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CSC 424 Advanced Data Analysis
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Predicting Facial Attractiveness in Portraits

NON- TECHNICAL PROJECT SUMMARY

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1) Introduction

This text summarizes our efforts to quantify human facial features and their attractiveness. From the start, this problem seems unfounded as it is easy for a human to judge the attractiveness of human facial features, however, teaching a computer program to do the same may require many more steps. We will now see how we can teach a computer to do this task with a fair amount of accuracy.

2) Motivation/ Applications

Before we jump into details, let's talk about why we would need a computer to look at human faces and make discriminatory choices. We humans have a pair of eyes that are programmed to capture stimuli and help us reason about our surroundings. How one person will perceive something will be different from another person. More importantly, we can only be in one place at one time. Giving computers the power to see and analyze faces like we do can create a lot of efficiencies and take away a lot of personal bias from the task at hand.

According to [1], in the era of visual information explosion, the amount of emotion and sentiment in the form of images and visual stimuli on social media and the internet is large. This gives rise to the need for fast programs that can interpret these sentiments and emotions and turn them into actionable decisions or interpretations. Being able to predict the attractiveness of a face is just an example of the various applications that can be created. [1] mentions salient object detection, attribute extraction and attribute categorization as a few applications that can have varying domain specific use cases.

3) Data/ Methods

Link to the dataset website:
http://www.hcii-lab.net/data/SCUT-FBP/EN/introduce.html

For the purposes of our project, we utilized images collected by researchers at South China University of Technology (SCUT). These images contain portraits of Asian females. Also, as part of the data, we have a spreadsheet which contains numbers representing levels of attractiveness on a scale of 1 to 5 representing the extreme levels of perceived attractiveness [2].

Our goal here is to make the computer see through the lens of a human and assign a number to a portrait between 1 and 5. Now, we know that our computer doesn't have eyes, so how do we enable it to see these images in the first place? We break down the images into what the computer understands. Every image is created by pixels which is a 2 dimensional array of boxes with varying intensities that when put together looks like an image. These pixels and their intensities are represented to the computer as a 2D array of numbers and are stored in the computer's memory as so. Every image or 2D array can then be analyzed in the way of the numerical characteristics of its colors and intensities which create the relationships and interconnections between various objects in the image. Transferring the same to our problem, our images and the 2D array of numbers represent eyes, noses, lips and jaw-lines etc. The computer does not see the eyes but understands that there is a part of the image where a circular blob has low intensities and is surrounded by high intensities on the sides. In the same way, on the 2D plane, it can extract the pixel location of the eyes as well and do so for the other features as well. So now, the program knows the relative pixel locations of the various features. Basically, as humans, these relative locations are really what define our perception of attractiveness as well. The learning task arises when we use machine learning techniques to bridge this gap between human and machine perception. Given enough examples of human perceived subjects, the machine can draw conclusions about patterns and relationships that give rise to human perception. It can then utilize this learned behavior to make predictions about subjects that were not used in training the machine for the task.

A preliminary process that might seem necessary is to make the data simpler to be understood by the machine. As in traditional numerical datasets, we have features that contribute a value for a particular variable, in the same way, in images, every pixel contributes a value of intensity as we previously talked about. Since there can be thousands of such values, we have a problem of high dimensionality. This problem may add to redundancies and inefficiencies and makes it hard for the machine to learn the task at hand.

4) Analysis

Segway-ing into Analysis, we employ techniques that reduce the burden of high dimensionality and test if it is helpful for the program to learn or for us to interpret the results better that way. We then try to use Regression techniques as the primary training method for our program.
Analysis…2 graphs required.

5) Conclusion

We have successfully taught the computer to perceive like humans. Although not the most accurate model, our methodology can make meaningful differentiations just like a human would.

6) References

[1] Honglin Zheng, Tianlang Chen , Jiebo Luo, *When Saliency Meets Sentiment: Understanding How Image Content Invokes Emotion and Sentiment.*

[2] Duorui Xie, Lingyu Liang, Lianwen Jin*, Jie Xu, Mengru Li SCUT-FBP-A Benchmark Dataset for Facial Beauty Perception, submit to SMC2015.