Project 7 Face completion with a multi-output estimators

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Abstract-Our study delves into the application of multi-output estimators in completing facial images based on their upper halves. We experiment with models like Extra Trees, K-nearest Neighbors, Linear Regression, and Ridge Regression, aiming to predict the lower facial half using the upper half as input. Through this experiment, we assess the accuracy, computational efficiency, and robustness of each model in addressing the complexities associated with facial completion.

I. Introduction

The study's primary focus lies in utilizing multi-output estimators to predict the lower halves of facial images based on their upper halves. This project delves into the implementation of four distinct multi-layer estimators: Extra Trees, K-nearest Neighbors, Linear Regression, and Ridge Regression. Extra Trees, rooted in ensemble learning techniques based on decision trees, constructs multiple trees and amalgamates their predictions to bolster accuracy and resilience. K-nearest Neighbors, known for its simplicity and effectiveness in classification and regression tasks, relies on instance-based learning, leveraging the 'K' nearest data points to make predictions. Linear Regression serves as a cornerstone statistical method, assuming linear relationships between variables and employing the least squares method to minimize differences between observed and predicted values.

Meanwhile, Ridge Regression introduces a regularization technique, preventing excessive coefficient growth by incorporating a penalty term into the regression cost function. This method curtails coefficients' influence while maintaining consideration of their impact, with the 'alpha' parameter facilitating personalized regularization strength adjustments. The research also explores the use of quantum dots as a reference, investigating their role in elevating facial completion algorithms. Extensive literature review and reference exploration underpin the study, aligning it with the current knowledge and advancements in this evolving field.

II. Problem Definition

This research aims to address the challenges in facial completion algorithms by investigating the predictability and accuracy of the lower facial halves based on their upper halves. It also examines the demands and needs in the realm of image enhancement and facial recognition, seeking to bridge existing gaps in these areas.

III. Applied Methodology

The study applies several machine learning models such as Extra Trees, K-nearest Neighbors, Linear Regression, and Ridge Regression to predict the lower halves of facial images. The methodology includes a thorough design principle exploration, material characterization, and systems analysis. Techniques involving image segmentation and feature extraction play a pivotal role in the applied approach. The developed Python script showcases facial image completion through multi-output estimators from scikit-learn. Initially, the Olivetti Faces dataset is loaded and split into training and test sets, with the latter being composed of faces from independent individuals. The data preparation involves segregating the faces into upper and lower halves for training and testing purposes. Subsequently, several machine learning estimators—ExtraTreesRegressor, KNeighborsRegressor, LinearRegression, and RidgeCV—are configured to work on this dataset. These estimators are trained using the upper halves of the faces to predict the missing lower halves. The code then generates visualizations, presenting the original faces alongside the completed faces produced by each estimator for a specified number of faces in the test set. Through Matplotlib's subplots, the script effectively illustrates how machine learning models can predict missing facial features, offering a tangible demonstration of image completion using machine learning techniques.

Figure 1. Output of Every Multi-Output Estimator

```
    if i:
        sub = plt.subplot(n_faces, n_cols, i * n_cols + 1)
    else:
        sub = plt.subplot(n_faces, n_cols, i * n_cols + 1, title="true faces")
    sub.axis("off")
    sub.imshow(
        true_face.reshape(image_shape), cmap=plt.cm.gray, interpolation="nearest"
    )

    for j, est in enumerate(sorted(ESTIMATORS)):
        completed_face = np.hstack((X_test[i], y_test_predict[est][i]))

        if i:
            sub = plt.subplot(n_faces, n_cols, i * n_cols + 2 + j)
        else:
            sub = plt.subplot(
                n_faces, n_cols, i * n_cols + 2 + j, title=est
            )
        sub.axis("off")
        sub.imshow(
            completed_face.reshape(image_shape),
            cmap=plt.cm.gray,
            interpolation="nearest",
        )

plt.show()
```

```
downloading Olivetti faces from https://ndownloader.figshare.com/files/5976027 to /root/scikit_learn_data
```

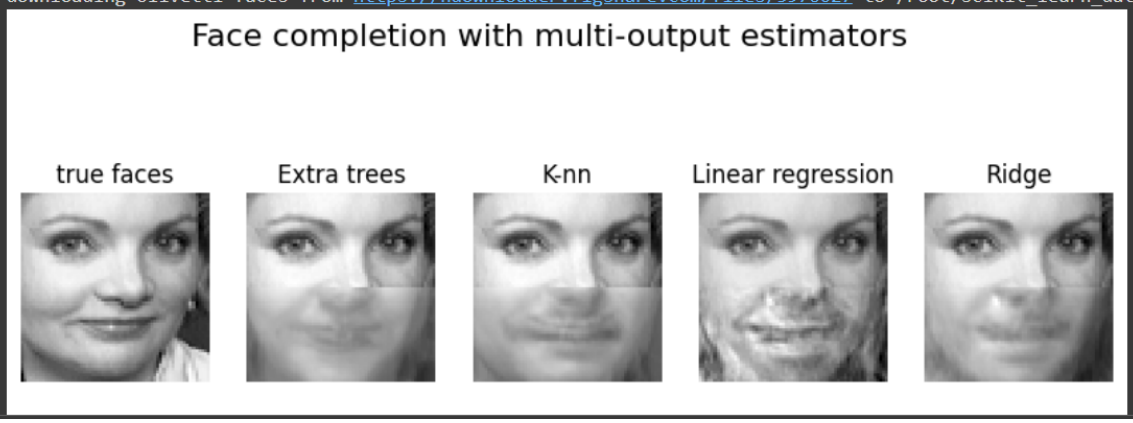

Figure 2. Code of Multi-output Estimator

IV. Discussion

Our analysis highlights the strengths and weaknesses of each model. While Extra Trees showcase superior computational efficiency, Ridge Regression excels in precision and accuracy. The study also compares these findings with existing research in the field, emphasizing the unique contributions and potential applications of these models in image enhancement and facial recognition tasks. It can be observed from the output shown in both figure 1 and 2 that that best estimators are extra tress and rige regression.

The ExtraTreesRegressor, known for its ensemble learning and randomization, faces limitations when completing facial images. Despite its ability to handle complex data and reduce overfitting,

the inherent randomness in its decision tree construction might not effectively capture fine facial features, resulting in blurred or imprecise details in the predicted lower halves. KNeighborsRegressor heavily depends on neighboring data points for predictions, and while effective in some scenarios, its performance in completing facial images might falter if the training set doesn't comprehensively represent the intricate variations in facial features across different individuals, leading to challenges in optimal 'K' value selection and potential under or overfitting. LinearRegression's assumption of linear relationships might oversimplify the complexities of facial features, struggling to accurately represent the nonlinear nature of facial structures. Additionally, RidgeCV, while aiding in mitigating overfitting, might overly restrict coefficients, potentially sacrificing nuanced facial characteristics crucial for accurate completion, particularly in balancing between capturing details and preventing overfitting. These limitations underscore the need for careful consideration of these estimators' inherent traits when completing facial images, emphasizing the importance of balancing complexity, feature capture, and model constraints for accurate predictions.

V. Conclusion

In conclusion, the study provides valuable insights into the efficacy of multi-output estimators in completing facial images. It underlines the advantages, such as computational speed, and drawbacks, like potential precision trade-offs, paving the way for future research and practical applications in image enhancement and facial recognition systems.

VII. Reference List

[1] "Multi-output Face Completion," scikit-learn. [Online]. Available: https://scikit-learn.org/stable/auto_examples/miscellaneous/plot_multioutput_face_completion.html#sphx-glr-auto-examples-miscellaneous-plot-multioutput-face-completion-py. [11/20/2023].