TinderMachine: Classifying Facial Preferences

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This project is centered around the Tinder dating app, which we can interact with through the Tinder API. Using Mike's responses (swiping yes or no) to the real people shown by Tinder, we will train the classifier to predict his swiping preferences. In order to get a large dataset, we will set the radius to ~80 miles (in order to include the Boston area) and use a wide age range. Hopefully, this will also give us a diversity of faces in order to discover Mike's specific facial preferences. From this large dataset, we will generate eigenfaces that will be used as the benchmarks for comparing new faces.

Visual face information is relayed through the retina, superior colliculus, and lateral geniculate nucleus to reach the primary visual cortex (V1, in the occipital lobe). From V1, face information is parsed out through the ventral stream, which has connections to higher-order face processing areas like the fusiform face area, as well as direct connections to structures like the amygdala in the limbic system. Face perception can be separated into phases with distinct properties: the fast phase, driven by input from V1 to low-level occipitotemporal areas, and the plateau phase, involving reentrant signals and feedback loops to build high-level facial representations (Cauchoix 2014).

In the first phase, identification of the stimulus as a "face" produces fast saccades to fixate on the stimulus. These saccades exhibit a "face bias," tending to be much faster for face stimuli than for other objects, and often instinctive, bypassing instructional control (i.e., even when told to fixate on another object, saccades to the face will still win out) (Crouzet 2010). In addition, these early (100-145ms) event-related potentials (ERPs) and ensuing saccades are driven by low-level cues like amplitude spectrum (intensity) and color; thus, specificity remains phase-invariant and similar outputs are produced by normal and phase-scrambled face images (Roisson 2011, Honey 2008). The speed and generality of this response points to a ***subcortical*** pathway driving face recognition—the amygdala, an emotional center in the brain, has been implicated, but it is likely that the superior colliculus and brainstem structures are involved as well (Gavert 2014).

In contrast, the plateau phase integrates the visual information to build a higher-level conception of the "face," recognizing the image as a holistic entity. The fusiform face area (FFA) is an essential structure in this integration, containing category selective face patches that display a "whole-agent" response to faces—indicating that faces are being seen as a concept outside of their basic sensory input to the visual system (Kanwisher 1991, Fisher 2015). In addition, prior computational models of the ventral stream pointed to the translation-invariance within object categories as an essential aspect of categorization in the visual system (Leibo 2015). Our model needs to replicate these higher order visual pathways, requiring phase-dependent and translation-invariant properties in order to apply the learned preferences onto novel stimuli in the face category. From this model, we should produce a whole-agent understanding of the face, putting visual stimuli into a social and personal context that allows us to use visual information to make inferences about social identity and other human conceits tied to the face, including preferences for certain faces over others.

Once categorized using higher-level face areas, certain themes arise in face preferences. Beyond the standard canon of symmetry, indicators of good health, and hormones driving facial preferences, we see that individual face preferences can be clearly defined and seem to have an environmental basis, rather than genetic (Germine 2015). Some computational models combine environmental and genetic factors to explain the face biases described above, but these models do not parse out specific preferences or judgments--likely because preferences are so specific to individual experience (Bednar 2003). For example, the emotional cues provided by faces are often used to make personality judgments, which play a large role in determining individual preferences: personality is a source of preference variability, and expressions like smiling are read as evidence of good dispositions (Otta 1996). Self concept plays a large role in determining preference as well: when we have a positive self image, we tend to prefer more objectively attractive traits, but when we are less confident in our attractiveness, we choose more average traits (Little 2006). In addition, both exposure and experience affect preference; positive experiences with certain individual traits generalize to encompass preferences when faced with novel stimuli (Jones 2007). Thus, we can conclude that facial preferences must be unique to individuals—therefore, it is possible to develop a model of a single person’s facial preferences, as we are attempting to do in our final project.

GENERAL METHODS

1. Get images from Tinder
2. Recognize faces in images
3. Swipe “Yes” or “No” on faces
4. Train a classifier on our preferences
    a. Eigenfaces
        i. SVM
        ii. K Nearest Neighbors
    b. Deep Learning
        i. CNN (faces only)
        ii. CNN (full image)

DATA

Scraped Tinder

>9,000 tinder images

>4,000 faces

FACIAL DETECTION

Viola-Jones Algorithm:

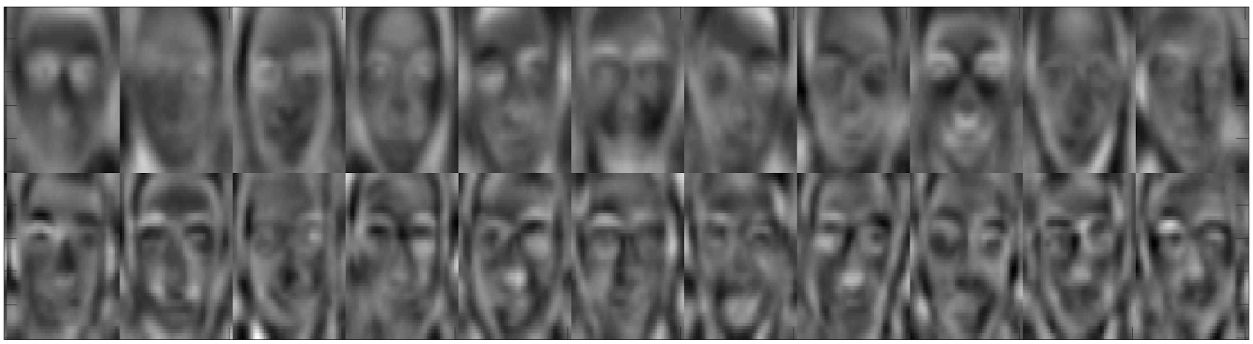
1. Haar Features
2. Integral Image

3. Adaptive Boosting
4. Cascading Classifier

EIGENFACES

Eigenfaces represent the principal components of the data set as an uncorrelated linear combination of observations. They seek to capture the variation across the collection of images.

1. Methods:
2. Principal Component Analysis
3. Extract feature vectors
4. Classify using K-Nearest Neighbors or using SVM classifier



RESULTS

Female Face Preference Results:

	Subject 1	*Subject 2*	*Subject 3*	*Subject 4*	*Subject 5*
Eigenfaces SVM	51.91%	51.82%	54.25%	53.00%	56.65%
Eigenfaces K Nearest	52.38%	58.18%	50.24%	54.21%	52.60%
CNN (faces)	53.44%	56.36%	54.13%	55.71%	54.90%
CNN (full)	55.68%	60%	58.25%	59.46%	57.35%

Male Face Preference Results:

	Subject 1	*Subject 2*	*Subject 3*	*Subject 4*	*Subject 5*

Eigenfaces SVM	n/a	49.87%	46.73%	51.62%	54.20%
Eigenfaces K Nearest	n/a	62.87%	54.23%	51.78%	53.73%
CNN (faces)	n/a	56%	58.25%	50%	63.57%
CNN (full)	n/a	62.67%	60.31%	57%	59.54%