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Springboard Data Science Career Track
Capstone Project #1

Detection of smiles in face images

Milestone Report
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The problem

Detect smiles in images of faces.

In other words, build a model that will classify images of faces as either smiling or not smiling.

Why is this interesting?

The smile detector may find eventual implementation in:

- A human-machine interface, in enabling emotional communication tools, which may allow:
    - control of such things as musical instruments via MIDI
    - more safe and reliable human-robot interactions

Potential clients:

- Music, robotics, and physical programming fields

- May be interested in smile detection as step towards emotional classification from facial expression
    - Market research, to better gauge interest in and reaction to products
        - Guide decisions on product design
    - Gaming
        -Support decisions to create more immersive and exciting player experiences

Description of data

A labelled subset of the cropped version of the Labeled Faces in the Wild (LFW) dataset LFWcrop:
https://conradsanderson.id.au/lfwcrop/

Faces are centered on the image with the background largely omitted.
- Resolution of 64x64 pixels

LFWcrop dataset consists of 13,233 images, available as both 3-color and grayscale.

The smiles dataset is balanced:

- List of face images labelled as smiles: 600 images

- List of face images labelled as non-smiles: consists of 603 images

https://data.mendeley.com/datasets/yz4v8tb3tp/5

Features

Maximum dimensionality of each image is 12,288 with 3 colors (64x64x3).

Limiting to grayscale images yields reduced dimensionality, D, of approximately 4,096.

- Gives a D/N ratio of 6.8 (4,096/600)

Data wrangling

Data accessed via AWS S3 buckets
- Pipeline from the Jupyter notebook to the S3 buckets using Boto

Missing values
- Two file names in the smile list did not have matching image files
    - 'listt.txt'
    - 'SMILE_list.txt'
- Did not interfere with the correct matching of image file names.

Outliers
- Images reviewed individually to check validity of the smile/non-smile labels
    - Found to be consistent with the given labels

- Diversity of age, sex, ethnicity, head position, facial hair, and presence of eyeglasses in both the smile and non-smile sets

Young children are absent from both sets

Additional wrangling and preparation for analysis

The data were split into train and test datasets:
- 1000 images in the train dataset
- 203 images in the test dataset

To remove possible index-specific biases embedded in the data, a randomly shuffled index was created and applied to both the feature (pixels) and target (labels) datasets.

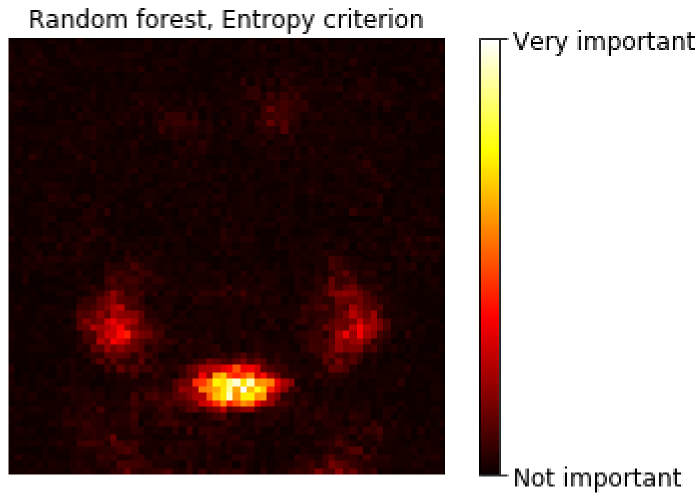
Initial findings from exploratory analysis

Exploratory data analysis (EDA) conducted after an initial machine learning approach, random forest:
- Performed to classify the images into smile and non-smile categories
- Before the random forest was performed:
    - Gini vs. entropy impurity criteria compared using a lone decision tree classifier
- Entropy criterion selected for random forest classifier

EDA:
- Colormapping pixel feature importances and reviewing at a contingency table in conjunction with that

- Feature importances colormapped to a plot of pixel location show clustering of high importances in:
    - Mouth and cheek regions
    - Fainter clusters in the forehead and inferolateral cheek regions
    - Very faint signal is also seen in inferior nose/nostril and nasolabial folds regions

A face image example (labelled as smiling)



Mapping of pixel (feature) importance using the random forest smile classifier, after training on 1000 face images

Contingency table showing images from the test set comparing random forest smile classification against the target labels.

Initial findings from exploratory analysis

Mapping of pixel importances, coupled with contingency table, suggests some higher-level features might have a role in random forest misclassification:

- False negatives may in part result from face rotation, scaling and centering/cropping differences.

- False positives may in part result from prominent nasolabial folds (as might be seen in smirking or grimacing), presence of facial hair, as well as face rotation, scaling and centering/cropping differences.

Future directions

Next machine learning steps:
- Support vector machines
- Neural networks, including convolutional neural networks

Important pixel regions may change, and with that the types of misclassification seen.

To improve smile detection, this overall EDA approach will:
- Allow ongoing monitoring and adjustment of the models
- Guide possible transformations and filtering of the image data

Links:

https://github.com/adriatic13/springboard/blob/master/dsct_capstone1/Adrian_Marinovich_Cap1_smiles_data_wrangling.ipynb

https://github.com/adriatic13/springboard/blob/master/dsct_capstone1/Adrian_Marinovich_Cap1_smiles_eda.ipynb

References:

Arigbabu, Olasimbo Ayodeji, et al. "Smile detection using hybrid face representation." Journal of Ambient Intelligence and Humanized Computing (2016): 1-12.

Huang GB, Mattar M, Berg T, Learned-Miller E (2007) Labeled faces in the wild: a database for studying face recognition in unconstrained environments. University of Massachusetts, Amherst, Technical Report.