Examples-Rules Guided Deep Neural Network for Makeup Recommendation

Taleb Alashkar[1], **Songyao Jiang**[1], **Shuyang Wang**[1], **and Yun Fu**[1,2]
[1]Department of Electrical & Computer Engineering,
[2]College of Computer & Information Science,
Northeastern University, Boston, MA, USA
{taleb, syjiang, shuyangwang, yunfu}@ece.neu.edu

Abstract

In this paper, we consider a fully automatic makeup recommendation system and propose a novel examples-rules guided deep neural network approach. The framework consists of three stages. First, makeup-related facial traits are classified into structured coding. Second, these facial traits are fed into examples-rules guided deep neural recommendation model which makes use of the pairwise of *Before-After* images and the makeup artist knowledge jointly. Finally, to visualize the recommended makeup style, an automatic makeup synthesis system is developed as well. To this end, a new *Before-After* facial makeup database is collected and labeled manually, and the knowledge of makeup artist is modeled by knowledge base system. The performance of this framework is evaluated through extensive experimental analyses. The experiments validate the automatic facial traits classification, the recommendation effectiveness in statistical and perceptual ways and the makeup synthesis accuracy which outperforms the state of the art methods by large margin. It is also worthy to note that the proposed framework is a pioneering fully automatic makeup recommendation systems to our best knowledge.

Introduction

For thousands of years, people have used facial makeup to improve or change their look. Facial Makeup can increase their perceived attractiveness, cancel age cues and give them different looks for different occasions and events. The first basic question that faces almost every person who likes to wear makeup is: ***What is the best makeup style to wear today?*** Actually, it is not an easy question due to the highly diversified makeup styles. The second question after choosing the makeup style is: ***How will I look like after wearing this makeup style?*** It is difficult to foretell that in advance due to the different look-and-feel of the same makeup style on different faces. The efforts to answer these both questions computationally receive more attention in machine learning, multimedia and image analysis domains recently. Heading in this direction started by creating tools online to implement virtual makeup on the user's photo manually like TAAZ[1] and DailyMakever[2], but such tools require user's intervention for every step. Some works tried to make the process more automatic by transferring a complete makeup style from one face to another like in (Guo and Sim 2009; Xu, Du, and Zhang 2013). More recently, some works tried to close the loop by recommending and implementing the makeup style (Scherbaum et al. 2011; Liu et al. 2013). In this paper, we aim to answer these two questions by proposing a fully automatic facial makeup recommendation and an efficient synthesis system. We use a deep neural network model trained by before and after makeup labeled images and harnessed by makeup knowledge base system rules. Our proposed system is based on two main premises: 1) *makeup style elements should be chosen according to the facial attributes.* 2) *makeup expert knowledge comes from certain rules of makeup art and their own experience in this domain*. The proposed framework starts by analyzing the user's facial attributes, then the values of these facial attributes are passed, as input, to a deep learning based recommendation system. The suggested makeup style will be synthesized automatically on the user facial image to show how the face will look like after makeup. Fig.1 illustrates a general overview of our proposed examples-rules guided makeup recommendation framework. Related work to makeup and symbolic neural network are discussed briefly.

Makeup recommendation: recently, few works addressed the problem of facial makeup style suggestion and implementation. In (Scherbaum et al. 2011), they collected 2D images and 3D models for 56 females before and after professional makeup. Relying on the difference in the facial appearance of the same female, they learned a mapping model between facial space and makeup space. Makeup suggestion was done by finding the closest face in the database to the test face using Eigen features distance and transferring its professional makeup to the test face. The few number of examples in the dataset and the ability to transfer the makeup under different conditions make the generality of this recommendation system questionable. In (Liu et al. 2013), beauty e-Expert suggestion system for makeup and hair style was presented. A generative recommendation model was built by learning the relation between the beauty-related attributes (facial traits) and beauty attributes (makeup style). The unavailability of images before makeup in the database makes extracting important facial traits for makeup suggestion like real skin color, eye shapes and eyes color very difficult. Also

Copyright © 2017, Association for the Advancement of Artificial Intelligence (www.aaai.org). All rights reserved.

[1]taaz.com
[2]dailymakeover.com

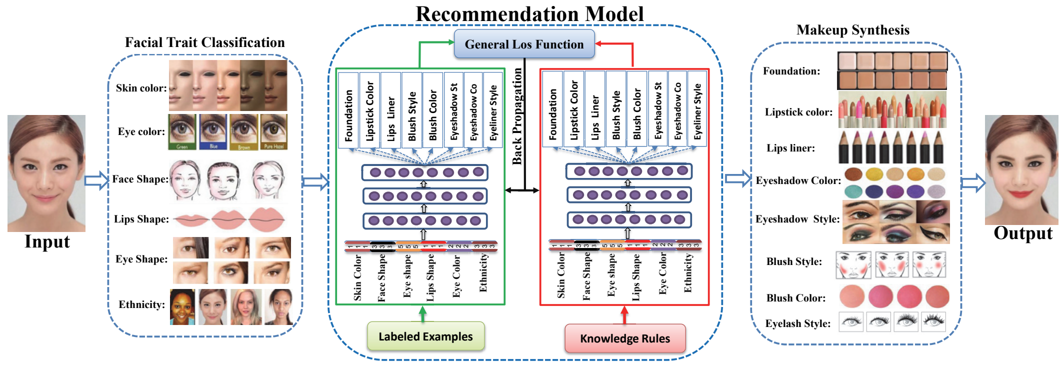

Figure 1: Overview of our proposed framework. It shows the automatic classification of the facial attributes, Examples-Rules deep learning recommendation system and the synthesis results of the recommended makeup .

updating such systems to follow up with new makeup trends is quiet complex. In (Liu et al. 2016), a localized deep learning framework was proposed with similarity based recommendation step. The similarity measured by the Euclidean distance between the l-2 normalized deep facial features proposed in (Parkhi, Vedaldi, and Zisserman 2015). In our recommendation the availability of high number of before and after makeup images, considering facial traits and makeup rules make our recommendation system more efficient.

Neural network combined with rules: combining knowledge represented as logic-rules with available data examples for training neural networks showed interesting results in several domains. Several works addressed the problem of constructing neural networks from defined rules to model knowledge and make reasoning such as Neural-Symbolic systems in (Garcez, Broda, and Gabbay 2002), (Garcez, Lamb, and M. 2009) and CLIPS++ in (Frana, G., and d'Avila Garcez 2014). In (Towell, Shavlik, and Noordewier 1990), they proposed to learn neural network parameters using domain knowledge, and the temporal synchronization for rules is addressed using a connectionist cognitive model in (Lamb, Borges, and d'Avila Garcez 2007). The recent success of deep learning in different applications (You et al. 2015),(Krizhevsky, Sutskever, and Hinton 2012) motivated us to revisit combining deep neural networks with logic rules for our recommendation system. In (Hu et al. 2016), they proposed a general framework to train deep neural network structures simultaneously from labeled examples and logic rules. Most recent advancement in neural-symbolic learning and reasoning, challenges and its potential with deep learning are reviewed in (d'Avila Garcez et al. 2015).

Motivated by the high performance of deep learning, the availability of labeled images before and after makeup and our ability to represent makeup expert knowledge as rule-based system, we proposed this Examples-Rules guided network based framework. We can sum up the main contributions of this work by: 1) Proposing a novel Example-Rules guided deep neural network (DNN) for makeup recommendation and it outperforms the state of the art methods. 2) A new *Before-After* facial makeup database is collected and labeled which is the largest and most complete one in the literature. 3) An effective and automatic facial makeup synthesis system is developed to visualize our recommendation.

Table 1: Facial attributes and their classes

Facial Attribute	Classes
Skin color	Light, Fair, Medium, Black
Face shape	Oval, Square, Round
Eye shape	Monolid, Upturned, Downturned, Hooded, Round, Almond
Lips shape	Thin, Normal, Thick
Eye color	Green, Hazel ,Blue, Brown, Black
Ethnicity	African, Asian, Caucasian, Hispanic

Before-After Makeup Dataset

The research on facial makeup analysis and recommendation is a new direction. The few previous works are based on small collected databases which are not available for public use like in (Scherbaum et al. 2011; Liu et al. 2016). In our database, there are 961 different females with two images, one with clean face and another after professional makeup. Females are spanned on four different ethnic groups as follows: 224 Caucasian, 187 Asian, 300 African and 250 Hispanic. All photos are in good quality, frontal face with no occlusion. Makeup-related facial traits are defined and classified into certain classes as presented in Table.1. Also, every makeup style can be described precisely by knowing the value or the class of each makeup element such as foundation color, eye shadow style and lipstick color. So, Table.2 summarizes makeup style elements considered in our system and their classes as labeled in our database. Table.1 and Table.2 contents have been decided carefully by interviewing makeup artists.*This dataset will be available to the public use after publishing this work.*

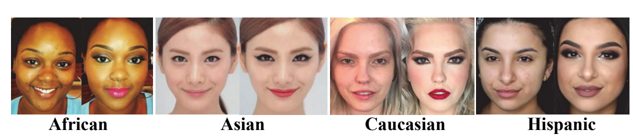

Figure 2: Four females from Before-After makeup database

Table 2: Makeup style attributes and their classes

Makeup Attribute	Classes
Foundation color	Light, Fair, Medium, Dark
Foundation intensity	Light, Heavy
Blush style	Oval, Square, Round
Blush color	Blanc, Pink, Plum, Beige, Bronze, Coral, Copper, Orange
Blush intensity	Light, Heavy
Lipstick color	Pink, Red, Orange, Purple, Nude
Lip liner	Yes, No
Eyeshadow style	Cut Crease, Gradient, Smoky, Cat Eye, Halo Eye, Natural eye
Eyeshadow color	Brown, Cream, Blue, Warm, Smoky
Eye liner	Light, Heavy, Winged

DNN Makeup Recommendation Model

The success of deep learning models in different recommendation systems (Van den Oord, Dieleman, and Schrauwen 2013; Lin et al. 2015; Florez 2014) and the flexibility of learning DNN parameters from different resources of knowledge (Lake, Salakhutdinov, and Tenenbaum 2015) motivated us to propose this makeup recommendation method. In this work, we adapt Multiple Layer Perceptron with input layer that receives the facial traits classes as input vector, L hidden fully connected layers with W hidden units in each layer and multiple outputs layer (one for each makeup element), as depicted in Fig.1.

Deep Neural Network: Given $L-$layer network, and a^l is the output vector of the *l*-th layer, starting with the input layer a^1 and finishing with linear combination of variables a^{L-1}. In a fully connected neural network, we can recursively define for $l = 2$ to $L - 1$:

$$a_j^l = \Phi_j^l(z_j^l), \quad z_j^l = \Sigma_i \omega_{ji}^{l-1} a_i^{l-1} + b_j^{l-1}, \tag{1}$$

where ω_{ji}^{l-1} denotes the weights from the $i-th$ unit of the lth layer to the jth unit of the $(l+1)$th layer, b_j^l denotes the bias term for the jth unit of the $(l+1)$th layer, and $\Phi_j^l(.)$ is an activation function (sigmoid in our case). The model parameters are $\{w_{ji}^l, b_j^l\}$, and the activation functions are fixed. The objective of learning is to find the optimal network parameters, so that the network output a^L matches the target as close as possible. The output a^l can be compared with a target vector t through a loss function $\psi(a^l, t)$. There are two main loss functions, the squared loss and the negative log-likelihood loss. In makeup recommendation problem, there are more than one good option, and maybe one choice is much worse than another. Thus, for color-related makeup element, we used squared loss function between the predicted color and the ground truth color in *L*a*b* color space given by the *DeltaE* distance (Sharma, Wu, and Dalal 2005):

$$\psi(C_1, C_2) = \sqrt{(L_2 - L_1)^2 + (a_2 - a_1)^2 + (b_2 - b_1)^2}. \tag{2}$$

For makeup element styles (masks) such as eye shadow, eye liner, Blush and Eye liner styles, the loss between every pair is given as a prior knowledge between every two possible masks defined by makeup expert.

Learning Sources: The first source of knowledge to train our proposed model is creating a knowledge base rules system for makeup recommendation. Considering that we have a facial image before makeup with labeled traits as in Table 1, this face can be represented as $F \in \mathcal{F}$ where $\mathcal{F}$ is the set of facial images before makeup and $F = \{f_i\}_{i=1}^D$ where f_i is the i-th facial attribute's value, and D is the number of facial attributes for one face. Following the same notation we represent the makeup styles set as $\mathcal{M} \ni M = \{m_i\}_{i=1}^K$ where m is one makeup style and m_i is the makeup i-th attribute's value illustrated in Table 2 and K is the total number of makeup attributes. After building the knowledge base rules, by interviewing makeup experts, the other important part in the rule-based expert system is the *inference engine* (Hayes-Roth, Waterman, and Lenat 1983). The inference engine is responsible for reasoning on the knowledge base for certain query in (forward chaining, backward chaining, or both). The output of the inference engine is the values of the makeup attributes which will be used to train the network of recommendation system along the labeled examples. This represents the second source of knowledge for our proposed recommendation system. Two examples of our rules are presented here.

- **Rule 1:** If *(Skin Color = Medium)* then *(foundation color = Medium)*
- **Rule 2:** If *(Skin Color = medium)* and *(Lips shape = thin)* then *(lipstick color= Red)* and *(Lip Liner = Yes)*

Rule 1 decides the foundation tone according to the skin color, and from *Rule 2*, we decide lipstick color and if we have lip liner or not according to the lips shape.

Proposed Model: To exploit the two available Knowledge resources for makeup recommendation, we used two identical networks. The first one is trained by the makeup elements values predicted via the rule-based system and the second is trained by the labeled professional makeup examples in the database. The parameters of both two networks will be updated simultaneously to minimize the general cost function given by:

$$\begin{aligned} E(\theta) = \Sigma_{n=1}^N \{ \Sigma_{k=1}^K \{ (1-\beta)(\psi_k(a_n^{lk}(x_n, \theta_1), y_n^k) \\ + \eta ||\theta_1||_2) + \beta(\psi_k(a_n^{lk}(x_n, \theta_2), s_n^k) + \eta ||\theta_2||_2) \\ + \Sigma_{i \neq k}^K ||P(y_n^i | y_n^k) - P(a_n^{lk}(x_n, \theta_1))||_2 \} \}. \end{aligned} \tag{3}$$

where θ_1, θ_2 are parameters of rules-based and examples-based learned networks respectively. a_n^{lk} is the output layer for the k-th makeup element. y_n^k is the labeled class and s_n^j is the rule-based recommended class of the k-th makeup element for the input x_n (facial traits). β is the learning ratio between the examples and knowledge rules. N is the number of training examples, K is the number of makeup elements (outputs of the deep network). ψ_k is the loss function for the k-th makeup element. η is the l-2 regularization parameter. The term $(1-\beta)(\psi_k(a_n^{lk}(x_n, \theta_1), y_n^k) + \eta||\theta_1||_2)$ represents learning by examples part, and $\beta(\psi_k(a_n^{lk}(x_n, \theta_2), s_n^k) + \eta||\theta_2||_2)$ represents learning by rules.

To enforce homogeneous recommendation among the different makeup elements (for example: eye shadow color y_n^i

and lipstick color y_n^j) in the same makeup style we added this term: $\Sigma_{i \neq k}^{K} ||P(y_n^i|y_n^k) - P(a_n^{lk}(x_n, \theta_1))||_2$ to our cost function which penalizes the recommendation of two non-homogeneous makeup elements. The homogeneity between every two makeup elements knowledge is learned from our labeled database. It is given by $P(y_n^i|y_n^k)$ which tells how frequent every other makeup element class comes with y_n^k in the same makeup style and $P(a_n^{lk}(x_n, \theta_1))$ which represents the confidence score that *softmax* classifier has for this kth recommended makeup element class. To solve this cost function with the minimum error rate, we implemented the Back Propagation algorithm (Bishop 2006) which can be divided into three phases: forward propagation, error BP, and parameter update as detailed in (Li et al. 2016).

Model Input: The six makeup-related facial traits listed in Table.1 will be classified automatically and coded as feature vector. This feature vector is fed as input to our proposed deep neural network recommendation model in the testing phase. In training phase, we will use the available labels from the database. The face detection, region of interest for every facial trait, feature selection and classification is fully automatic as will be detailed in experiments section. The class number of every facial trait will be coded as feature vector v of size s, the six feature vectors will be concatenated to have a full description of the facial traits in vector $V = \{v_1, ..., v_6\}$.

Algorithm 1 summarizes our learning process steps. Where x_n represents the facial attributes vector described in

Algorithm 1 Example-Rules based DNN Learning

Require: Training data: $\mathbb{D} = \{x_n, Y_n, S_n\}_{n=1}^{N}$;
  Parameter: β learning ration between rules and examples.
  1: Initialize the DNNs with parameter θ
  2: repeat:
    2.1: Sample a mini-batch $(x, Y) \subset \mathbb{D}$
    2.2: Train Example-based network by (x, Y)
    2.3: Train rule-based network by (x, S)
    2.4: Solve Equation.3
  3: until: convergence
Ensure: DNN model parameter

Model Input; Y_n: is makeup style labels in the Dataset that corresponds x_n; S_n: is the generated makeup style for x_n from Rule-based system. The main novelty of this recommendation model is summed up by:1) The DNN structure is trained by examples and it is guided by rules; 2) It has multiple outputs to recommend every makeup element; 3) It recommends homogeneous makeup style.

Automatic Makeup Synthesis

Makeup synthesis step is important to visualize how the recommended makeup will look like on the subject face. Several works addressed makeup synthesis as a transfer of visual effects from one face to another (Liu et al. 2016) or as rendering visual effects (Huang et al. 2013). Since our recommendation system is able to recommend every makeup element features (mask and color) independently, we develop a makeup add-on library of different masks and flexible colors selection. In our system, every makeup element implementation consists of two phases: 1) mask determination to decide where on the face will be applied; 2) the color blending that decides what color change will be applied at that region. For the first step, we have two main methods to create the appropriate mask for makeup style element. First, by creating a mask starting from the detected landmarks on the face that fit exactly the facial region shape in the photo and this method is followed in foundation and lipstick. The second method is followed in eye shadow, blush, and eye liner where we have already created different templates to fit different styles mentioned in the Table 2. After selecting the template, Thin-Plate Spline wrapping method (Bookstein 1989) is used to adjust these predefined masks with the input face region shape by matching the landmarks on the facial region with mask predefined corresponding points.

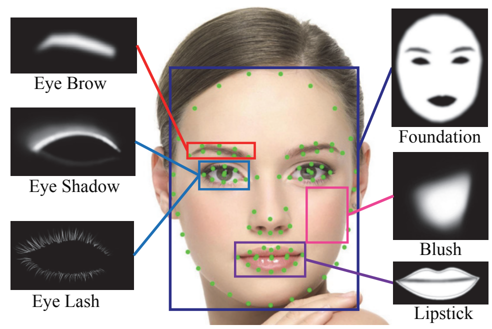

Figure 3: Facial regions of interest and masks of makeup

For the recommended color blending on the facial image, we use different types of blending for different makeup elements. Soft light blend is considered when we need to keep the contrast of the original image such as in lipstick and foundation elements implementation. It is given by:

$$\gamma(x, y) = \begin{cases} 2xy + a^2(1-2y) & \text{if } y < 0.5 \\ 2x(1-y) + \sqrt{x}(2y-1), & \text{otherwise,} \end{cases} \tag{4}$$

where x is the image layer and y is the mask layer and it is implemented for every RGB channel separately. This notation and settings are followed in all blend modes. *Alpha* blend is used alone in lip liner and eye lashes to make the makeup color intense and thick. The *alpha* blend is given as: $\gamma(x, y) = \alpha \times x + (1 - \alpha) \times y$; Where the value of α is between $[0, 1]$ and it is selected empirically for every makeup mask. Both of the *alpha* and *soft light* blend modes are used sequentially in eye shadow and blush masks to combine the advantages of both of them to obtain clear effect while keeping the contrast of the original image unchanged.

Experimental Evaluation

In this section, a qualitative and quantitative experimental analyses are conducted to evaluate the facial attribute classification, recommendation and makeup synthesis.

Facial attributes classification

In order to propose a fully automatic makeup recommendation framework, we start by analyzing the facial traits auto-

Table 3: Facial attributes classification Accuracy (%), where # denotes number of classes, ROI is facial region used.

Face att.,#	ROI	Descriptor	Accuracy
Skin color,4	R1	RGB-Hist, HOG	87.20
Face shape,3	R1	HOG	89.95
Eye Shape,6	R2	HOG,LBP	61.05
Lips Shape,3	R4	HOG,LBP	79.41
Eye Color,5	R3	RGB-Hist	81.00
Ethnicity,4	R1	RGB-Hist, LBP	87.42

matically. To this end, 83 facial landmarks are detected on the face using face++ framework[2] and different regions of interest are extracted for different facial attributes as illustrated in Fig.3. We can see that the whole facial region called R_1 is used for skin color, face shape and ethnicity classification, the R_2 region for eye shape, R_3 for eye color and R_4 for lips shape. After cropping the region of interest for a certain attribute, a combination of color and shape descriptors like RGB-Histogram of 8 bins, HOG (Dalal and Triggs 2005) and LBP (Ojala, Pietikainen, and Maenpaa 2002) are selected empirically to extract the best feature vector for every attribute. After data reduction and noise removal the resulting feature vector is passed to multi-class SVM classifier (Chang and Lin 2011). These experiments are conducted on 900 before makeup facial images following 10-fold cross validation. Table 3 summarizes the facial attribute, and the facial region of interest cropped, descriptors, and the average classification accuracy. We obtained a good classification rate for most of the attributes as presented in Table 3. For the eye shape, it is 61.05%, there are 6 different classes and it is a challenging task even for people.

Statistical evaluation

Experimental settings: the statistical evaluation of the proposed system is conducted on 961 pairs of images from our collected database. 80% pairs of images (examples) are used for training, 10% for validation and 10% for testing in 9-fold cross validation. Mini-batch gradient descent algorithm (Vincent et al. 2010) is used for more robust gradient descent performance with min-batch size 10. Number of epoches in the training is 100 and learning ration $\beta = 0.1$ selected empirically. The network has one input layer, 3 hidden layers each has 100 hidden units, learning rate: $\eta = 10^{-4}$, and one output layer with 8 different outputs (*softmax*). The class number for every facial trait is repeated 10 times to make feature vector of size 10 and the six concatenated in one feature vector V of size 60 to serve as input for the model.

Experiment: to validate the merit of combining rules and examples together in training, we trained our system with examples alone and we applied the same loss function on the suggested makeup from the rule-based recommendation system to compare both of them statistically with Example-Rules guided system. In training, we used the labeled values for the facial traits and for testing the automatic facial traits classification is applied. To compare with state of the art, we compared with distance-based similarity makeup recommendation approaches followed in (Liu et al. 2016), (Scherbaum et al. 2011) where *Deep* features and *Eigen* features are used respectively to compute similarity metric between the test face and available images in the dataset. We repeated these two methods on every 100 testing images (without makeup) and computed the lose between the closest face makeup style and the makeup style of the testing image using the same loss functions used in our deep learning model. The statistical loss values are reported for in Table 4.

Table 4: Statistical results of the loss values for each makeup element. **Eigen:(Scherbaum et al. 2011)**, **Rule:** Rule-based recommendation, **Exp:** Examples trained network, **Deep:(Liu et al. 2016)** and **Exp-Rul:** Examples-Rules Guided network. # indicates to the number of the classes of the makeup element. In makeup elements, *C* denotes to Color.

Makeup,#	Eigen	Rule	Exp	Deep	Exp-Rul
Foundation, 4	0.37	0.55	0.42	0.23	**0.1**
Lipstick C, 5	0.50	0.62	0.45	0.47	**0.31**
Lip liner, 2	0.40	0.32	0.23	0.35	**0.20**
Blush, 3	0.27	0.02	0.02	0.19	**0.01**
Blush C, 8	0.55	0.52	0.47	0.56	**0.34**
Eyeshad, 6	0.53	0.65	0.57	0.60	**0.32**
Eyeshad C, 5	0.70	0.59	0.45	0.67	**0.36**
Eyeliner, 3	0.37	0.48	0.39	0.32	**0.27**
Average	0.46	0.43	0.38	0.32	**0.24**

We can see from these statistical results that the combination of rules and examples gives the lowest loss values for every makeup element and it is less than the two state of the art methods **Deep** and **Eigen**. Also, it is less than Rule-based recommendation and Examples-alone trained system. These results approve our hypothesis about the advantage of combining the rules and examples to learn the model parameters for makeup recommendation and shows the superiority of this method over the state of the art similarity based makeup recommendation methods. Also, the makeup elements which are related strongly to the facial traits such as foundation tone, lip liner and blush style loss are less than other makeup elements such as lipstick color, eye shadow colors which may have more than one good choice.

Model parameters analysis

To investigate the effect of the homogeneity term in the cost function, we repeated the same statistical analysis experiments with and without this term and the results showed that loss is less for every makeup and by 0.9 in average with this term by comparison with the case without it. This demonstrates the importance of enforcing homogeneity between different makeup style elements. Also, we compared the proposed network structure single network multiple outputs (SNMO) against using multiple networks single output (MNSO) for every makeup style independently. From the obtained results in Table 5, we can see that the average loss for MNSO is higher than SNMO adopted structures since we lose the ability to enforce homogeneity among multiple

[2]www.faceplusplus.com

Table 5: SNMO structure vs. MNSO comparison

	MNSO	SNMO (ours)	Difference
Average Loss	0.31	0.24	0.7 less
# of Paramters	208,800	26,800	88% less
# of Epoches	50	100	2× more

outputs of the same network. Also, the total number of parameters of the 8 networks (MNSO) is much higher than one network with 8 outputs (SNMO), but it requires half the number of epochs to train for every single network alone.

Perceptual evaluation

To evaluate the performance in perceptual manner, we designed two qualitative experiments. First, we randomly selected 20 images without makeup from our collected dataset and applied the automatic facial attribute classification and obtained the recommended makeup style and synthesized it on the images. We presented two photos of those 20 subjects without and with recommended makeup to 20 persons (10 males and 10 females from different cultures). We asked the participants to give an evaluation for every makeup style as {Very bad, Bad, Fine, Good, Very good} and reported the percentage that every evaluation obtained. The evaluation of females and males are presented separately. Perceptual survey results are given in Fig.4(A) where we obtain the highest score for *fine* evaluation and we obtained *Good and Very good* higher than *Bad and Very bad*. The evaluation is positive and it shows that our recommendation and implementation is good from the view point of human perception.

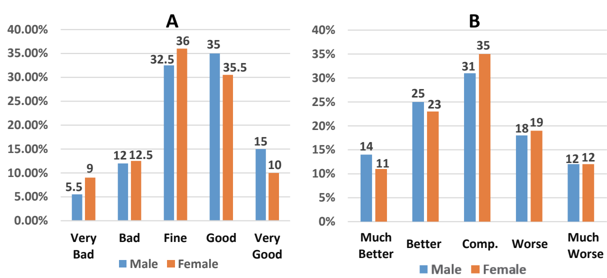

Figure 4: Male-Female qualitative evaluation experiments

In Fig.5(A), there are three samples of the 20 testing images used for the experiment. The face before makeup, with professional makeup, with suggested makeup are presented.

The second experiment is more challenging, where we compared our suggested makeup with professional one. We showed 3-tuple contains: *before, professional, our* makeup for the same participants in last experiment. We exchanged randomly between the position of our and the professional makeup and asked: *Do you think that the left is (Much worse, Worse, Comparable, Better, Much better) than the right makeup?*. The statistical results are presented in Fig.4(B). From the obtained results, we can see that the evaluation *Comparable* has the highest evaluation from males and females, and the evaluations *Much better, Better* got more votes than *Worse, Much worse* too. These two experiments demonstrate the efficiency of our proposed makeup recommendation system versus professional makeup images from the view point of the end user.

Makeup synthesis results

To demonstrate the efficiency of our makeup synthesis implementation as illustrated in Fig.5(B), we compare our synthesis results with two main makeup synthesis websites *TAAZ* and *DailyMakever*. From this figure, we can see that in TAAZ, it is not possible to work on the eye brows, and the eye lashes effect is not natural. In *Dailymakeover*, the ability to control the effect intensity is limited, and the lips shape detection is not accurate. We can see here the positive effect of using different blending types and combining two types in some cases in makeup implementation. For example, we have a natural effect for foundation and blush that requires homogeneous blending with the skin, and have elegant eye shadows and eye lashes effect where the contrast with the nearby facial area need to be preserved. Besides, our synthesis is fully automatic where these two websites require manual intervention. Our makeup synthesis system accuracy is higher in spite of it is fully automatic where TAAZ and Daily Makeover requires user intervention.

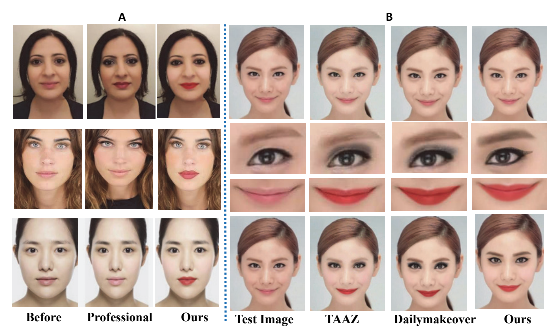

Figure 5: A) Three samples show the face before, after professional and after our makeup. B) Comparison of our synthesis results with TAAZ and DailyMakeover. From top to down, foundation, eye shadow, lipstick, blush, overall effect.

Conclusion and Future Work

In this paper, a deep neural network based makeup recommendation model is trained from examples and knowledge base rules jointly. We demonstrated its ability to recommend homogeneous makeup style that fits face according to its automatically classified facial traits. The recommended makeup style can be synthesized efficiently as well. Another contribution of this work is the Before-After makeup database. This system can be improved by several aspects which we consider them as a future work like extending the database for more robust learning and evaluation, make the recommendation flexible for new trends, and able to recommend different hairstyles and accessories, enriching the makeup synthesis system by adding more trends, templates and colors to have richer suggestions. Also generalizing the proposed approach beyond the makeup recommendation.

References

Bishop, C. 2006. *Pattern Recognition and Machine Learning (Information Science and Statistics)*.

Bookstein, F. L. 1989. Principal warps: thin-plate splines and the decomposition of deformations. *IEEE Trans. on Patt. Anal. and Mach. Int (PAMI)* 11(6).

Chang, C.-C., and Lin, C.-J. 2011. Libsvm: A library for support vector machines. *ACM Trans. Intell. Syst. Technol.*

Dalal, N., and Triggs, B. 2005. Histograms of oriented gradients for human detection. In *IEEE Conference on Computer Vision and Pattern Recognition*.

d'Avila Garcez, A. S.; Besold, T. R.; Raedt, L. D.; Fldiak, P.; Hitzler, P.; Icard, T.; Khnberger, K.-U.; Lamb, L. C.; Miikkulainen, R.; and Silver, D. L. 2015. A connectionist cognitive model for temporal synchronisation and learning. In *AAAI Spring Symposium on Knowledge Representation and Reasoning: Integrating Symbolic and Neural Approaches. Technical Report*.

Florez, O. U. 2014. *Deep Learning of Semantic Word Representations to Implement a Content-Based Recommender for the RecSys Challenge'14*. 199–204.

Frana, M.; G., Z.; and d'Avila Garcez, A. 2014. Fast relational learning using bottom clause propositionalization with artificial neural networks. *Machine Learning* 94.

Garcez, A. d.; Broda, K. B.; and Gabbay, D. M. 2002. *Neural-Symbolic Integration: The Road Ahead*. London: Springer London.

Garcez, A. S. d.; Lamb, L. M.; and M., G. D. 2009. *Neural-Symbolic Cognitive Learning: Cognitive Technologies*. Springer.

Guo, D., and Sim, T. 2009. Digital face makeup by example. In *IEEE Conference on Computer Vision and Pattern Recognition*, 73–79.

Hayes-Roth, F.; Waterman, D. A.; and Lenat, D. B. 1983. *Building Expert Systems*. Boston, MA, USA: Addison-Wesley Longman Publishing Co., Inc.

Hu, Z.; Ma, X.; Liu, Z.; Hovy, E. H.; and Xing, E. P. 2016. Harnessing deep neural networks with logic rules. In *54th Annual Meeting of the Association for Computational Linguistics*.

Huang, C.-G.; Lin, W.-C.; Huang, T.-S.; and Chuang, J.-H. 2013. Physically-based cosmetic rendering. In *Proceedings of the ACM SIGGRAPH Symposium on Interactive 3D Graphics and Games*, I3D '13. ACM.

Krizhevsky, A.; Sutskever, I.; and Hinton, G. E. 2012. Imagenet classification with deep convolutional neural networks. In *Advances in Neural Information Processing Systems 25*.

Lake, B. M.; Salakhutdinov, R.; and Tenenbaum, J. B. 2015. Human-level concept learning through probabilistic program induction. *Science* 350(6266):1332–1338.

Lamb, L. C.; Borges, R. V.; and d'Avila Garcez, A. S. 2007. A connectionist cognitive model for temporal synchronisation and learning. In *Proceedings of the 22Nd National Conference on Artificial Intelligence*, AAAI Press, 827–832.

Li, J.; ; Zhang, T.; Luo, W.; Yang, J.; Yuan, X.; and Zhang, J. 2016. Sparseness analysis in the pertraining of deep neural networks. *IEEE Transactions on Neural Networks and Learning Systems* to appear.

Lin, K.; Yang, H.-F.; Liu, K.-H.; Hsiao, J.-H.; and Chen, C.-S. 2015. Rapid clothing retrieval via deep learning of binary codes and hierarchical search. In *Proceedings of the 5th ACM on International Conference on Multimedia Retrieval*.

Liu, L.; Xu, H.; Xing, J.; Liu, S.; Zhou, X.; and Yan, S. 2013. "wow! you are so beautiful today!". In *ACM International Conference on Multimedia*.

Liu, S.; Ou, X.; Qian, R.; Wang, W.; and Cao, X. 2016. Makeup like a superstar: Deep localized makeup transfer network. In *25th International Joint Conference on Artificial Intelligence, IJCAI'16*.

Ojala, T.; Pietikainen, M.; and Maenpaa, T. 2002. Multiresolution gray-scale and rotation invariant texture classification with local binary patterns. *IEEE Trans. on Pattern Analysis and Machine Intelligence* 24(7).

Parkhi, O. M.; Vedaldi, A.; and Zisserman, A. 2015. Deep face recognition. In *British Machine Vision Conference*.

Scherbaum, K.; Ritschel, T.; Hullin, M.; Thormählen, T.; Blanz, V.; and Seidel, H.-P. 2011. Computer-suggested facial makeup. *Proc. Eurographics*.

Sharma, G.; Wu, W.; and Dalal, E. N. 2005. The ciede2000 color-difference formula: Implementation notes, supplementary test data, and mathematical observations. *Color Research & Application*.

Towell, G. G.; Shavlik, J. W.; and Noordewier, M. O. 1990. Refinement of approximate domain theories by knowledge-based neural networks. In *In Proceedings of the Eighth National Conference on Artificial Intelligence*, 861–866.

Van den Oord, A.; Dieleman, S.; and Schrauwen, B. 2013. Deep content-based music recommendation. In *Advances in Neural Information Processing Systems*. Curran Ass. Inc.

Vincent, P.; Larochelle, H.; Lajoie, I.; Bengio, Y.; and Manzagol, P. 2010. Stacked denoising autoencoders: Learning useful representations in a deep network with a local denoising criterion. *Journal of Machine Learning Research* 11.

Xu, L.; Du, Y.; and Zhang, Y. 2013. An automatic framework for example-based virtual makeup. In *IEEE ICIP*.

You, Q.; Luo, J.; Jin, H.; and Yang, J. 2015. Robust image sentiment analysis using progressively trained and domain transferred deep networks. In *Proceedings of the 29th AAAI Conference on Artificial Intelligence*, 381–388.