Transfer learning with the ResMem model on Facial images

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Abstract

Even though facial memorability is an integral part of how we interact with the world (remembering people in social media posts, school textbooks, movies, magazines, etc.), we do not have a good way of explaining why some faces are more memorable than others. In this study, we seek to explore whether the memorability of an image can be predicted based on facial attribute ratings. We correlate the 31 mean facial attribute ratings of 1004 images from the One Million Impression (OMI) dataset with the ResMem model’s predicted memorability scores, using linear regression and nonlinear Extreme Gradient Boosting (XGBoost) regression. We then examine the contributions of individual attributes theorized to impact memorability in previous studies and observe that they weakly correlate with ResMem memorability scores. On the other hand, the correlation of attribute ratings to the *subjective* “memorable” rating from the OMI dataset is observed to support the Von Restorff effect and U-shaped relationship between attractiveness and memorability.

**Keywords:** facial recognition, memorability, regression

# Introduction

Over the course of our lives, we encounter a countless number of new faces, whether it’s from scrolling through social media, watching television, or seeing people in person. However, some faces are more memorable than others. Facial memorability is important to study because it can influence our actions and our conceptualization of the world greatly–a person might buy a product because of a celebrity whose face we remember well, a person with a more memorable face might make a better impression at an interview, and so on. As such, knowledge of what makes a face memorable could be very useful in societal application. However, the question is, how can we explain and quantify the memorability of a face to allow for the development of useful applications that take advantage of this?

The difficulty of this research lies in the struggle to aptly describe memorability in terms of attributes–the dilemma between focusing on certain attributes as measures of memorability vs. a combination of a few or many attributes. Memorability is hard to describe because it may be affected by a variety of different aspects–from facial attributes to subjective experience– and the list increases with more and more research. Some factors (i.e. the own-race bias effect) are also specific to individual circumstance, leading to variability between experiments where the identities of the participants differ. Therefore, there have been many conflicting theories offered up on what makes people or faces memorable, which complicates our search for a common explanation for facial memorability.

**Approach**

The ResMem model is a machine learning model that was developed to predict the intrinsic memorability of an image (independent of observers). The model was built with techniques based around residual neural networks (ResNets), a specialization of convolutional neural networks. It was trained on a combination of the LaMem dataset (which included a vast majority of scene images), and the MemCat dataset (consisting of images focused on objects like a cat). Successful validations of the model have been documented on image categories such as “black and white indoor and outdoor scenes,” color photographs of various animals, people, and landscapes, and overhead photographs of common food items on white plates on a black table (Bainbridge and Berron and Schutze, 2019; Dubey et. at, 2015; Lloyd et. al, 2020; Needell and Bainbridge, 2022). However, no study so far has attempted to test the ResMem model on images of faces. Our study seeks to see how ResMem performs on the novel problem of predicting facial memorability, and how facial attribute ratings may correlate to ResMem’s memorability predictions. We will examine how the results compare to the existing theories about facial memorability (the effects of attributes such as attractiveness, trustworthiness, etc.) and further speculate about what it may suggest. We will also investigate if the memorability scores outputted by ResMem correlate with the observers’ ‘memorable’ ratings, to simulate the disparity between subjective and objective memory scores without actual experimental data.

To investigate ResMem’s performance and how attribute ratings may correlate to its outputted memorability scores, we will use the One Million Impressions (OMI) dataset. The OMI dataset has collected approximately 1.3 million human judgments on 1004 synthetic face mages, for 34 different facial attributes such as “attractive,” “trustworthy,” “typical,” “looks-like-you,” and so on. Judgments were averaged across all participants to get a mean rating of each attribute for each image stimulus. ResMem outputs one score from 0 to 1 for memorability, and thus assumes memorability to be an intrinsic feature that is shared among all observers, so the mean of attribute ratings is a representative measure given this assumption. Therefore, we will look for correlation between the mean ratings of each attribute (summarized from the 1.3 million participants) with ResMem’s memorability scores for each image.

**Real-world Applications**

Finding the correlation of ResMem’s memorability scores with facial attributes could inform our attempts to develop a model to capture the recognizability of faces. Being able to pinpoint the most important aspects of facial recognition could lend itself to many useful applications in the real world. Companies could find celebrities with the most memorable faces to endorse their product. Furthermore, a model that can predict facial memorability could aid the production of textbooks that include pictures of the most memorable faces, so students can memorize material faster. Bainbridge et. al (2013)’s study also notes a novel potential application in neuroscience: studying memory without using specific questionnaires. Patients with social or memory impairments such as autism and Alzheimer’s could be shown highly memorable/forgettable faces, and one could study the differences in their cortical activation levels during the process.

# Background

Early research on memorability centered around the belief that it depended on previous experience that was subject to the individual (Chiroro and Valentine, 1995). However, newer research by Bainbridge et. al (2013) found that memorability is an intrinsic aspect of facial photographs that is independent from the observer. They exposed observers to many faces, measured hit rates on recurring photographs to quantify memorability, and found consistent results across observers on which photographs were remembered more often or forgotten.

## Theorized contributors to memorability

The Bainbridge study looked at a set of twenty facial attributes and found that memorability correlated not only with memory-related traits like typicality and subjective memorability, but also personality and social traits, such as descriptors like “interesting,” “unhappy,” and “emotionally unstable.” However, the study also emphasized that 29.4% of the variability in the memory performance on the facial photographs was unexplained by the attributes and individual variance between participants. Furthermore, there are varying theories on how specific attributes may affect the memorability of a face. A leading theory is that more distinctive faces are more memorable, following what is termed the Von Restorff effect, where atypical or distinctive objects are thought to be more memorable than common ones (Hunt, 1995). However, what defines a face as typical or distinctive is subject to much controversy. Two competing theories are that 1) attractiveness follows a U-shaped curve where highly attractive and highly unattractive people are the most distinctive and memorable (Shepherd and Ellis, 1973) and 2) highly attractive people are the most typical and therefore least memorable, indicating a negative relationship between them (Light et al., 1981). Meanwhile, some other studies have found no relationship whatsoever between attractiveness and the memorability of a face (Brigham 1990; Cutler and Penrod, 1989).

Other claims have been made about what attributes contribute to memorability, and they have been similarly contested. Mueller et. al (1984) and Rule et. al (2012) found that more positively-connotated attributes such as “happy,” or “trustworthy” made a face less memorable. However, Sarno and Alley (1997) had an opposing finding; they stated the existence of a “familiarity effect,” where memorability increased with increased kindness and trustworthiness ratings; however, they also stipulated that some elevated measure of atypicality was also necessary. Other interesting theories worth exploring is that an observer more strongly remembers people who look like them. This includes the “own-race bias” effect (Chiroro and Valentine, 1995) and the “own-age bias” where people remember the faces of people similar in age to themselves better than older or younger faces (Meissner and Brigham, 2001).

## Conflict between subjective and objective memorability

Another interesting finding about memorability that we will look at in this study is the variation between subjective and objective memorability. The Isola et. al (2014) study found that images (mostly centered around objects or scenes) that people believed would be the most memorable are often not the actual images that ended up being successfully remembered in the memory tests. This suggested that there is some misguidedness in the intuition of observers on what makes a photo memorable.

# Methods

We correlated the mean attribute ratings of image stimuli with the memorability scores produced when the same images are fed to the ResMem model through two forms of regression: linear and nonlinear (xgboost). To regularize our data, we generated a correlation matrix of the 34 attributes against each other to see if any pair of attributes was highly correlated (Figure 1). This would prevent an attribute from causing a drastic increase in the p-value (and therefore reducing the significance level) of a highly correlated attribute, which would make it difficult to reliably estimate their individual regression coefficients.

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Figure 1: Correlation Matrix of the 34 attributes in OMI.

The correlation of each attribute with itself was 1 (represented by the dark red squares along the diagonal). We found the attribute columns that had a correlation of 0.9 or greater with a different attribute, and we dropped those attributes. With this process, we dropped 3 attributes: “outgoing,” “native,” and “white.” “Outgoing” had a correlation of 0.93 with “happy,” while “islander” had a correlation of 0.92 with “native” and -0.9 with “white.” Therefore, we removed the attributes “outgoing,” “native,” and “islander” before performing regression on the 34 attributes to make our results more reliable.

We standardized the mean attribute ratings as z-scores approximately between 0 and 1, to eliminate the potential confounding factor in which an attribute would have a greater coefficient after regression merely because it took on higher values. Note that the memorability scores outputted by ResMem for all 1004 face images were all relatively high: greater than 0.7 (out of 1).

We performed linear regression and then nonlinear regression (XGBoost) on the remaining 31 mean attribute ratings of the 1004 image stimuli vs. the memorability scores produced by the same images when they were fed to the ResMem model. XGBoost stands for “Extreme Gradient Boosting,” and it is a regularized regression model that minimizes the squared error loss function and builds successive trees that will minimize weakness (residual errors) in the previous tree. Following the application of these algorithms to the dataset, we look at the top contributing attributes to the ResMem memorability score, and the correlation of the score with individual attributes of interest (as mentioned in the Background section), which included trustworthiness, attractiveness, typicality, and the own-race/own-age bias (which we represented with OMI’s “looks-like-you” rating). We also compare the ResMem memorability scores with the subjective mean “memorable” ratings on the 1004 images to see what insights it could reveal and how it compared with the finding from the Isola (2014) study that subjective memorable ratings differ from true, experimental measures of memorability (hit rates). In this case, ResMem’s predicted memorability scores on the face images act as a simulated proxy for the “true” memorability scores of the images.

Lastly, we examined how the subjective ‘memorable’ score correlated to the 30+ mean attribute ratings, using the same methods of linear regression and XGBoost that we had utilized to compare the mean attribute ratings against the ResMem memorability scores. This last aspect offers some insight into how people may rely on various facial attributes to determine their belief on how “memorable” a face is.

# Results

**Regression Approaches**

Firstly, linear regression seemed to be a fairly reasonable model for the data based on the plots of the original target vs the predicted target, both of which varied between 0 and 1 (Figure 2). The red dashed diagonal line is the ideal performance line. We observe that the predicted and target values are scattered around the red line, indicating that there may be some linear relationship between the target (memorability score) and facial attributes.

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Figure 2: Linear Regression, target vs predicted.

However, the correlation between the mean attribute ratings and ResMem’s memorability scores was low–an R-squared value of 0.368, which indicated that only 36.8% of the variance in the memorability score predicted by ResMem could be explained by the 31 mean attribute ratings. This surprisingly aligned with the findings of the Bainbridge study, which found that a combination of 20 personality, social, and memory-related attributes only accounted for 23.5% of the variance in hit rates (with a “hit” being defined as when the participant correctly identified an image that repeated, by pressing “r” on their keyboard).

We then attempted to fit the data using a nonlinear regression model XGBoost; the model’s predictions appear to align slightly better with the red dashed line (Figure 3).

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Figure 3: XGBoost, target vs predicted values.

We picked out the top ten contributing attributes for both regression approaches. For the linear regression approach, the attributes with the highest coefficients were 'long-haired', 'age', 'liberal', 'skin-color', 'privileged', 'trustworthy', 'gay', 'memorable', 'hair-color', and 'black.’ The two attributes ‘black’ and 'trustworthy' have p-values greater than 0.05 (0.181 and 0.166 respectively), so it is likely that what we are seeing is due to random chance and therefore the two attributes are not reliable contributors to the memorability score. Though linear regression is based on the simple linearity assumption, the sign of regression coefficients can indicate some intuitive insights of attribute contributions to the target (enhancement vs reduction). Out of these remaining eight factors, six had a positive coefficient after regression and two (‘long-haired’ and ‘liberal’) had a negative coefficient, meaning that a higher rating for ‘long-haired’ or ‘liberal’ generally has a negative impact on the memorability of a particular face (assuming that ResMem is a good predictor of memorability).

XGBoost regression results had a different but somewhat overlapping set of attributes. From the highest to least importance, the attributes picked out by the XGBoost algorithm were 'long-haired', 'electable', 'gender', 'gay', 'age', 'middle-eastern', 'asian', 'hispanic', 'alert', and 'black', with the greatest importance being ‘long-haired’ (0.1866). XGBoost’s attribute importances are defined as the average gain across all splits where the attribute was used. Therefore, the higher the importance, the more the attribute contributed to the ResMem memorability score.

XGBoost does not indicate the signs of the importances, however, so we cannot make any determinations about the nature of the relationship between these attributes and the ResMem memorability score as we did for linear regression. It is noted that there was significant overlap, however, with 4/10 (40%) of the top contributing attributes the same for both regression approaches. These shared attributes were ‘long-haired,’ ‘gay’, ‘age’ and ‘black,’ the latter of which we established to be an unreliable predictor in linear regression. Furthermore, a notable observation was that compared to the attributes that linear regression picked out, the regression with XGBoost picked out less emotionally/socially descriptive attributes as having the most significant importance (with 80% (8/10) of the attributes being concrete demographic attributes such as race).

## Examining Attributes of Interest

Next, we investigated individual attributes of interest closer–specifically the attributes in our dataset related to those that had been proposed to affect memorability in varying theories: ‘attractive’, ‘trustworthy’, ‘kind’, ‘typical,’ and ‘looks-like-you’ (which addresses both own-race and own-age biases). Out of these, ‘trustworthy’ was the only attribute that had a relatively more significant contribution to the linear regression, with a coefficient of 0.303. However, since its p-value exceeded 0.05, this meant that the attribute was likely an unreliable predictor of the ResMem memorability score (Table 1). We looked closer into the trustworthy score however, and indeed found that trustworthiness did not seem to have any pronounced or defined effect on the ResMem memorability score (Figure 4). The points seem to be scattered mostly randomly, with no well-defined direction of increase, indicating the weak correlation of the ‘trustworthy’ rating with ResMem’s predicted memorability of the image. Thus, the results do not provide much support for either Mueller et. al (1984)’s theory that likable attributes make a face less memorable or Sarno and Alley (1994)’s “familiarity effect.”

Table 1: Top 10 Linear Regression Coefficients

| Attribute | Coefficient | P-value |
| --- | --- | --- |
| Long-haired | -0.0545094 | 0.000 |
| Age | 0.05040620 | 0.013 |
| Liberal | -0.04290215 | 0.007 |
| Skin color | 0.0423 | 0.038 |
| Privileged | 0.0316840 | 0.019 |
| Trustworthy | 0.030273 | 0.166 |
| Gay | 0.028872 | 0.024 |
| Memorable | 0.02787216 | 0.020 |
| Hair-color | 0.02715125 | 0.001 |
| Black | -0.024992 | 0.181 |
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Figure 4: Trustworthy rating correlated with ResMem’s memorability score.

We also looked at the other attributes that had been theorized to contribute to memorability: specifically, the ratings for the attributes ‘attractive,’ ‘typical,’ ‘happy,’ and ‘looks-like-you’ that were recorded in the OMI dataset. These attributes, however, had even less of an impact on the memorability score, and correlation was very weak. They all had coefficients that were very close to 0 (Table 2). Therefore, it seems that these attributes do not seem to correlate well with ResMem’s predicted memorability scores at all; we can see a lack of a clear pattern in the graphs that plot these attribute ratings individually against the memorability scores predicted by ResMem (Figure 5). We can also note that the p-values for all four of these attributes were too high for these to be very reliable regressors (>0.05) (Table 1 and 2). Thus, our results did not align with any existing theories about the contribution of these features to the memorability of faces.

Table 2: Attributes of Interest

| Attribute | Coefficient | P-value |
| --- | --- | --- |
| Attractive | 0.0095 | 0.589 |
| Typical | -0.0032 | 0.829 |
| Happy | -0.0149 | 0.232 |
| Looks-like-you | 0.0082 | 0.411 |

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Figure 5: Various attribute ratings correlated with ResMem’s memorability score.

ResMem’s memorability predictions overall, however, seem to support a conclusion similar to that of the Brigham (1990) and Cutler and Penrod (1989) studies that find no relation between attractiveness and memorability. It also does not offer much support for the own-race-bias and the own-age-bias theories, because the ‘looks-like-you’ rating is very weakly correlated to ResMem’s memorability scores. However, note that these conclusions are not absolute because it is also possible that ResMem may not work as a model for predicting the memorability of facial images.

Yet, one revealing observation that we *can* make is that the “memorable” rating was within the strongest ten correlating attributes to the ResMem memorability score and was a reliable regressor (p-value = 0.02), which seems to offer some support for the use of the model in the context of facial images. However, the coefficients were generally very low across the board: for the “memorable” rating, the coefficient was only 0.0278, indicating that the contributions of attributes were very weak and that memorability (as predicted by ResMem) was mostly unexplained by these attributes. We visualized the relationship, and we also saw the same weak correlation that the low regression coefficient indicated, as the data did not have any clear upward or downward trend (Figure 6). This weak contribution of “memorable” to the memorability score seems to align with the Isola et. al (2014) study’s conclusion that individual beliefs about what photos are memorable are different from the true memorability calculated from hit rates. The results might indicate that what people thought was memorable differed from what the model predicted to be more memorable.

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Figure 6: Memorable rating correlated with ResMem’s memorability score.

## Attribute ratings vs. subjective memorability rating

To explore the findings from the Isola et. al (2014) study further, we can simulate their comparison of subjective vs objective memorability by comparing the correlation of the ResMem model’s memorability scores and the 31 attribute ratings to the correlation of the subjective mean ‘memorable’ ratings and the 30 attributes (since we exclude the ‘memorable’ rating to itself), for the 1004 images.

Surprisingly, the 30 attribute ratings were much more descriptive of the subjective memorable rating. We received a much higher R-squared value of 0.604, so 60.4% of the variability in the subjective memorable rating was accounted for by the other attribute ratings. Both linear regression and XGBoost had similar performances: the fit looked relatively similar when we compared the true targets vs predictions by the two models side by side (Figure 7).

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Figure 7: Comparison of linear regression and XGBoost for subjective memorability.

We picked out the ten features with greatest importance/contribution to subjective memorability scores for both linear regression and XGBoost, in the same way we did before. The top ten contributing attributes for linear regression were 'typical', 'cute', 'age', 'attractive', 'dominant', 'hispanic', 'black', 'dorky', 'middle-eastern', and 'islander.’ We observe that the top ten features are dominated by race judgments, and they include ‘attractive’ and ‘typical,’ which are two of our attributes of interest.

We will perform the same analysis on the five features ‘attractive’, ‘trustworthy’, ‘kind’, ‘typical,’ and ‘looks-like-you,’ for comparison to previous results.

‘Typical’ had a large negative coefficient of -25.543, indicating a strong negative correlation to the memorable score. Thus, the participants rated more typical faces as generally less memorable. Therefore, we can see that the participants’ own conceptualization of what is “memorable” is in accordance with the proposed Von Restorff effect that atypical faces are more likely to be remembered (Hunt, 1995). Moreover, the coefficient for the “attractive” attribute was 12.908, indicating that participants generally believed that more attractive faces were more memorable and used that belief to rate facial memorability. From Figure 8, we can see that the relationship is generally defined as such, with a general upwards increase in subjective memorability as attractiveness increases, and a prominent decrease as typicality increases. In fact, the attractiveness trend seems to support the U-shaped curve that was proposed by Shepherd and Ellis (1973), since the faces on the two extremes of the ‘attractive’ rating (where the rating is low and where it is very high) tend to have higher subjective memorability ratings. However, the other attributes like ‘trustworthy’ and ‘happy’ (which fall into the category of “likable” characteristics that Mueller et. al (1984) and Rule et. al (2012) postulated have a negative relationship with the memorability of a face) did not seem to show any clear correlation with the mean subjective memorability rating of the images. Likewise, the “looks-like-you” rating also does not seem to have any defined correlation with the subjective memorability score (the points seem to be randomly scattered), which indicates that when the participants decided which faces were more memorable, they did not factor in the own-race and/or own-age bias into their considerations.

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Figure 8: Attribute ratings of interest vs. subjective memorability ratings.

**Discussion**

## Key Insights

The search to quantify and explain facial memorability offers much promise for many useful potential applications in society, from making more memorable educational materials to allowing for advancements in testing for memory and social impairments.

Our study explored the correlation between the ResMem model’s predictions on a large set of facial attributes, to explore how they may align with existing theories about what attributes are the most influential in determining a face’s memorability. We addressed theories about attractive faces, likable faces, typicality, and own-race/own-age bias. Lastly, we concluded with a similar statistical evaluation of what attributes might be important in driving an individual’s subjective conceptualization of how memorable an image may be.

## Limitations

An important limitation to this study is that we do not have the ground-truth memorability of the faces in the OMI dataset to compare ResMem’s memorability scores to, which prevents us from accurately evaluating the effectiveness of the model’s usage on the face images. Since we cannot ascertain that the model is accurately predicting the memorability of the face images, this means that our exploration of the 31 attributes’ individual effects on memorability scores (in relation to the ResMem model) can only be taken as speculations of each attribute’s contributions to memorability. However, our analysis of the attributes’ correlation to the subjective mean “memorable” rating is not similarly constrained by a lack of knowledge.

## Implications/Future Directions

Future directions of this study may include validating the ResMem model on a dataset that already has ground-truth memorability scores from experiments. Acquiring human judgments on more attributes not included in the OMI dataset would also be useful for seeing how to explain more of the variability in memorability scores. The Bainbridge study noted that the 20 attributes that it only explained 23.5% of facial attributes, and we found a similar shortcoming when fitting ResMem’s memorability scores to the 31 features (only 36.8% of the variance in memorability was accounted for). This means that more than just facial attributes affect facial memorability, so further studies are needed to discover other factors that account for this variance.

## Conclusion

Our study analyzed the contribution of 31 facial features to ResMem memorability scores of 1004 images using two regression approaches, and we found that the memorability scores were generally weakly correlated with attributes theorized to affect memorability (‘attractive’, ‘trustworthy’, ‘kind’, ‘typical,’ and ‘looks-like-you’). “Memorable” mean ratings also did not relate very well to ResMem memorability scores, which resembles the disparity between subjective and objective memorability reported by Isola et al. (2014). However, after correlating the subjective mean “memorable” ratings to the remaining 30 attributes, we observe support for theories like the U-shaped memorability curve for attractiveness (Shepherd and Ellis, 1973) and the Von Restorff effect relating atypicality to distinctiveness/memorability (Hunt, 1995).

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