Attributes for Improved Attributes

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Abstract

We introduce a method for improving facial attribute predictions using other attributes. In the domain of face recognition and verification, attributes are high-level descriptions of face images. Attributes are very useful for identification as well as image search as they provide easily understandable descriptions of faces, rather than most other image descriptors (i.e. HOG, LBP, and SIFT). A facial attribute is typically considered a binary variable: 0 meaning the face does not exhibit the attribute, and 1 meaning that it does. Work up to the present has considered all attributes of a face to be independent. However, we know that many face attributes are highly correlated, i.e. gender *and* facial hair. *We propose to take advantage of these correlations to improve attribute classification. We study the attribute correlations in a very challenging face dataset, and demonstrate that both automatic correlation discovery and manual correlation rules result in an increase in classification for binary attributes. This is the first work to utilize the relationship amongst binary attributes for improved classification performance. Using a deep convolutional neural network for feature extraction and classification, along with our automatic correlation discovery method, we achieve state-of-the-art results for attribute classification.*

1. Introduction

Attributes are high-level descriptions of images, objects, and people. As image descriptors, they have found success in the domains of object recognition [2], action recognition [11], and face recognition and verification [6]. Attributes as a feature have gained popularity in recent years due to their alignment with intuition as well as their easily-understandable nature. Face recognition and verification has been the most active domain in the use of attributes. Kumar et. al introduced the concept of attributes as image descriptors for face verification in [5]. They used a collection of 65 binary attributes to describe each face image. They later extended this work with an addition of 8 attributes and applied their method to the problem of image search in addition to face verification [6]. Berg et. al created classifiers for each pair of people in a dataset and then used these classifiers to create features for a face verification classifier [1]. Here, rather than manually identifying attributes, each person was described by their likeness to one person vs. another. This was a way of automatically creating a set of attributes without having to exhaustively hand-label attributes on a large dataset. Prior to this, there has been decades of research on gender and age recognition from face images [3] [9].

Reliable estimation of facial attributes is useful for many different tasks. HCI applications may require information about gender in order to properly greet a user (i.e. Mr. or Ms.). Facial attributes can be used for identity verification in low quality imagery, where other verification methods may fail. Suspects are often described in terms of attributes, and so they can be used to automatically search for suspects in surveillance video.

Deep convolutional neural networks (CNNs) have been widely used for feature extraction and have shown great improvement over hand-crafted features for many problems. CNNs have been successful in attribute classification as well. Pose Aligned Networks for Deep Attributes (PANDA) achieved state-of-the-art performance by combining part-based models with deep learning to train pose-normalized CNNs for attribute classification [10]. Focusing on age and gender, [7] applied deep CNNs to the relatively unknown Adience dataset. Liu et. al used two deep CNNs - one for face localization and one for attribute recognition - and achieved impressive results on the new CelebA dataset, outperforming PANDA on many attributes [8]. All of these methods require some form of preprocessing, whether it is the extraction of parts, alignment, or pretraining the CNN with external data.

We introduce a method for improving facial attribute predictions using other attributes. Facial attributes are typically considered to be independent variables. However, we know that many face attributes are highly correlated such as *Gender* and *Makeup*. We propose to take advantage of these correlations to improve attribute classification. Our method requires no pretraining, and no costly alignment or part extraction preprocessing steps. To the best of our knowledge, we are the first to take advantage of the relationship amongst facial attributes for improved classification accuracy.

The contributions of our work are as follows:

- We apply a deep CNN to the problem of binary attribute classification, achieving state-of-the-art results on the CelebA dataset.
- Using correlations amongst attributes, we improve classification accuracy for individual attribute classifiers using the output of the classifiers for the remaining attributes.
- We use the same CNN architecture for each attribute classifier.
- Our method requires no pretraining on external data, and no expensive preprocessing steps such as alignment and fiducial extraction.

The remainder of the paper is structured as follows: Section 2 discusses our approach, including feature learning, our automatic attribute relationship dicovery method, and manually specified attribute relationships. Section 3 details experiments including the data used, and the results obtained. Section 4 then discusses our results, and in Section 5, we summarize our work and discuss future research directions.

2. Our Approach

2.1. Feature Learning

We use Caffe to implement our deep CNN feature extraction [4]. We adopt the architecture from [7], which contains three convolutional layers and 3 fully connected layers. The input to the network is 256x256 color images and random crops of 227x227 are taken for training. The first convolution layer contains 96 7x7 filters and is followed by a ReLU operation, max pooling, and normalization. The second convolution layer consists of 256 5x5 filters again followed by a ReLU, max pooling, and normalization. The third convolution layer has 384 3x3 filters. This is followed by ReLU and max pooling, but no normalization. The first two fully connected layers each have 512 units and the final fully connected layer has two units and determines the class probabilities. There is a 50% dropout between each of the fully connected layers. This architecture has been shown to perform well on *Gender* and *Age* classification tasks. [7] requires an alignment preprocessing step before inputting the images to the network, which is not required by our method.

We train 40 binary CNNs (one for each attribute), 1 indicating the presence of the attribute, and 0 indicating the lack of an attribute in a face image. Each CNN is trained for 25000 iterations, and every 1000 iterations the model is tested on the validation set. The final model for each attribute is chosen to be the model with the highest validation accuracy. For the validation and test images, a 227x227 crop is taken out of the center of the image, the features learned with the CNN models are extracted, and softmax is used for classification.

2.2. Automatic Correlation Discovery

For each attribute, we use the labeled training data to determine correlations amongst attributes. We use Pearson's correlation coefficient to determine if two attributes are correlated. Let A and B be two random variables representing two attributes. Pearson's correlation between A and B is defined as:

$$\rho_{A,B} = \frac{cov(A,B)}{\sigma_A \sigma_B}$$

Where $cov(A,B)$ is the covariance between A and B, and σ_A and σ_B are the standard deviations of A and B respectively. For each set of two attributes A and B, we compute $\rho_{A,B}$. Table 1 shows some correlations of interest. The complete correlation matrix for all 40 attributes is presented in two parts at the end of the paper in tables 6 and 7.

There are many insignificant attribute correlations, and so we decided to focus on attribute pairs with $|\rho| > 0.2$, which are bolded in table 1. This resulted in 128 attribute pairs. We note a few interesting results in the correlation tables. First, *Bangs*, *Narrow Eyes*, and *Pale Skin* show no significant correlations with any other attributes. There are some obvious correlations which align with our intuitions, such as *No Beard* and *5 o'clock Shadow* being negatively correlated (-0.53), and *Heavy Makeup* and *Wearing Lipstick* being strongly positively correlated (0.8). Table 2 shows the 5 most postively and negatively correlated attributes.

Heavy Makeup	Wearing Lipstick	0.8
High Cheekbones	Smiling	0.68
Chubby	Double Chin	0.53
Mouth Slightly Open	Smiling	0.53
Goatee	Sideburns	0.51
Male	Wearing Lipstick	-0.79
Heavy Makeup	Male	-0.67
Goatee	No Beard	-0.57
No Beard	Sideburns	-0.54
5 o'clock Shadow	No Beard	-0.53

Table 2. Five most positively (top) and negatively (bottom) correlated attributes.

Another interesting thing to note is that while *Blond Hair* and *Black Hair* have a negative correlation (-0.23), it is not as high as we would expect. Similarly with *Gray Hair* and *Brown Hair* compared with the other hair colors. This is

	5 o'clock Shadow	Arched Eyebrows	Attractive	Big Nose	Black Hair	Blond Hair	Bushy Eyebrows	Chubby	Goatee	Gray Hair	Heavy Makeup	High Cheekbones	Male	No Beard	Rosy Cheeks	Smiling	Wearing Lipstick	Young
5 Shadow	1.00	-0.16	-0.07	0.15	0.10	-0.13	**0.22**	-0.01	0.15	-0.04	**-0.28**	-0.16	**0.42**	**-0.53**	-0.09	-0.07	**-0.33**	0.01
Big Nose	0.15	-0.09	**-0.28**	1.00	0.08	-0.16	0.14	**0.32**	**0.20**	**0.20**	**-0.28**	0.06	**0.37**	**-0.26**	-0.06	0.10	-0.31	**-0.29**
Black Hair	0.10	0.00	0.00	0.08	1.00	**-0.23**	**0.25**	0.01	0.06	-0.12	-0.05	0.01	0.11	-0.09	-0.04	-0.00	-0.06	0.12
Blond Hair	-0.13	0.13	0.16	-0.16	**-0.23**	1.00	-0.15	-0.09	-0.10	-0.05	**0.25**	0.12	**-0.31**	0.17	0.14	0.09	**0.29**	0.06
B. Eyebrows	**0.22**	-0.01	0.04	0.14	**0.25**	-0.15	1.00	-0.00	0.11	-0.05	-0.12	-0.05	**0.24**	**-0.20**	-0.03	-0.00	-0.17	0.08
Double Chin	0.00	-0.08	**-0.21**	**0.30**	-0.03	-0.08	0.00	**0.53**	0.07	**0.26**	-0.15	0.07	**0.21**	-0.09	-0.03	0.10	-0.17	**-0.31**
Eyeglasses	0.01	-0.15	**-0.22**	0.14	-0.01	-0.08	-0.07	0.17	0.08	0.17	-0.19	-0.09	**0.20**	-0.11	-0.07	-0.04	**-0.21**	**-0.22**
Goatee	0.15	-0.11	-0.15	**0.20**	0.06	-0.10	0.11	0.16	1.00	0.00	**-0.21**	-0.10	**0.31**	**-0.57**	-0.07	-0.07	**-0.24**	-0.11
Gray Hair	-0.04	-0.10	**-0.20**	**0.20**	-0.12	-0.05	-0.05	**0.21**	0.00	1.00	-0.15	-0.00	0.19	-0.01	-0.04	0.01	-0.16	**-0.37**
H. Makeup	**-0.28**	**0.44**	**0.48**	**-0.28**	-0.05	**0.25**	-0.12	-0.17	**-0.21**	-0.15	1.00	**0.27**	**-0.67**	**0.35**	**0.30**	0.18	**0.80**	**0.25**
Male	**0.42**	**-0.41**	**-0.40**	**0.37**	0.11	**-0.31**	**0.24**	**0.23**	**0.31**	0.19	**-0.67**	**-0.25**	1.00	**-0.52**	**-0.21**	-0.14	**-0.79**	-0.29
Mouth S. O.	-0.07	0.07	0.02	0.05	-0.02	0.07	-0.03	0.02	-0.06	0.01	0.10	**0.42**	-0.10	0.08	0.14	**0.53**	0.10	-0.01
Mustache	0.09	-0.09	-0.14	**0.21**	0.06	-0.09	0.11	0.18	**0.44**	0.04	-0.16	-0.09	**0.24**	**-0.45**	-0.05	-0.07	-0.19	-0.14
Oval Face	-0.08	-0.01	**0.20**	-0.10	0.03	0.05	0.02	-0.02	-0.02	-0.06	**0.21**	**0.22**	-0.12	0.06	0.12	**0.21**	0.16	0.11
Pointy Nose	-0.02	0.16	**0.23**	-0.16	-0.05	0.12	-0.01	-0.12	-0.08	-0.06	**0.26**	0.06	**-0.21**	0.10	0.17	0.04	**0.25**	0.09
R. Hairline	-0.02	-0.02	-0.18	**0.20**	-0.00	-0.07	-0.03	0.19	0.06	**0.26**	-0.11	0.03	0.12	-0.05	-0.03	0.02	-0.12	**-0.20**
Rosy Cheeks	-0.09	**0.22**	0.16	-0.06	-0.04	0.14	-0.03	-0.04	-0.07	-0.04	**0.30**	**0.25**	**-0.21**	0.11	1.00	**0.22**	**0.27**	0.05
Sideburns	**0.26**	-0.12	-0.10	0.13	0.04	-0.10	0.13	0.12	**0.51**	0.01	-0.19	-0.13	**0.29**	**-0.54**	-0.06	-0.08	**-0.23**	-0.09
Smiling	-0.07	0.09	0.15	0.10	-0.00	0.09	-0.00	0.04	-0.07	0.01	0.18	**0.68**	-0.14	0.11	**0.22**	1.00	0.18	-0.03
Wavy Hair	-0.12	**0.20**	**0.22**	-0.13	-0.09	0.13	-0.06	-0.10	-0.10	-0.09	**0.32**	0.11	**-0.32**	0.16	0.13	0.08	**0.36**	0.09
W. Earrings	-0.16	**0.29**	0.13	-0.06	0.00	0.10	-0.07	-0.06	-0.10	-0.06	**0.35**	**0.23**	**-0.37**	0.19	**0.21**	0.17	**0.37**	0.04
W. Lipstick	**-0.33**	**0.46**	**0.48**	**-0.31**	-0.06	**0.29**	-0.17	-0.19	**-0.24**	-0.16	**0.80**	**0.28**	**-0.79**	**0.42**	**0.27**	0.18	1.00	**0.26**
W. Necklace	-0.12	**0.22**	0.07	-0.04	-0.04	0.14	-0.07	-0.05	-0.08	-0.04	**0.20**	0.12	**-0.27**	0.14	0.14	0.09	**0.26**	0.02
W. Necktie	0.10	-0.13	-0.16	**0.21**	0.02	-0.11	0.06	0.19	0.06	**0.25**	**-0.22**	-0.05	**0.33**	-0.11	-0.07	-0.00	**-0.26**	**-0.25**
Young	0.01	0.15	**0.39**	**-0.29**	0.12	0.06	0.08	**-0.30**	-0.11	**-0.37**	**0.25**	-0.01	**-0.29**	0.12	0.05	-0.03	**0.26**	1.00

Table 1. Pearson correlation coefficients of interest.

due to the way that the data was collected. The labeling was treated as 40 independent binary tasks for each image. So, rather than a person having one and only one hair color, they could have no hair color or multiple hair colors. We found this to be true in the data with a significant overlap between those labeled as having *Brown Hair* and those labeled as having *Black Hair*. Despite some errors in the labels, we are able to find some meaningful correlations from the training set.

We use the validation set to determine which of the 128 correlations of interest can be used to improve classification accuracy. For each attribute, we order its correlations from strongest to weakest. Let A be the attribute of interest. We want to determine which attributes improve the classification of A. Suppose B is the attribute with the strongest correlation with A. For each image in the validation set, we classify the image using both the A and B classifiers (C_A and C_B). We get a yes or no answer along with a confidence value from both C_A and C_B. Given an image, if $\rho_{A,B} < 0$ then we want C_A and C_B to give different answers, and if $\rho_{A,B} > 0$ we want C_A and C_B to agree. If $\rho_{A,B}$ is negative and C_A and C_B give opposite answers, then we do nothing. Similarly if $\rho_{A,B}$ is positive and C_A and C_B give the same answer (both yes, or both no). If $\rho_{A,B}$ is negative and both C_A and C_B give the same answer, or if $\rho_{A,B}$ is positive and C_A and C_B give different answers, then we use the confidence values to determine which response to change. We use empirical evaluations to find a lower threshold (T_L) and an upper threshold (T_H) for the confidence of each attribute pair. Let $CONF_A$ and $CONF_B$ be the confidence returned from a single image classification using C_A and C_B respectively. For each image in the validation set, if $CONF_A < T_L$ and $CONF_B > T_H$ then we take the output of C_B to be the truth for B and we choose A according to its correlation with B. Similarly, if $CONF_A > T_H$ and $CONF_B < T_L$, we take the output of C_A to be the truth for A and we change B accordingly.

Then, for each pair of attributes, we determine if the correlation improved results in either direction (if A improved B or vice versa) by comparing the validation accuracy with-

Automatically Discovered Relationships

Independent Attribute	Dependent Attribute	T_L	T_H
Male	5 o'clock Shadow	0.52	0.8
Male Wearing Lipstick	Big Nose	0.54	0.76
Bushy Eyebrows	Black Hair	0.57	0.74
Black Hair	Blond Hair	0.51	0.8
5 o'clock Shadow	Bushy Eyebrows	0.55	0.71
Chubby	Double Chin	0.64	0.65
Male Wearing Lipstick Rosy Cheeks	Wearing Earrings	0.54	0.82
Young	Eyeglasses	0.55	0.72
Wearing Lipstick No Beard	Male	0.59	0.93
Mustache	Goatee	0.61	0.76
Young	Gray Hair	0.55	0.88
High Cheekbones Blond Hair	Heavy Makeup	0.54	0.75
Heavy Makeup Arched Eyebrows Wearing Earrings	Wearing Lipstick	0.65	0.9
High Cheekbones	Mouth Slightly Open	0.55	0.82
Big Nose	Mustache	0.63	0.86
Arched Eyebrows	Wearing Necklace	0.54	0.9
Male Big Nose	Wearing Necktie	0.52	0.91
Heavy Makeup Smiling	Oval Face	0.51	0.89
Heavy Makeup Wearing Lipstick	Pointy Nose	0.54	0.9
Gray Hair	Receding Hairline	0.56	0.76
Arched Eyebrows	Rosy Cheeks	0.53	0.69
No Beard Goatee 5 o'clock Shadow	Sideburns	0.53	0.82
High Cheekbones	Smiling	0.52	0.74
Arched Eyebrows	Wavy Hair	0.62	0.81
Attractive	Young	0.53	0.81

Manual Correlation Relationships

Independent Attribute	Dependent Attribute	T_L	T_H
Male	5 o'clock Shadow	0.52	0.90
Blond Hair	Black Hair	0.53	0.91
Black Hair	Gray Hair	0.53	0.9
Brown Hair	Blond Hair	0.57	0.91
Blond Hair	Brown Hair	0.51	0.86
No Beard	Male	0.6	0.91
Male	Wearing Necktie	0.52	0.8
Pale Skin	Rosy Cheeks	0.53	0.75

Table 3. Automatically discovered and manually specified relationships which improved validation accuracy.

out correlations with the new validation accuracy including correlations. We consider each direction of the relationship separately. Let $R(A, B)$ indicate that A improves B through their relationship, and $R(B, A)$ indicate that B improves A through their relationship. If A improves B, then we save this relationship ($R(A, B)$) , but if B did not improve A then we do not save $R(B, A)$. The resulting automatically discovered relationships and their confidence thresholds are shown in the first part of table 3, where A as the independent attribute and B as the dependent attribute means that A improved B or $R(A, B)$. This method for determining correlation amongst attributes is completely automatic. It can be used on any dataset provided that there is a validation separate from the training and testing sets.

2.3. Manual Correlation Rules

Before performing our automatic correlation discovery method, we constructed a list of attribute relationships one would expect given common sense. We list the manual correlation rules in table 4, where $+$ and $-$ mean that A and B are expected to have a positive or negative correlation respectively. We again use the validation set to choose which correlation rules produce improvements in accuracy, and through empirical evaluations, we determine the optimal T_L and T_H for each attribute pair. The manual relationships and threshold values which result in an increase in validation accuracy are shown in the second part of table 3. Far fewer relationships result from the manual correlation rules than from the automatic correlation discovery. This is due to the mislabeling in the dataset. If the hair color attributes were not labeled independently, but rather in a pick-one-out-of-four method, then the manual correlation rules would fit much better with the data. Regardless, we do see that our manual correlation rules align nicely with the rules discovered in the previous section, with four out of the eight being present in the discovered relationships.

3. Experiments

3.1. Data

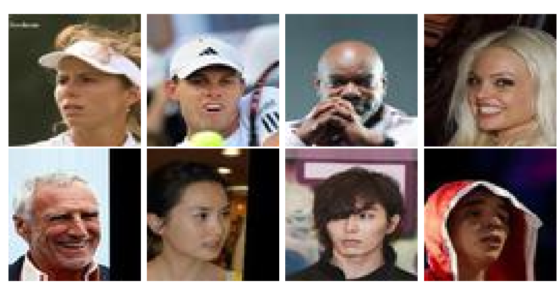

Figure 1. Example images from the CelebA dataset.

We use the CelebA dataset [8] for our testing as it is a large publicly available dataset with 40 binary attributes labeled for each image. The dataset contains over 200,000 color images, with about 160,000 for training, 20,000 for validation, and 20,000 for testing. Figure 1 shows example

A	B	Correlation
Bangs	Bald	-
Bangs	Receding Hairline	-
Black Hair	Blond Hair	-
Black Hair	Brown Hair	-
Black Hair	Gray Hair	-
Blond Hair	Brown Hair	-
Blond Hair	Gray Hair	-
Brown Hair	Gray Hair	-
Male	Arched Eyebrows	-
Male	Heavy Makeup	-
Male	Wearing Earrings	-
Male	Wearing Lipstick	-
Male	Wearing Necklace	-
Male	No Beard	-
Male	5 o'clock Shadow	+
Male	Bald	+
Male	Bushy Eyebrows	+
Male	Goatee	+
Male	Mustache	+
Male	Receding Hairline	+
Male	Sideburns	+
Male	Wearing Necktie	+
Pale Skin	Rosy Cheeks	-
Straight Hair	Wavy Hair	-
Young	Bald	-
Young	Gray Hair	-
Young	Receding Hairline	-

Table 4. Manual Correlation Rules.

images from the CelebA dataset, demonstrating the difficulty of determining attributes for images in this dataset.

3.2. Tests

We trained 40 binary CNNs (one for each attribute) using the architecture described in Section 2. We tested our classifiers on the 20,000 images in the CelebA test data, getting a response for each attribute in each image. We then separately applied our automatically discovered attribute relationships and our manually specified relationships to the output of the CNNs. We present the results in the following section.

3.3. Results

In this work, we are interested in showing improvement over a baseline using correlations between attributes. We show results presented by [8] and our deep CNN, as well as the proposed deep CNN with automatically discovered attribute relationships and with manually specified relationships. Using our deep CNN method without including attribute relationships, we outperform the state-of-the-art employed by Liu et. al on the CelebA dataset on all but two attributes (*Pale Skin* and *Wearing Hat*). Table 5 shows the results for all 40 attributes, with Ours meaning our deep CNN method, Auto. meaning the proposed deep CNN with automatically discovered attribute relationships, and Man. meaning our deep CNN with manually specified attribute relationships. N/A indicates that there were no correlation rules for that attribute.

We can see from table 5 that the deep CNN method alone makes great improvements over the Liu et. al method. In particular there is an improvement of over 15% for *Wearing Necklace*, over 12% for *Blurry*, an 8% improvement for *Brown Hair*, *Oval Face*, and *Wearing Earrings*, and many 5% and 6% percent improvements. Adding in the automatically discovered attribute relationships, we see additional improvements. On average, our deep CNN method outperforms Liu et. al by 3.6% and with the proposed correlation method, this increases to 3.76% improvement on average. Figures 2- 7 show some face images which were corrected by our correlation method.

Figure 2. Results for *Black Hair* changes. First two: $no \rightarrow yes$, second two: $yes \rightarrow no$.

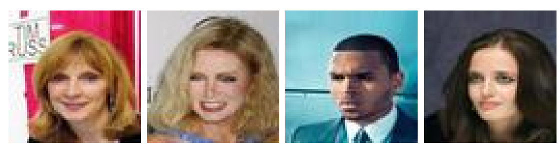

Figure 3. Results for *Blond Hair* changes. First two: $no \rightarrow yes$, second two: $yes \rightarrow no$.

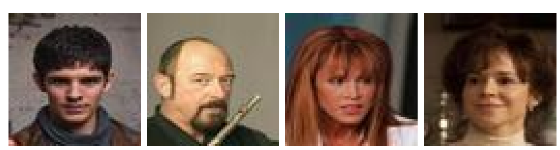

Figure 4. Results for *Male* changes. First two: $no \rightarrow yes$, second two: $yes \rightarrow no$.

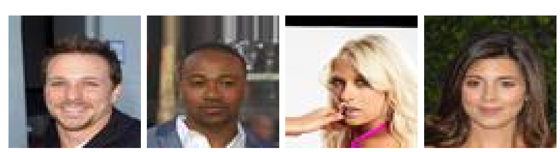

Figure 5. Results for *Mustache* changes. First two: $no \rightarrow yes$, second two: $yes \rightarrow no$.

Attribute / Method	Liu et. al	Ours	Auto.	Man.
5. Shadow	91	94.33	**94.49**	**94.49**
A. Eyebrows	79	**83.53**	N/A	N/A
Attractive	81	**82.30**	N/A	N/A
Bags U. Eyes	79	**85.07**	N/A	N/A
Bald	98	**98.82**	N/A	N/A
Bangs	95	**95.99**	N/A	N/A
Big Lips	68	**70.60**	N/A	N/A
Big Nose	78	83.88	**84.36**	N/A
Black Hair	88	89.70	**90.56**	89.32
Blond Hair	95	**96.05**	96.04	95.90
Blurry	84	**96.16**	N/A	N/A
Brown Hair	80	**88.99**	N/A	88.93
B. Eyebrows	90	92.58	**93.10**	N/A
Chubby	91	**95.70**	N/A	N/A
Double Chin	92	96.38	**96.52**	N/A
Eyeglasses	99	99.66	**99.67**	N/A
Goatee	95	97.14	**97.33**	N/A
Gray Hair	97	98.16	**98.29**	98.11
Heavy Makeup	90	91.12	**91.49**	N/A
H. Cheekbones	87	**87.31**	N/A	N/A
Male	98	98.26	**98.40**	98.38
Mouth S. O.	92	93.87	**94.06**	N/A
Mustache	95	96.66	**96.79**	N/A
Narrow Eyes	81	**87.04**	N/A	N/A
No Beard	95	**96.07**	N/A	N/A
Oval Face	66	74.74	**74.85**	N/A
Pale Skin	**91**	89.72	N/A	N/A
Pointy Nose	72	77.27	**77.98**	N/A
Receding Hairline	89	93.43	**94.15**	N/A
Rosy Cheeks	90	95.02	**95.09**	94.68
Sideburns	96	97.82	**97.93**	N/A
Smiling	92	92.62	**92.74**	N/A
Straight Hair	73	**82.62**	N/A	N/A
Wavy Hair	80	82.61	**83.31**	N/A
Wearing Earrings	82	90.52	**90.83**	N/A
Wearing Hat	**99**	98.98	N/A	N/A
Wearing Lipstick	93	93.80	**94.23**	N/A
Wearing Necklace	71	86.45	**86.56**	N/A
Wearing Necktie	93	96.66	**96.72**	96.71
Young	87	87.94	**88.11**	N/A
Average	87.3	90.90	**91.06**	90.08

Table 5. Accurcies for our deep CNN method (with and without correlation) compared with the method of Liu et. al.

3.4. Discussion

We see from table 5 that with the exception of one attribute (*Blond Hair*), the inclusion of automatically discovered relationships improves the accuracy of attribute classifiers on the CelebA dataset. The addition of manually specified attribute relationships degrades the performance of some attributes and negligibly improves the performance of some over our deep CNN method, and never outperforms the automatically discovered relationships. This makes sense, because the automatically discovered relationships better represent the dependencies that exist in the dataset from which they were created. Therefore, they can take advantage of relationships that may not hold in general, such as the high correlation between *Bags Under Eyes* and *Male* (0.33) and the lack of strong negative correlation between *Receding Hairline* and *Young* (-0.20) as common sense would dictate.

The 0.86% increase in accuracy for the *Black Hair* classifier may be considered small, but if we think of it in terms of numbers, 172 additional people were classified correctly as having black hair. This is important for automated surveillance tasks. If a suspect has black hair and is misclassified, then they will be missed on the surveillance video. Every additional correct classification helps in these types of tasks. Also, we believe that the increase would be much larger in other datasets with better labeling. We leave this for future work.

Another important thing to note is the simplicity of our method. Our very simple attribute discovery technique improved results in 25 attribute categories. More complex approaches for discovering attribute relationships can be employed, likely resulting in even better performance. The simplicity of our method and the results it obtains speak to the necessity for viewing attributes as highly correlated variables rather than independent features.

We point out that this method can be used for datasets without attribute labels. We can use the trained CNNs for the 40 CelebA attributes and test on other datasets. We can use the rules we learned for attribute correlations, perhaps with a larger threshold for ρ for better generalizability, and we can visually verify the improvements on the dataset by looking at the images for which the labels were changed.

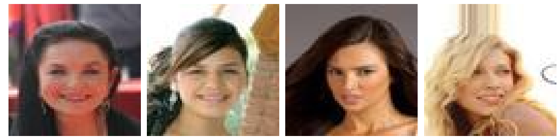

Figure 6. Results for *Wearing Earrings* changes. First two: $no \rightarrow yes$, second two: $yes \rightarrow no$.

Figure 7. Results for *Smiling* changes. First two: $no \rightarrow yes$, second two: $yes \rightarrow no$.

4. Conclusion

We proposed a method for using facial attributes to improve the classification accuracy of other facial attributes. We introduced a technique for automatically discovering attribute relationships using the training and validation portions of a dataset. Using a deep CNN for feature extraction and classification and integrating automatically discovered attribute relationships, we were able to achieve state-of-the-art results on the challenging real-world CelebA dataset. We are the first group to take advantage of the relationship between facial attributes for improved classification performance. Using manually specified attribute relationships, we verified that the automatically discovered relationships aligned with common sense, and also took advantage of dependencies in the dataset. We improve upon previous research in attribute classification by considering the dependencies between attributes rather than treating them as independent classification tasks. In future work, we plan to explore the extent to which these correlations can be used during training to improve attribute classification.

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Table 6. Pearson correlation coefficients for the 40 CelebA attributes. Part 1

	5 o'clock Shadow	Arched Eyebrows	Attractive	Bags Under Eyes	Bald	Bangs	Big Lips	Big Nose	Black Hair	Blond Hair	Blurry	Brown Hair	Bushy Eyebrows	Chubby	Double Chin	Eyeglasses	Goatee	Gray Hair	Heavy Makeup	High Cheekbones
5 Shadow	1.00	-0.16	-0.07	0.17	0.01	-0.09	-0.04	0.15	0.10	-0.13	-0.03	-0.01	**0.22**	-0.01	0.00	0.01	0.15	-0.04	**-0.28**	-0.16
A. Eyebrows	-0.16	1.00	**0.26**	-0.09	-0.07	-0.03	**0.24**	-0.09	0.00	0.13	-0.08	0.02	-0.01	-0.09	-0.08	-0.15	-0.11	-0.10	**0.44**	0.15
Attractive	-0.07	**0.26**	1.00	-0.18	-0.15	0.06	0.07	**-0.28**	0.00	0.16	-0.18	0.13	0.04	**-0.24**	**-0.21**	**-0.22**	-0.15	**-0.20**	**0.48**	0.15
Bags U. Eyes	0.17	-0.09	-0.18	1.00	0.12	-0.06	-0.01	**0.36**	-0.00	-0.11	-0.04	-0.05	0.11	0.15	0.19	-0.04	0.09	0.17	**-0.29**	0.07
Bald	0.01	-0.07	-0.15	0.12	1.00	-0.06	-0.01	0.18	-0.08	-0.06	-0.01	-0.08	-0.02	**0.22**	**0.21**	0.10	0.12	0.16	-0.12	-0.00
Bangs	-0.09	-0.03	0.06	-0.06	-0.06	1.00	0.03	-0.07	-0.03	0.10	-0.01	0.07	-0.07	-0.08	-0.07	-0.06	-0.09	-0.06	0.12	0.05
Big Lips	-0.04	**0.24**	0.07	-0.01	-0.01	0.03	1.00	0.07	0.07	0.02	-0.04	-0.01	0.02	0.00	-0.01	-0.05	0.02	-0.09	0.15	0.05
Big Nose	0.15	-0.09	**-0.28**	**0.36**	0.18	-0.07	0.07	1.00	0.08	-0.16	-0.04	-0.13	0.14	**0.32**	**0.30**	0.14	**0.20**	**0.20**	**-0.28**	0.06
Black Hair	0.10	0.00	0.00	-0.00	-0.08	-0.03	0.07	0.08	1.00	**-0.23**	-0.04	**-0.25**	**0.25**	0.01	-0.03	-0.01	0.06	-0.12	-0.05	0.01
Blond Hair	-0.13	0.13	0.16	-0.11	-0.06	0.10	0.02	-0.16	**-0.23**	1.00	-0.01	-0.17	-0.15	-0.09	-0.08	-0.08	-0.10	-0.05	**0.25**	0.12
Blurry	-0.03	-0.08	-0.18	-0.04	-0.01	-0.01	-0.04	-0.04	-0.04	-0.01	1.00	-0.04	-0.07	-0.01	-0.01	0.02	-0.03	0.01	-0.14	-0.08
Brown Hair	-0.01	0.02	0.13	-0.05	-0.08	0.07	-0.01	-0.13	**-0.25**	-0.17	-0.04	1.00	-0.06	-0.09	-0.08	-0.08	-0.07	-0.10	0.09	0.02
B. Eyebrows	**0.22**	-0.01	0.04	0.11	-0.02	-0.07	0.02	0.14	**0.25**	-0.15	-0.07	-0.06	1.00	-0.00	0.00	-0.07	0.11	-0.05	-0.12	-0.05
Chubby	-0.01	-0.09	**-0.24**	0.15	**0.22**	-0.08	0.00	**0.32**	0.01	-0.09	-0.01	-0.09	-0.00	1.00	**0.53**	0.17	0.16	**0.21**	-0.17	0.04
Double Chin	0.00	-0.08	**-0.21**	0.19	**0.21**	-0.07	-0.01	**0.30**	-0.03	-0.08	-0.01	-0.08	0.00	**0.53**	1.00	0.15	0.07	**0.26**	-0.15	0.07
Eyeglasses	0.01	-0.15	**-0.22**	-0.04	0.10	-0.06	-0.05	0.14	-0.01	-0.08	0.02	-0.08	-0.07	0.17	0.15	1.00	0.08	0.17	-0.19	-0.09
Goatee	0.15	-0.11	-0.15	0.09	0.12	-0.09	0.02	**0.20**	0.06	-0.10	-0.03	-0.07	0.11	0.16	0.07	0.08	1.00	0.00	**-0.21**	-0.10
Gray Hair	-0.04	-0.10	**-0.20**	0.17	0.16	-0.06	-0.09	**0.20**	-0.12	-0.05	0.01	-0.10	-0.05	**0.21**	**0.26**	0.17	0.00	1.00	-0.15	-0.00
H. Makeup	**-0.28**	**0.44**	**0.48**	**-0.29**	-0.12	0.12	0.15	**-0.28**	-0.05	**0.25**	-0.14	0.09	-0.12	-0.17	-0.15	-0.19	**-0.21**	-0.15	1.00	**0.27**
High Cheek.	-0.16	0.15	0.15	0.07	-0.00	0.05	0.05	0.06	0.01	0.12	-0.08	0.02	-0.05	0.04	0.07	-0.09	-0.10	-0.00	**0.27**	1.00
Male	**0.42**	**-0.41**	**-0.40**	**0.30**	0.18	-0.16	-0.17	**0.37**	0.11	**-0.31**	0.03	-0.11	**0.24**	**0.23**	**0.21**	**0.20**	**0.31**	0.19	**-0.67**	**-0.25**
Mouth S. O.	-0.07	0.07	0.02	0.05	-0.00	0.01	0.05	0.05	-0.02	0.07	-0.02	-0.01	-0.03	0.02	0.07	-0.00	-0.06	0.01	0.10	**0.42**
Mustache	0.09	-0.09	-0.14	0.11	0.08	-0.07	0.03	**0.21**	0.06	-0.09	-0.00	-0.07	0.11	0.18	0.12	0.09	**0.44**	0.04	-0.16	-0.09
NarrowEyes	0.01	0.03	-0.07	0.11	0.01	0.01	0.12	0.07	-0.01	-0.00	0.07	-0.02	0.01	0.04	0.06	-0.04	-0.01	0.02	-0.04	0.05
No Beard	**-0.53**	**0.20**	**0.20**	-0.14	-0.12	0.13	0.02	**-0.26**	-0.09	0.17	-0.01	0.08	**-0.20**	-0.17	-0.09	-0.11	**-0.57**	-0.01	**0.35**	0.18
Oval Face	-0.08	-0.01	**0.20**	-0.13	0.01	0.00	-0.11	-0.10	0.03	0.05	-0.08	0.05	0.02	-0.02	-0.05	-0.06	-0.02	-0.06	**0.21**	**0.22**
Pale Skin	-0.04	0.05	0.09	-0.03	-0.02	0.04	0.04	-0.05	-0.04	0.06	-0.02	-0.01	-0.02	-0.03	-0.03	-0.03	-0.04	-0.01	0.05	-0.08
Pointy Nose	-0.02	0.16	**0.23**	-0.11	-0.06	0.01	0.06	-0.16	-0.05	0.12	-0.05	0.05	-0.01	-0.12	-0.09	-0.10	-0.08	-0.06	**0.26**	0.06
R. Hairline	-0.02	-0.02	-0.18	0.11	0.14	-0.12	0.02	**0.20**	-0.00	-0.07	0.01	-0.10	-0.03	0.19	0.18	0.08	0.06	**0.26**	-0.11	0.03
Rosy Cheeks	-0.09	**0.22**	0.16	-0.09	-0.04	0.06	0.08	-0.06	-0.04	0.14	-0.06	0.01	-0.03	-0.04	-0.03	-0.07	-0.07	-0.04	**0.30**	**0.25**
Sideburns	**0.26**	-0.12	-0.10	0.10	0.06	-0.07	-0.04	0.13	0.04	-0.10	-0.02	-0.03	0.13	0.12	0.03	0.04	**0.51**	0.01	-0.19	-0.13
Smiling	-0.07	0.09	0.15	0.11	0.01	0.05	0.01	0.10	-0.00	0.09	-0.06	0.02	-0.00	0.04	0.10	-0.04	-0.07	0.01	0.18	**0.68**
Straight Hair	0.05	-0.05	0.04	0.02	-0.07	0.03	-0.04	-0.03	0.11	0.00	-0.04	-0.01	0.07	-0.03	-0.03	-0.02	-0.05	-0.01	-0.06	-0.02
Wavy Hair	-0.12	**0.20**	**0.22**	-0.12	-0.10	0.06	0.13	-0.13	-0.09	0.13	-0.02	0.15	-0.06	-0.10	-0.08	-0.09	-0.10	-0.09	**0.32**	0.11
W. Earrings	-0.16	**0.29**	0.13	-0.10	-0.06	0.06	0.12	-0.06	0.00	0.10	-0.06	0.00	-0.07	-0.06	-0.05	-0.08	-0.10	-0.06	**0.35**	**0.23**
W. Hat	0.04	-0.10	-0.14	-0.01	-0.03	-0.08	-0.02	0.07	-0.10	-0.08	0.02	-0.10	-0.02	0.06	0.03	0.07	0.09	-0.04	-0.14	-0.09
W. Lipstick	**-0.33**	**0.46**	**0.48**	**-0.28**	-0.14	0.16	**0.20**	**-0.31**	-0.06	**0.29**	-0.13	0.10	-0.17	-0.19	-0.17	**-0.21**	**-0.24**	-0.16	**0.80**	**0.28**
W. Necklace	-0.12	**0.22**	0.07	-0.05	-0.05	0.11	0.15	-0.04	-0.04	0.14	-0.01	-0.00	-0.07	-0.05	-0.04	-0.04	-0.08	-0.04	**0.20**	0.12
W. Necktie	0.10	-0.13	-0.16	**0.20**	0.17	-0.09	-0.07	**0.21**	0.02	-0.11	-0.02	-0.07	0.06	0.19	**0.22**	0.13	0.06	**0.25**	**-0.22**	-0.05
Young	0.01	0.15	**0.39**	**-0.24**	**-0.20**	0.03	0.11	**-0.29**	0.12	0.06	-0.07	0.10	0.08	**-0.30**	**-0.31**	**-0.22**	-0.11	**-0.37**	0.25	-0.01

Table 7. Pearson correlation coefficients for the 40 CelebA attributes. Part 2

	Male	Mouth Slightly Open	Mustache	Narrow Eyes	No Beard	Oval Face	Pale Skin	Pointy Nose	Receding Hairline	Rosy Cheeks	Sideburns	Smiling	Straight Hair	Wavy Hair	Wearing Earrings	Wearing Hat	Wearing Lipstick	Wearing Necklace	Wearing Necktie	Young
5 Shadow	**0.42**	-0.07	0.09	0.01	**-0.53**	-0.08	-0.04	-0.02	-0.02	-0.09	**0.26**	-0.07	0.05	-0.12	-0.16	0.04	**-0.33**	-0.12	0.10	0.01
A. Eyebrows	**-0.41**	0.07	-0.09	0.03	**0.20**	-0.01	0.05	0.16	-0.02	**0.22**	-0.12	0.09	-0.05	**0.20**	**0.29**	-0.10	**0.46**	**0.22**	-0.13	0.15
Attractive	**-0.40**	0.02	-0.14	-0.07	**0.20**	**0.20**	0.09	**0.23**	-0.18	0.16	-0.10	0.15	0.04	**0.22**	0.13	-0.14	**0.48**	0.07	-0.16	**0.39**
Bags U. Eyes	**0.30**	0.05	0.11	0.11	-0.14	-0.13	-0.03	-0.11	0.11	-0.09	0.10	0.11	0.02	-0.12	-0.10	-0.01	**-0.28**	-0.05	**0.20**	**-0.24**
Bald	0.18	-0.00	0.08	0.01	-0.12	0.01	-0.02	-0.06	0.14	-0.04	0.06	0.01	-0.07	-0.10	-0.06	-0.03	-0.14	-0.05	0.17	**-0.20**
Bangs	-0.16	0.01	-0.07	0.01	0.13	0.00	0.04	0.01	-0.12	0.06	-0.07	0.05	0.03	0.06	0.06	-0.08	0.16	0.11	-0.09	0.03
Big Lips	-0.17	0.05	0.03	0.12	0.02	-0.11	0.04	0.06	0.02	0.08	-0.04	0.01	-0.04	0.13	0.12	-0.02	**0.20**	0.15	-0.07	0.11
Big Nose	**0.37**	0.05	**0.21**	0.07	**-0.26**	-0.10	-0.05	-0.16	0.20	-0.06	0.13	0.10	-0.03	-0.13	-0.06	0.07	-0.31	-0.04	**0.21**	**-0.29**
Black Hair	0.11	-0.02	0.06	-0.01	-0.09	0.03	-0.04	-0.05	-0.00	-0.04	0.04	-0.00	0.11	-0.09	0.00	-0.10	-0.06	-0.04	0.02	0.12
Blond Hair	**-0.31**	0.07	-0.09	-0.00	0.17	0.05	0.06	0.12	-0.07	0.14	-0.10	0.09	0.00	0.13	0.10	-0.08	**0.29**	0.14	-0.11	0.06
Blurry	0.03	-0.02	-0.00	0.07	-0.01	-0.08	-0.02	-0.05	0.01	-0.06	-0.02	-0.06	-0.04	-0.02	-0.06	0.02	-0.13	-0.01	-0.02	-0.07
Brown Hair	-0.11	-0.01	-0.07	-0.02	0.08	0.05	-0.01	0.05	-0.10	0.01	-0.03	0.02	-0.01	0.15	0.00	-0.10	0.10	-0.00	-0.07	0.10
B. Eyebrows	**0.24**	-0.03	0.11	0.01	**-0.20**	0.02	-0.02	-0.01	-0.03	-0.03	0.13	-0.00	0.07	-0.06	-0.07	-0.02	-0.17	-0.07	0.06	0.08
Chubby	**0.23**	0.02	0.18	0.04	-0.17	-0.02	-0.03	-0.12	0.19	-0.04	0.12	0.04	-0.03	-0.10	-0.06	0.06	-0.19	-0.05	0.19	**-0.30**
Double Chin	**0.21**	0.07	0.12	0.06	-0.09	-0.05	-0.03	-0.09	0.18	-0.03	0.03	0.10	-0.03	-0.08	-0.05	0.03	-0.17	-0.04	**0.22**	**-0.31**
Eyeglasses	**0.20**	-0.00	0.09	-0.04	-0.11	-0.06	-0.03	-0.10	0.08	-0.07	0.04	-0.04	-0.02	-0.09	-0.08	0.07	**-0.21**	-0.04	0.13	**-0.22**
Goatee	**0.31**	-0.06	**0.44**	-0.01	**-0.57**	-0.02	-0.04	-0.08	0.06	-0.07	**0.51**	-0.07	-0.05	-0.10	-0.10	0.09	**-0.24**	-0.08	0.06	-0.11
Gray Hair	0.19	0.01	0.04	0.02	-0.01	-0.06	-0.01	-0.06	**0.26**	-0.04	0.01	0.01	-0.01	-0.09	-0.06	-0.04	-0.16	-0.04	**0.25**	**-0.37**
H. Makeup	**-0.67**	0.10	-0.16	-0.04	**0.35**	**0.21**	0.05	**0.26**	-0.11	**0.30**	-0.19	0.18	-0.06	**0.32**	**0.35**	-0.14	**0.80**	**0.20**	**-0.22**	**0.25**
High Cheek.	**-0.25**	**0.42**	-0.09	0.05	0.18	**0.22**	-0.08	0.06	0.03	**0.25**	-0.13	**0.68**	-0.02	0.11	**0.23**	-0.09	**0.28**	0.12	-0.05	-0.01
Male	1.00	-0.10	**0.24**	0.01	**-0.52**	-0.12	-0.08	**-0.21**	0.12	**-0.21**	**0.29**	-0.14	0.06	**-0.32**	**-0.37**	0.13	**-0.79**	**-0.27**	**0.33**	-0.29
Mouth S. O.	-0.10	1.00	-0.06	0.11	0.08	0.09	-0.06	-0.00	0.02	0.14	-0.07	**0.53**	-0.01	0.04	0.13	0.00	0.10	0.08	-0.03	-0.01
Mustache	**0.24**	-0.06	1.00	0.01	**-0.45**	-0.05	-0.03	-0.06	0.06	-0.05	**0.33**	-0.07	-0.03	-0.08	-0.08	0.08	-0.19	-0.06	0.10	-0.14
Narrow Eyes	0.01	0.11	0.01	1.00	-0.00	-0.09	-0.00	-0.04	0.02	0.00	0.00	0.08	0.00	0.03	0.01	-0.01	-0.02	0.03	0.01	-0.03
No Beard	**-0.52**	0.08	**-0.45**	-0.00	1.00	0.06	0.06	0.10	-0.05	0.11	**-0.54**	0.11	0.03	0.16	0.19	-0.12	**0.42**	0.14	-0.11	0.12
Oval Face	-0.12	0.09	-0.05	-0.09	0.06	1.00	-0.04	0.01	-0.01	0.12	-0.05	**0.21**	0.00	0.04	0.08	-0.05	0.16	-0.06	-0.05	0.11
Pale Skin	-0.08	-0.06	-0.03	-0.00	0.06	-0.04	1.00	0.01	-0.03	-0.04	-0.04	-0.07	0.02	0.02	-0.02	-0.02	0.06	0.00	-0.03	0.04
Pointy Nose	**-0.21**	-0.00	-0.06	-0.04	0.10	0.01	0.01	1.00	-0.05	0.17	-0.05	0.04	-0.01	0.13	0.11	-0.08	**0.25**	0.07	-0.06	0.09
R. Hairline	0.12	0.02	0.06	0.02	-0.05	-0.01	-0.03	-0.05	1.00	-0.03	0.02	0.02	-0.06	-0.11	0.01	-0.07	-0.12	-0.04	0.15	**-0.20**
Rosy Cheeks	**-0.21**	0.14	-0.05	0.00	0.11	0.12	-0.04	0.17	-0.03	1.00	-0.06	**0.22**	-0.03	0.13	**0.21**	-0.05	**0.27**	0.14	-0.07	0.05
Sideburns	**0.29**	-0.07	**0.33**	0.00	**-0.54**	-0.05	-0.04	-0.05	0.02	-0.06	1.00	-0.08	-0.02	-0.07	-0.11	0.07	**-0.23**	-0.08	0.06	-0.09
Smiling	-0.14	**0.53**	-0.07	0.08	0.11	**0.21**	-0.07	0.04	0.02	**0.22**	-0.08	1.00	0.01	0.08	0.17	-0.06	0.18	0.09	-0.00	-0.03
Straight Hair	0.06	-0.01	-0.03	0.00	0.03	0.00	0.02	-0.01	-0.06	-0.03	-0.02	0.01	1.00	**-0.32**	-0.07	-0.11	-0.05	-0.03	0.08	0.05
Wavy Hair	**-0.32**	0.04	-0.08	0.03	0.16	0.04	0.02	0.13	-0.11	0.13	-0.07	0.08	**-0.32**	1.00	0.12	-0.12	**0.36**	0.13	-0.14	0.09
W. Earrings	**-0.37**	0.13	-0.08	0.01	0.19	0.08	-0.02	0.11	0.01	**0.21**	-0.11	0.17	-0.07	0.12	1.00	-0.05	**0.37**	0.19	-0.13	0.04
W. Hat	0.13	0.00	0.08	-0.01	-0.12	-0.05	-0.02	-0.08	-0.07	-0.05	0.07	-0.06	-0.11	-0.12	-0.05	1.00	-0.16	-0.04	-0.03	-0.04
W. Lipstick	**-0.79**	0.10	-0.19	-0.02	**0.42**	0.16	0.06	**0.25**	-0.12	**0.27**	**-0.23**	0.18	-0.05	**0.36**	**0.37**	-0.16	1.00	**0.26**	**-0.26**	**0.26**
W. Necklace	**-0.27**	0.08	-0.06	0.03	0.14	-0.06	0.00	0.07	-0.04	0.14	-0.08	0.09	-0.03	0.13	0.19	-0.04	**0.26**	1.00	-0.10	0.02
W. Necktie	**0.33**	-0.03	0.10	0.01	-0.11	-0.05	-0.03	-0.06	0.15	-0.07	0.06	-0.00	0.08	-0.14	-0.13	-0.03	**-0.26**	-0.10	1.00	**-0.25**
Young	**-0.29**	-0.01	-0.14	-0.03	0.12	0.11	0.04	0.09	**-0.20**	0.05	-0.09	-0.03	0.05	0.09	0.04	-0.04	**0.26**	0.02	**-0.25**	1.00