通过社交媒体上的头像分析用户的幸福感

**Abstract：**

Profile images, as a stable content, are posted by users on their social media, which is driven by users' gender, age, personality and other characteristics. In this paper, we investigated individual differences in profile picture choice between well-being traits. We concluded that each well-being trait has a specific style of profile images. For example, users high in positive relationship prefer to use pictures with bokeh and depth of filed style as their profile image. users high in engagement do not like to use pictures with surface texture, object details and quality of material as their profile image.

**Introduction：**

In recent years, researchers have tried to make use of profile images to study users’ online behaviors and offline psychological states. On the one hand, researchers try to figure out factors driving users to choose their profile images. On the other hand, they attempted to obtain the characteristics of users from their profile images. Several studies have examined the differences of users' profile images are related to age, gender and personality. For example, study[2] shows that users high in openness prefer more aesthetic photos, which tend to have higher contrast, sharpness, saturation and less blur. What attracts researchers is that users can choose profile images to enhance their physical attractiveness without being judged deceptive, this means profile images can reflect users' actual psychological states.

With the rise of social media, the way people express their feelings and opinions gradually shifts from offline to online. Online platform allow users to create their own profiles with text, images, videos, etc. And the opinions and feelings expressed by users in social media can be spread and communicated quickly. There profiles may be different from the user's actual profile, but it can reflect personal psychological characteristics [1]. Users' feeling and opinions is beneficial to the development of personalized search engines, recommendation systems and online markets. For the government, effective control of the focus of public opinion and emotional orientation is good to improve the decision-making mechanism and timely response to emergencies.

study [2] concluded that users with different personalities have differences in color, content and other characteristics when selecting profile image on personal social media, which also prompts us to shift our research goals to well-being and image style. Importantly, literature [2] did not consider the abstract content contained in images, such as atmosphere, it focused on colors, facial expressions, image composition and other certain content. study [21] reveals that texture information is also important for human perception of image style. Convolution neural network was used to extract style features and content information to identify image style, this method makes better use of the poor explanatory and abstract characteristics of CNNs to obtain abstract style of image. In this paper, we used the CNNs model proposed by study[3] to extract image style(（**Detailed, Pastel, Melancholy, etc**), then we uncover their relationships with well-being traits from the PERMA.我们同时对比研究了well-being与图像色彩、人物面部特征之间的关系。

Well-being is not just about simply positive emotions or mood. Psychologists, organizations, and governments measuring well-being are now using multi-dimensional measures that include a range of factors .PERMA[14] decomposes the well-being construct into five domains: Positive emotion, Engagement, Relationships, Meaning, and Accomplishment (PERMA). With these five elements of PERMA, people can have their own happiness and enjoy a vigorous life。In our study, we found high correlation between well-being traits and users‘ profile image style. we use existing state-of-the-art text prediction methods to estimated users’ well-being.

**Related work:**

Many experts now realize that income is not the only measure of individual well-being, and governments around the world are starting to rethink the way they measure citizens' well-being. In 2011, the psychologist Martin Seligman proposed PERMA [9], which is a five-dimensional model of well-being. Seligman’s new theory therefore posits that wellbeing consists of the nurturing of one or more of the five following elements: Positive emotion, Engagement, Relationships, Meaning, and Accomplishment (abbreviated as the PERMA). These five elements are the best approximation of human self-interest, which is why they have a place in wellbeing theory. PERMA also includes social and cognitive components that may show more differences in different languages and cultures. In a recent work, Schwartz et al. (2016) developed an English PERMA model using Facebook data.

There is a certain relationship between the style of users' profile image style and users' personality study[2] . For example, users with high openness prefer to use images with higher contrast, clarity and saturation. 与构建personality 模型相似，study [7] proposed a unified approach to construct a profile of subjective well-being based on social media language in Facebook status updates. they apply sentiment analysis to generate users’ affect scores, and train a random forest model to predict well-being using affect scores and other language features of the status updates. In a recent work, Schwartz et al. [8]developed an English PERMA model using Facebook data. they perform an additional evaluation at the user-level, finding that a multi-level cascaded model, using both message-level predictions and user-level features, performs best and outperforms popular lexicon-based happiness models.

Different image styles bring different feelings to people. For different image styles, people can feel subtle differences, but it is quite difficult to describe them. One reason is that the style information of an image may be encoded in any component of the image including local and global, shape and color features. Another reason is that the definition of a style is often subjective, especially for photography works, which may vary from person to person. study [12] use low-level statistics, color choices, composition, and content to construct the style prediction model, which has a good explanation of what is the image style. In addition, through comparative experiments, the literature found that the performance of their classifier was quite accurate compared with that of trained artificial markers. study[13] propose a CNN-based model that integrates both content (or object) information and texture information for image style recognition. And their work using the CNN-based model improves over the state-of-the-art results.

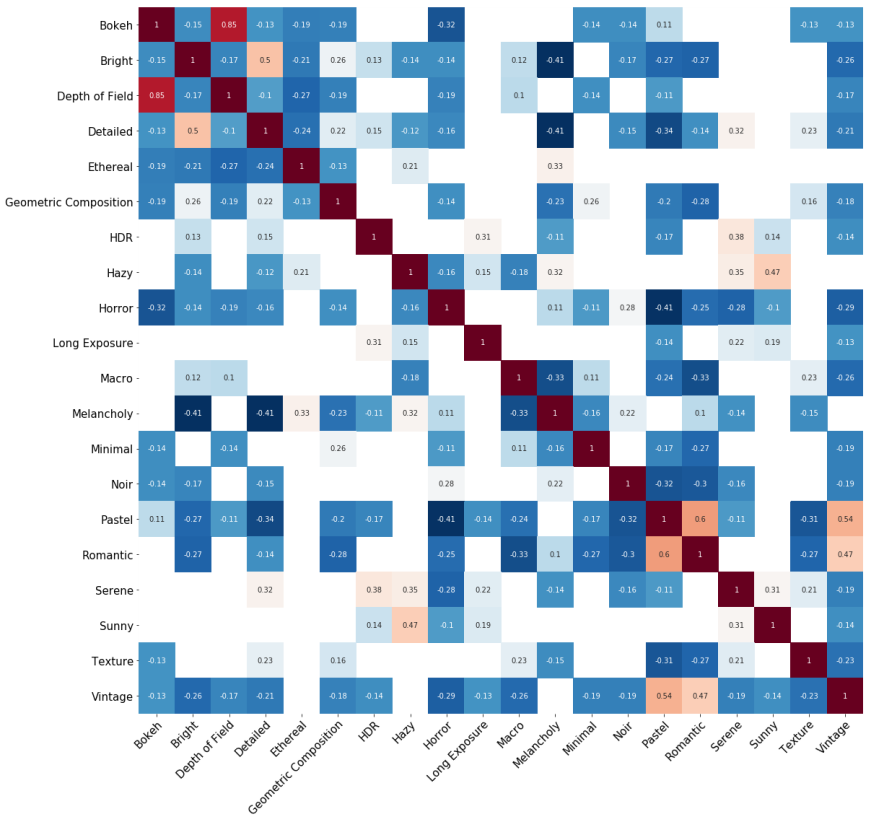
**Data**

twitter用户数据获取：

文献[11] focus on learning gender differences in the use of subjective language in English, Spanish and Russian Twitter data, and explore cross-cultural differences in emoticon and hashtag use for male and female users. We've used Scrapy to crawl 1721 English twitter users' tweets from January 1, 2010 to December 31, 2018. The number of users including tweets more than 100 were filtered out, and a total of 1523 users were screened and their images were obtained. DLATK[21] is used to process data, including filtering out English tweets and removing links, @data and repeated data in tweets。

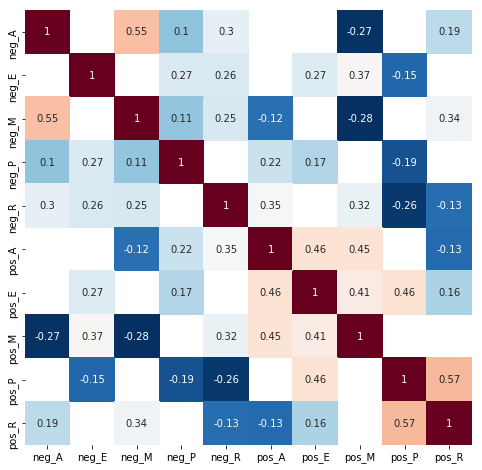
**图像风格提取**

The Flickr Style was also introduced by Karayev et al. [12]. It contains 80,000 images with 20 style labels. The labels were grouped into several categories and each category contains two to five labels. For example, the Atmosphere category has two labels, Hazy and Sunny. In this work, We used Flickr dataset established to train the style recognition model.



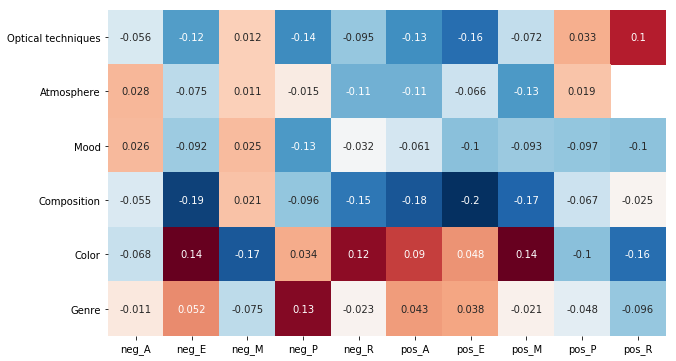
头像风格之间的相关性

We calculated the p value corresponding to the Pearson correlation between each feature and the target trait.

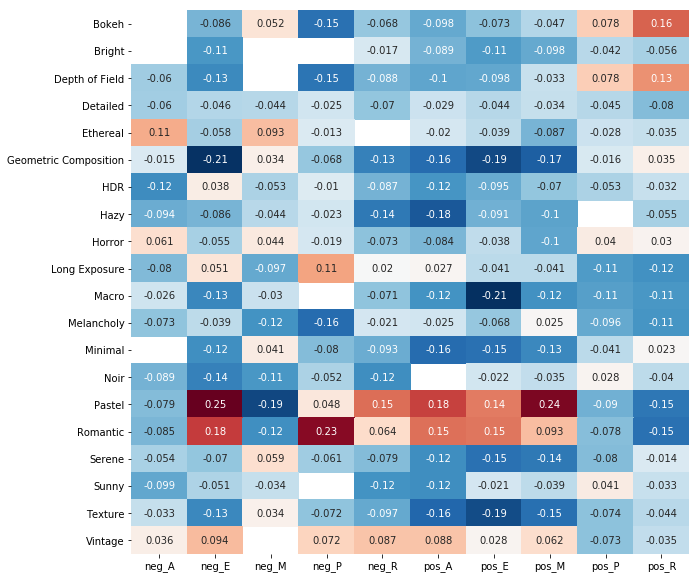
**well-being提取**

**well-being之间的相关性**

Text-based prediction methods have been successfully used to predict a wide range of traits including age (Rao et al. 2010), gender (Burger et al. 2011), political orientation (Pennacchiotti and Popescu 2011), location (Cheng, Caverlee, and Lee 2010), impact (Lampos et al. 2014), income (Preot¸iuc-Pietro et al. 2015), occupation (Preot¸iucPietro, Lampos, and Aletras 2015), mental illnesses (De Choudhury, Counts, and Horvitz 2013) and personality (Schwartz et al. 2013). We use the method developed by (Schwartz 2016[8]) to assign each user scores for well-being，According to study [9], this model divides happiness into five categories, including Positive emotion, Engagement, Relationships, Meaning, and Accomplishment, and each category has two polarities. for example, The Engagement category contains two categories: Engagement and lack of accomplishment. PERMA categories contain different but related information. Consistent with the psychological literature[22], the highest correlations were between positive relationships (pos\_R) and positive emotion (pos\_P).

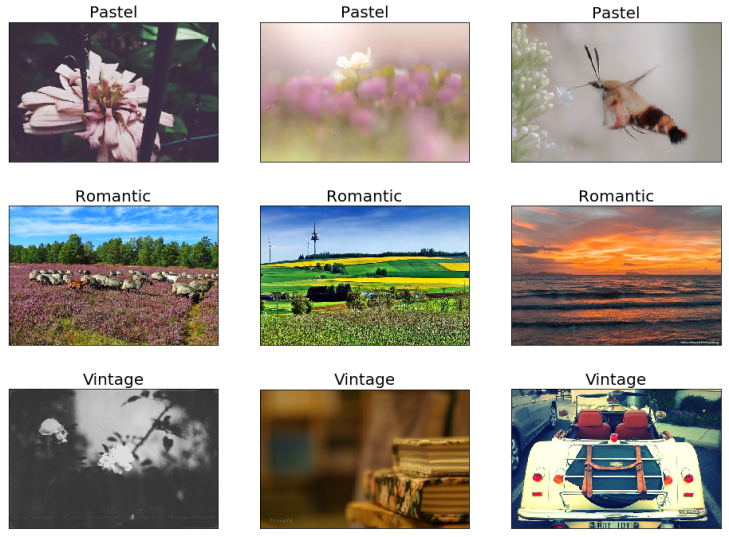
**分析**

**头像风格与幸福感PERMA之间的相关性**

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**头像风格与幸福感PERMA之间的相关性**

As can be seen from the figure above, Positive Engagement, Positive **Accomplishment** and Positive Meaning show a similar correlation with image style. On the one hand, there is a strong correlation between style Romantic and style Pastel (p=0.6), and also between Pastel and Vintage (p=0.54). On the other hand, there is a strong Positive correlation between Positive Engagement, Positive **Accomplishment** and Positive Meaning. These three styles of images are easier for ordinary people to distinguish as the names of the styles often come from the feeling the photos convey。



三种图片风格

**Positive Emotion：**

**Positive Emotion** Is one of the most studied aspects of well-being，positive emotion [14]includes positively valenced emotions such as joy, contentment, and excitement。

Most importantly, users high in Positive Emotion are correlated with Bokeh and Depth of filed. What these two styles have in common is different hierarchies of objects in the image, such as distance, clarity and blur.

**Engagement：**

**Engagement** is a multidimensional structure that includes behavioral, cognitive, and affinity components. It can mean participation and participation in a group or activity, enthusiasm and interest in the activity, commitment and dedication to the job, and focus on the task at hand [15]。Users of Engagement do not like to use pictures with textures and surface details as profile pictures (Macro, Texture and Geometric regularity are negatively correlated, and all of them show that the content of photos often contains details of objects.). On the contrary, users who lack Engagement are much more likely to use Pastel and Romantic style images than users with high positive Engagement scores. The same thing is that both groups rejected the Composition categories.

**Relationship：**

**Relationship** includes trusting others, perceiving others as being there if needed, receiving social support, and giving to others[16]. Plenty of evidence indicates the importance of positive Relationship to health, longevity, and other important qualities of life. Users who lack relationship prefer images in styles like Pastel. Typically, such users' profile images are not Hazy in style. For users with high Relationship scores, they prefer images involving optical techniques as profile images. Compared with those users who lack Relationship, they do not prefer rich profile image.

**Meaning:**

**Meaning** explains the purpose and importance of life, as well as the understanding of life [18]。Users with higher Meaning scores prefer the pastel style. This type of user does not like to use images in the Composition category, and does not like to use images in the Atmosphere category as profile images. For users with negative Meaning, their profile images are more likely to use detailed, transparent or translucent Ethereal style. , and rare Romantic and Pastel styles with rich color content.

**Accomplishment：**

**Accomplishment**通常根据奖励、荣誉和其他客观成就标志来定义。就个人成就感而言，它包括掌控力、感知能力和目标达成感。Accomplishment与Romantic和Pastel风格表现出较强的正相关性，与Hazy风格的负相关性最为强烈。

**总结：**

We used convolutional neural network to extract user image style, and Pearson correlation was used to measure the relationship between image style and user happiness. This study reveals that users' happiness degree affects users' image selection to some extent. It can provide clues and basis for relevant psychological research.

This study is the first to analyze the correlation between image style and user well-being. It is found that different well-being users choose different avatars. Positive emotion users prefer soft and delicate avatars. Engagement users do not like texture and detail in images, preferring portraits with larger scenes. While Relationship shows a similar trend with PE, users of negative emotion and lack of Relationship prefer to use avatars with more vivid and bright colors and geometric content. Users of meaning prefer layered avatars. And what lies behind 24 lies in front of us.

**Conferences**

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[4] Developing Age and Gender Predictive Lexica over Social Media

[5] Private traits and attributes are predictable from digital records of human behavior

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