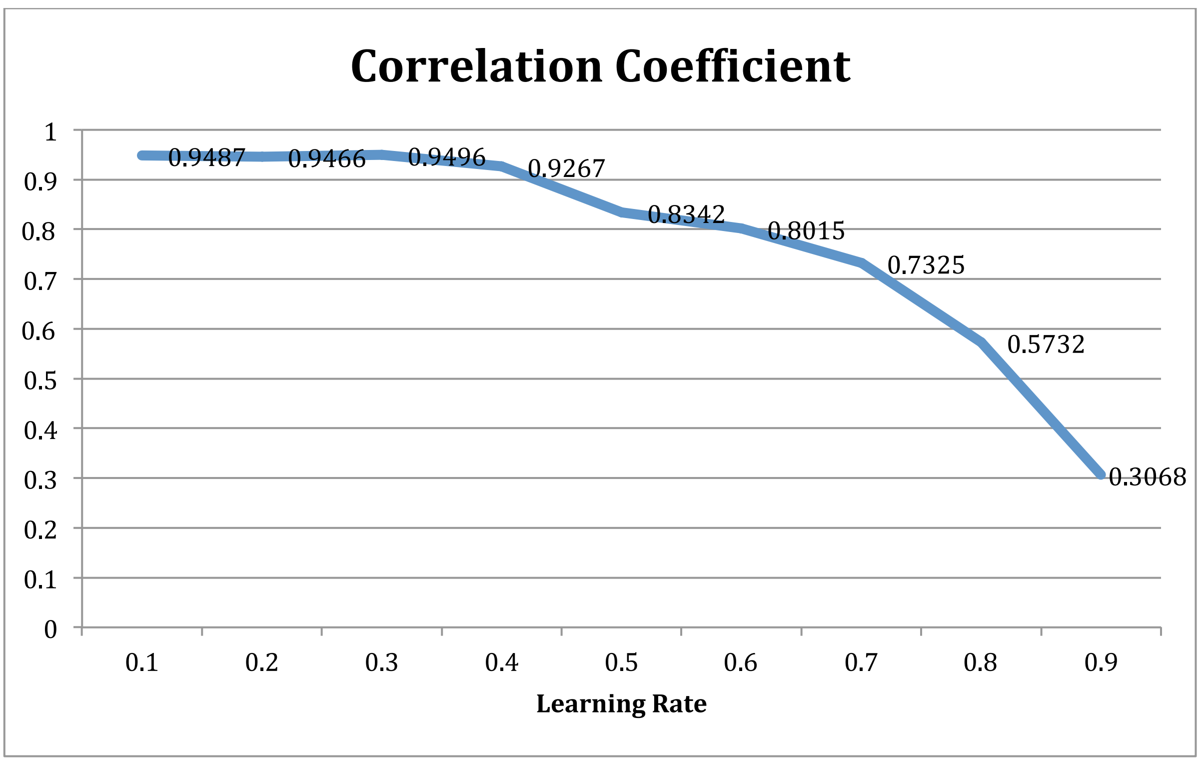


Figure 6: Learning rate and Correlation Coefficient

Our experiment tested the learning rate from 0.1 to 0.9 on this model (Table 13 and Figure 6). Experiment shows that model has highest correlation coefficient with a 0.3 learning rate.

### 3.5.4 Experiment 4: Momentum term and Correlation Coefficient

Momentum is a technique, which has been used to speed up the convergence and avoid local minima, and there are many ways to use it for improving the performance of the backpropagation algorithm (Istook & Marinez, 2002). We tested the momentum term starts from 0.1 to 0.9 for the model of one hidden layers with 20 hidden units and learning rate as 0.3 (*weka.classifier.functions.MultiplayerPerceptron –L 0.3, -M *, -N 500, -V 0, -S 0 –E 20 –H 20).* The Experiment shows that this model has the highest correlation coefficient with a momentum rate of 0.2 (Table 14 and Figure 5).

Table 14 Correlation coefficient and momentum term

| Momentum term | Correlation Coefficient |
|---|---|
| **0.1** | **0.9526** |
| 0.2 | 0.9466 |
| 0.3 | 0.9399 |
| 0.4 | 0.9343 |
| 0.5 | 0.9013 |
| 0.6 | 0.8407 |
| 0.7 | 0.6926 |
| 0.8 | 0.1298 |
| 0.9 | -0.0501 |

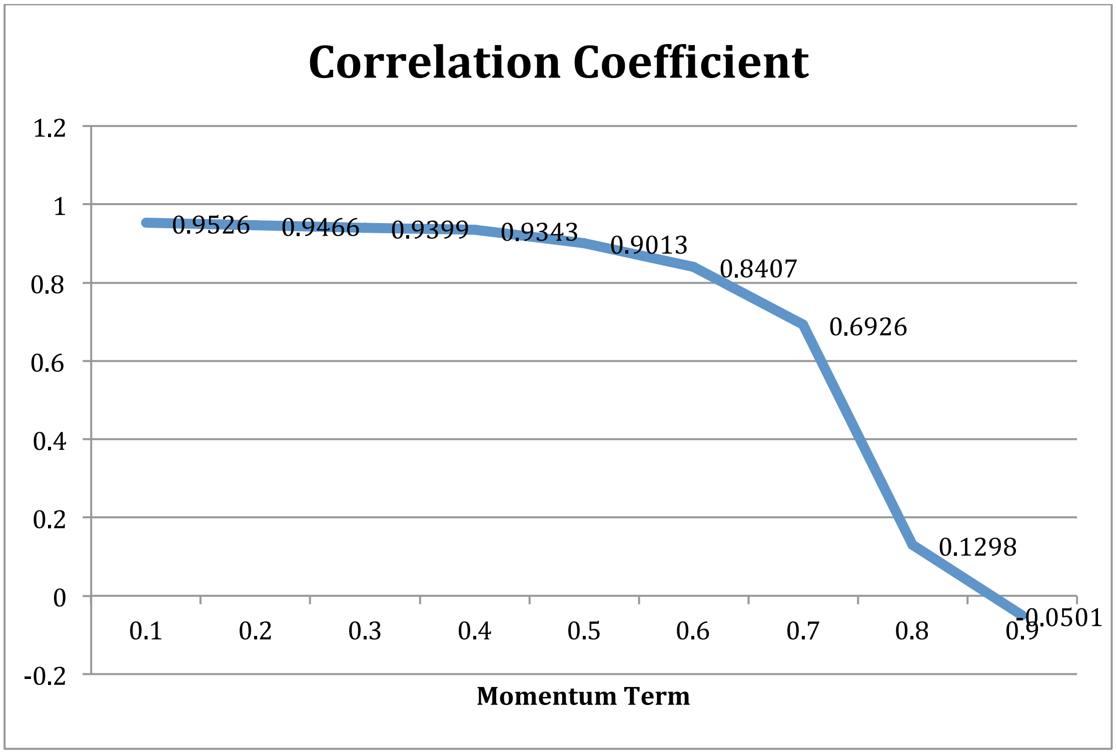


Figure 7: Momentum terms and Correlation Coefficient

3.5.5 Experiment 5: Users' preference modeling

In this experiment, we assume a user has a particular preference: "black dress goes with black shoes". We click one like on every "cColor.black and sColor.black" pairs in our training program and generated a trained dataset. We repeat experiment 1 on this dataset (Table 15) and compared with the result of experiment 2.1 (Figure 6). It has very similar correlation coefficient value as in experiment 1 which shows that this model can learn users' simple preference as well.

Table 15 Hidden units on single layer and Correlation Coefficient

| Number of Hidden Units | Correlation Coefficient |
| --- | --- |
| 3 | 0.6914 |
| 5 | 0.7933 |
| 10 | 0.8683 |
| 20 | 0.9254 |
| 25 | 0.9199 |
| **30** | **0.9445** |
| 31 | 0.9286 |
| 32 | 0.9336 |
| 33 | 0.9222 |
| 34 | 0.9291 |
| 35 | 0.9195 |
| 40 | 0.9113 |
| 45 | 0.9125 |
| 50 | 0.8746 |

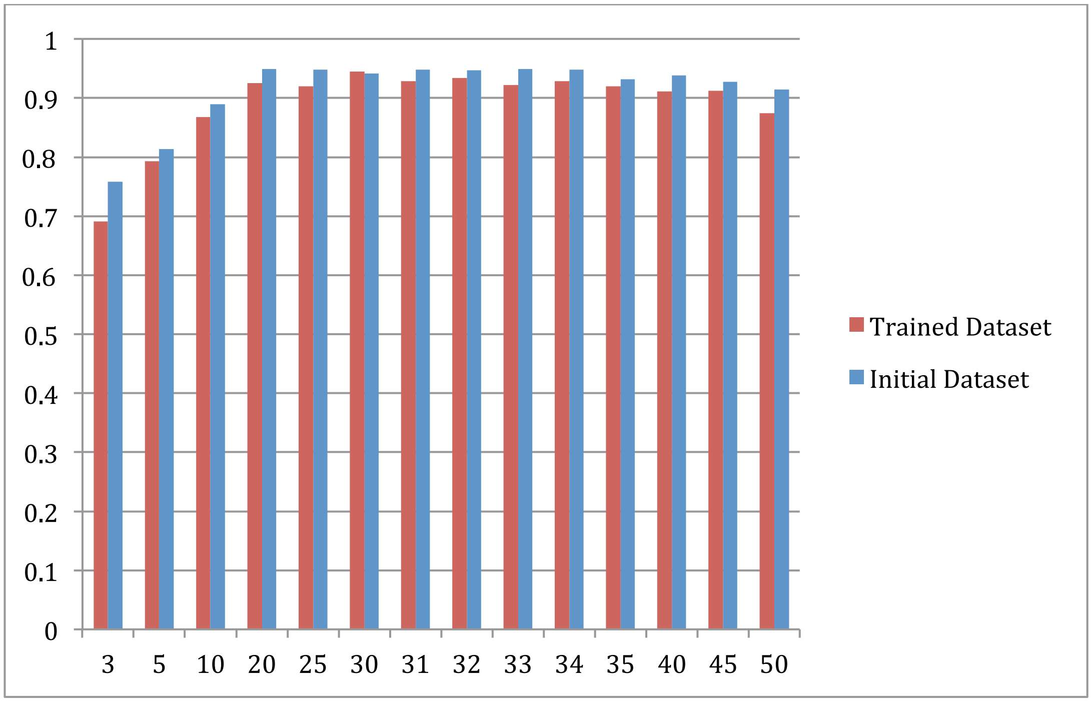


Figure 8: Comparison between experiment 1 on Trained Dataset and Initial Dataset

3.6 IMPLEMENTATION AND UI

We have implemented an MLP model in the Style-Me's demo. In the demo implementation, there are four parts: a database, a rule based recommender system, a learning component and a scoring system.

3.6.1 MLP model implementation

Figure 7 shows the ANN model in our implementation. There are 13 inputs and 1 output. We use the WEKA library (weka.jar) by following the instructions[4] and the documentation[5] from WEKA. Firstly, we applied *weka.filters.supervised.NominalToBinary* to normalize the nominal inputs into binary form and then put them in an array. The MLP model read this array and then outputs the scores to the UI.

[4] Use WEKA in your Java code: http://weka.wikispaces.com/Use+WEKA+in+your+Java+code
[5] WEKA library documentation: http://weka.sourceforge.net/doc.dev/overview-summary.html

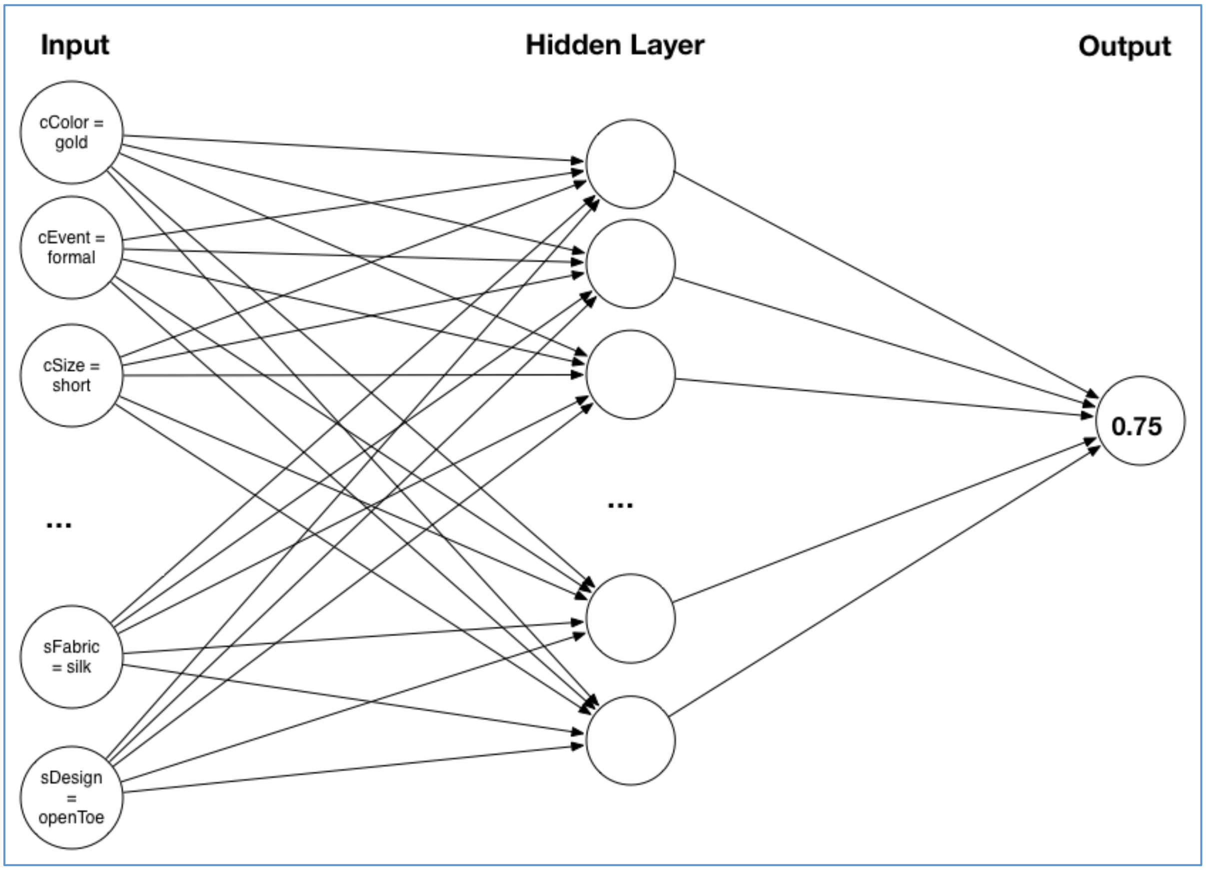


Figure 9: ANN model in implementation

3.6.2 User Interface

The UI is built with the Windowbuilder[6]. The design is simple and intuitive. In the main program, there are two drop-down menus asking users' choices of "event" and "dress color" (Figure 8). There are also two buttons in the UI. Users can click the "Style-Me" button to see recommended fashion looks and the "Reset DB" button is to reset the system back to the initial state. Additionally, there are three users' interaction buttons, "Like", "Dislike" and "Wear" to record users' history.

[6] Windowbuilder: http://www.eclipse.org/windowbuilder/

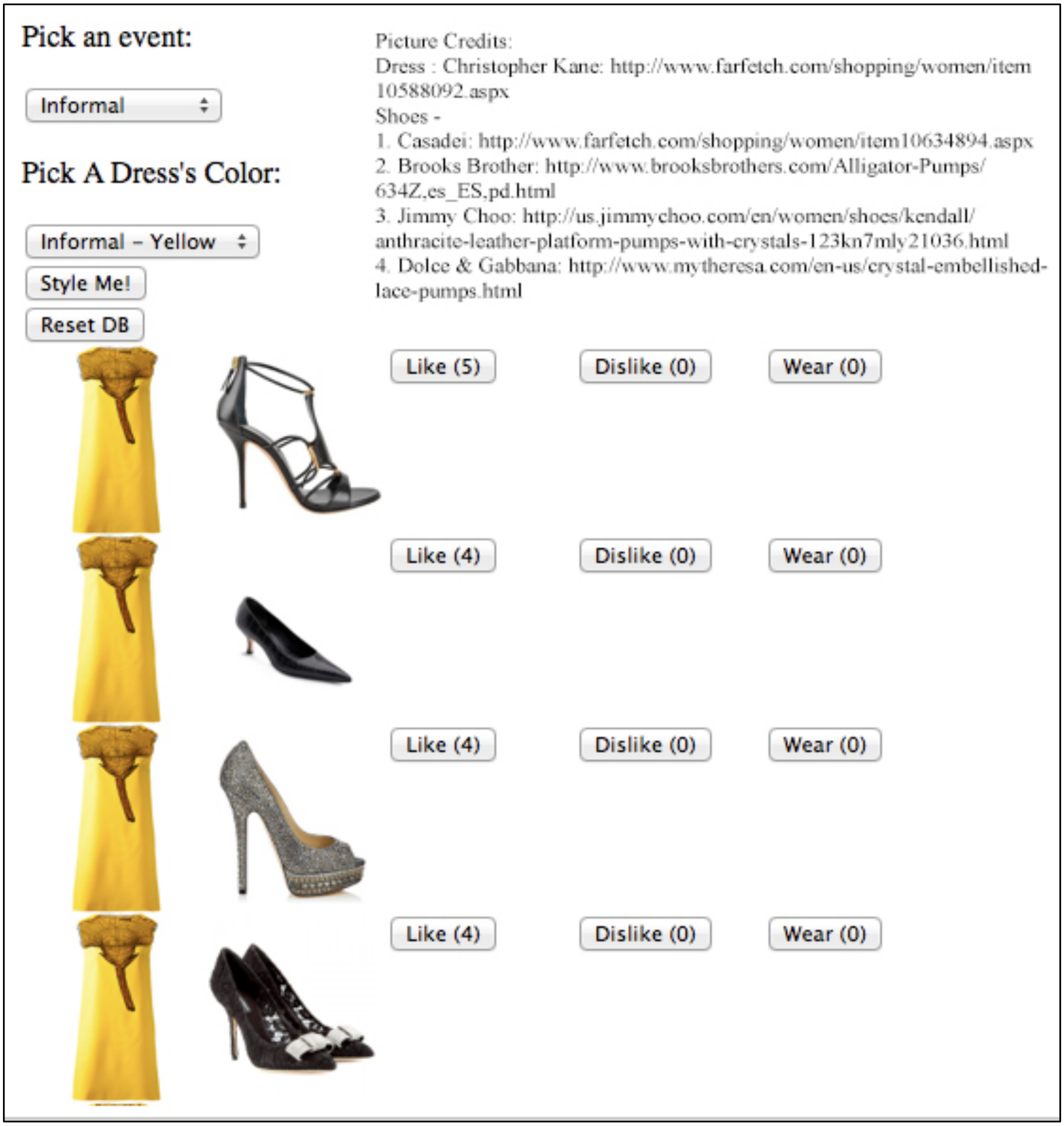


Figure 10: Main Program UI

In the score program, users load the WEKA model file from the path input and click the "load" button. There are 13 drop-down menus for users to select garment attributes. After selecting attributes, users click the "score" button and the system will output a score to the screen (Figure 9). The score indicates how fashionable the combination is.

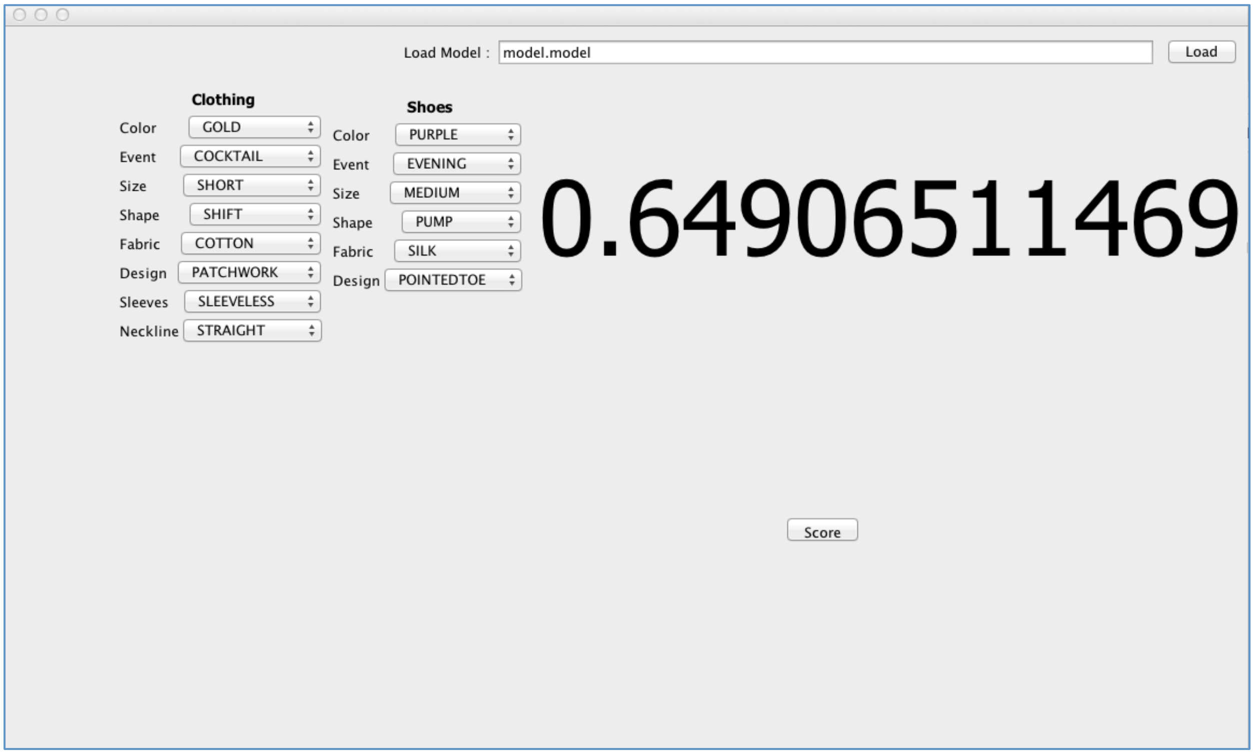


Figure 11: UI for score feature

3.7 SUMMARY

This study presents an experiment and implementation of AI techniques to fashion styling and consists of the following parts: a garment database which stores garment items by categories, a style engine that processes styling rules and assigns popularity to individual items and completed looks, a learning component which reads in users' feedback and adjusts weight in the style engine based on the popularity rank of a completed look and an intuitively designed UI for users to give their opinions on styling looks.

In this study, we demonstrate a completed process for garment computational representation, computational styling and user preference training and modeling. Our model and implementation show great performance on different datasets and proved the capable of modeling users' preferences.

However, there is still more interesting works can be done. For instance, our data structure and styling rules are too simple for practical use. Plus, a completed fashion look includes more than a top with a bottom or dress. For example, shoes, accessories, bags, hairstyles and make up might also be included in the process. Additionally, the weight for boredom needs to be more sophisticated.

3.7 REFERENCE


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# CHAPTER 4

## SUMMARY AND CONCLUSION

This study presents a survey and an implementation of AI techniques to fashion styling. AI based Stylist programs should consider the following three major components: (1) Visual Garment Representation, (2) Computational Styling and (3) Fashion Trend Tracking. The survey study has presented various ways to use AI techniques in a fashion stylist computational model.

Earlier works show that computer vision techniques can extract attribute information from an image and AI techniques such as semantic mapping give the program the ability to deal with tricky attributes, such as fabric. For cloth-piece styling, earlier researchers started off using Color Harmony Evaluation (Tokumaru, Muranaka, & Imanish, 2003) between garment pieces and then taking four basic attributes - color, outline, print and fabric - into consideration. Neural Networks with category learning techniques have been applied successfully (Cheng & Liu, 2008). However, a completed styling task requires more attributes, such as event, clothes, shoes, accessories, makeup and hairstyling. A stylist is also very personal. Earlier work used GAs and Decision Trees to model fashion personal preferences (Kokol, Verlic, & Krizmaric, 2006). Even though their study is not focused on a completed styling task, their model is a good example of a fashion personal preference model. Change is also central to fashion.  Computers have the ability to deal with large amounts of data and the ability to deal with large amounts of data and would be a good assistant for human stylists. Two research projects applied Bayesian Network Neural Networks and Knowledge Base Systems to fashion trend prediction (Mello, Storari, & Valli,

2008) (Yu, Hui, & Choi, 2012). Their experiments indicate that hybrid models and Bayesian Networks both have good performance on predicting color trends in the next season.

The implementation consists of the following parts: a garment database which stores garment items by categories, a style engine that processes styling rules and assigns popularity to individual items and completed looks, a learning components which reads in users' feedback and adjusts weights in the style engine based on the popularity rank of a completed look and an intuitively designed UI for users to give their opinions on styling looks.

In this study, we demonstrate a completed process for garment computational representation, computational styling and user preference training and modeling. Our model and implementation show great performance on different datasets and proved capable of modeling users' preferences.

However, there is still more interesting works to be done. For instance, our data structure and styling rules are too simple for practical use. Plus, a completed fashion look includes more than a top with a bottom or dress. For example, shoes, accessories, bags, hairstyles and make up might also be included in the process. Additionally, the weight for boredom needs to be more sophisticated.

# CHAPTER 5

# BIBLIOGRAPHY


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APPENDIX

A. FASHION PERSONALITY QUIZ

| Questions | Options |
|---|---|
| 1. What is your height? | A. Short; B. Moderate; C. Average; D.Tall |
| 2. What do your hangs and feet look like? | A. Average; B.Narrow; C.Small; D.Large |
| 3. Which description is the closest of your shoulder and hips? | A. Evenly proportioned; B. Curvy with rounded shoulder; C. Inverted triangle; D. Skinny with narrow shoulder |
| 4. What word does the best job to describe your overall body figure? | A. Balanced; B. Sinewy; C. Hourglass; D. Broad; E. Stocky |
| 5. What word does described your overall face feature? | A. Evenly shaped; B. Angular; C. Rounded; D. Youthful; E. Slightly sharp |
| 6. What do your lips look like? | A. Moderate, evenly shaped; Thin, angular and delicate; C. Full, luscious and thick |
| 7. What do your eyes look like? | A. Evenly shaped; B. Angular and pointed; C. Large; D. Soft and round |
| 8. What is your hair cut style? | A. Moderate to somewhat short in length, well-groomed, controlled style, smooth, cut usually blunt or some layering;<br>B. Long with curves and curls. Short with feather cut around the face best. Soft and bouncy, never straight or stringy;<br>C. If Long, a "Gibson Girl" style. If short, feather cut;<br>D. Sleek, geometric or asymmetrical cuts;<br>E. Tousled, loose, windblown, never fussy;<br>F. Short cropped boyish cuts. Layering on top or at temples, bangs and sides. |

B. FASHION PERSONALITY QUIZ REPORT

| Style | Report |
|---|---|
| Classic | Your fashion personality is Classic. A Classic woman looks elegant and fashionable in refined, well-tailored and simple lined clothes. Flowing and soft fabric such as Chiffon, Silk or Soft Woolen should be worn. Choose simple and balanced placed prints, such as Soft Flowing Abstract, Hounds Tooth or Herringbone. |
| Dramatic | Your fashion personality is Dramatic. You play with High Fashion, Edgy, Extreme or Exotic. Very well tailor garments, Straight lines, Sharp shoulder lines or Angular necklines should be worn. You would love to go for fabrics that hold up their shape, such as Gabardine, Stiff Brocade or Go Metallic. Bold color or Go All Dark color. Wear with Bold designed jewelry with angular shapes. |
| Gamin | Your fashion personality is Gamin. Your choices of clothing are all about fun and animated. Colorful, Snappy, Chic and Eye-catching. Have fun with light to moderate weight fabrics such as Crisp Cottons, Wool or Metallic with Multicolor, Animated and Contemporary kinds of prints. Go for small but geometric, or irregular shapes and trendy looking accessories. |
| Ingénue | Your fashion personality is Ingénue. A vintage feminine look with ruffles and lace has your name printed on it. Go for lightweight fabric such as Silk, Cashmere, Cotton, Gauze and Fine Cotton. You can rock any prints, from simple abstract to floral, from small to large. Wear dainty jewelries in a "more is more" way. |
| Natural | Your fashion personality is Natural. You fall in love with a minimalist look and exotic style, such as Indian or Bohemian. Go for clothing without strict lines and structured in soft feeling fabrics such as knits, silk and light cottons. Simple looking accessories such as chains and studs, or Indian style jewelry are always on your list. |
| Romantic | Your fashion personality is Romantic. Romantic women look charming in flowing, draped and feminine looking clothes. Put yourself in lightweight fabric such as Silk, Chiffon, Velvet, Soft Woolens, Suede and Sweater Knit with oversized Floral, Polka Dot and Feathery Shape prints. Wear dainty jewelry, but remember that more is more. |

C. “CLASSIC” STYLING RULES

| No. | Rules |
|---|---|
| 1 | (shoes.color IN ('Red', 'Yellow', 'Blue', 'Green', 'Purple') AND clothing.color IN ('White', 'Brown', 'Nude', 'Pink')) |
| 2 | (clothing.color IN ('Red', 'Yellow', 'Blue', 'Green') AND shoes.color IN ('Black', 'White', 'Gray', 'Brown')) |
| 3 | ((shoes.design = 'Opentoe') AND (NOT (shoes.event = 'Office' OR clothing.event = 'Office')) AND (NOT (clothing.design = 'V')) AND (clothing.size = 'Short')) |
| 4 | ((shoes.shape = 'Flats') AND NOT (clothing.event = 'Formal' OR clothing.event = 'Cocktail' OR shoes.event = 'Formal' OR shoes.event = 'Cocktail')) |
| 5 | (shoes.shape = 'Pump' AND shoes.color = 'Black') |
| 6 | "(shoes.shape = 'Stiletto' AND NOT clothing.color = 'Pink') ", |
| 7 | "(shoes.shape = 'Stiletto' AND (clothing.neckline = 'V' OR clothing.size = 'Short' OR clothing.sleeves = 'Sleeveless' OR clothing.design = 'Leopard' OR clothing.shape = 'Shift')) ", |
| 8 | "((clothing.neckline = 'V' OR clothing.size = 'Short' OR clothing.sleeves = 'Sleeveless' OR clothing.design = 'Leopard') AND (shoes.shape = 'High' OR shoes.design = 'Opentoe')) " |
| 9 | "(shoes.shape = 'Stiletto' AND (clothing.design = 'Lace' OR clothing.design = 'Sheer')) |
| 10 | (shoes.design = 'ClosedToe' AND clothing.event IN ('Office','Informal','Cocktail','Evening')) |
| 11 | "(clothing.size = 'Short' AND (shoes.shape = 'Flats' OR shoes.size = 'Low' OR shoes.size = 'Medium')) |
| 12 | "(shoes.color = 'Silver' AND clothing.color IN ('White','Nude','Pink','Black')) |
| 13 | "((clothing.design IN ('Patchwork','Floral')) AND (shoes.color IN ('Black','Gray') OR shoes.design = 'Solid')) |
| 14 | "((clothing.color = 'Gold' OR clothing.design = 'Sheer' OR clothing.fabric = 'Silk' OR clothing.Sleeves = 'Batwing') AND (shoes.shape = 'Pump' OR shoes.color IN ('Black','Brown','Gray','Nude'))) |
| 15 | "(shoes.event = 'Informal' AND ((clothing.color = 'Black' AND shoes.color = 'Brown') OR (clothing.color = 'Brown' AND shoes.color = 'Black'))) |
| 16 | "(shoes.color = 'Brown' AND (clothing.color IN ('White','Green','Orange','Brown'))) |
| 17 | "(shoes.color = 'Gold' AND clothing.color IN ('Green','Red','Brown','White','Black')) |
| 18 | "((clothing.fabric = 'Lace' AND clothing.color = 'Black') AND ((shoes.event='Office' AND shoes.shape = 'Flat')OR(shoes.color='Gold' AND shoes.design = 'Solid'))) " |
| 19 | "(clothing.shape = 'Gown' AND shoes.size = 'High' AND shoes.shape = 'Pump') ", |
| 20 | "(shoes.design = 'Leopard' AND (clothing.design = 'Solid' AND NOT (clothing.fabric IN ('Crystal','Leather'))))" |