

Introduction of Deepfake Representation with Multilinear Regression [paper](#)

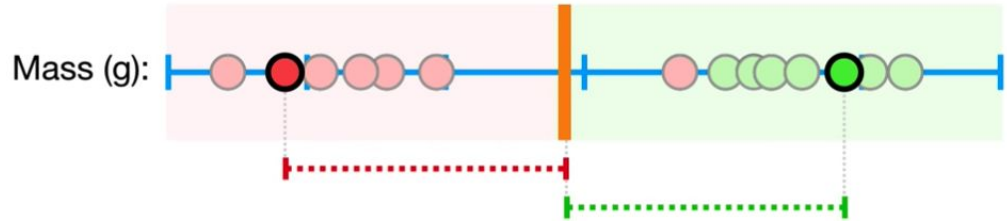
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Dateset

- Dataset: [FaceForensics](#) videos
- experiment on **images** manipulated by DeepFake technique.
- Each 30 sec. extract 1 frame, total 7 frames for each video using OpenCV
- Using pretrained **dlib face detector** for detecting **outer facial landmarks**
- Training videos: $720 * 7(\text{frames}) = 5040$ (images)
- Validation set : 140 videos
- Testing videos: 140 videos
- wd: Datasets/manipulated_sequences/Deepfakes/raw/videos

Support Vector Machine (SVM)

- Binary Classification
- Pros: effective in high dimensional spaces
- Cons: long training time for large datasets



The answer is simple: We use **Cross Validation** to determine how many misclassifications and observations to allow inside of the **Soft Margin** to get the best classification.

Algorithm 1 DeepFake Detection Algorithm

Input : $\mathbf{D}_{\text{real}}, \mathbf{D}_{\text{fake}}$ were centered by subtracting the mean of the real training data,

- (1) Preprocessing and data tensor organization:

$$[\mathbf{U}_{\text{real}}, \mathbf{S}_{\text{real}}, \mathbf{V}_{\text{real}}] \leftarrow \text{svd}(\mathbf{D}_{\text{real}})$$

$$[\mathbf{U}_{\text{fake}}, \mathbf{S}_{\text{fake}}, \mathbf{V}_{\text{fake}}] \leftarrow \text{svd}(\mathbf{D}_{\text{fake}})$$

$$\mathcal{D}(:, :, 1) = [\mathbf{U}_{\text{real}} \mathbf{S}_{\text{real}}]$$

$$\mathcal{D}(:, :, 2) = [\mathbf{U}_{\text{fake}} \mathbf{S}_{\text{fake}}]$$

- (2) Training data decomposition:

$$\mathcal{T} \times_2 \mathbf{U}_f \times_3 \mathbf{U}_c \leftarrow M\text{-mode SVD}(\mathcal{D})$$

- (3) Embed the class representations in the higher three dimensional space and set the third coordinate of the real and fake class to +1 and -1 respectively. Hence, $\mathbf{U}_c \in \mathbb{R}^{2 \times 2}$ now has dimensionality $\mathbb{R}^{2 \times 3}$. Normalize the rows of \mathbf{U}_c to have length 1.

- (4) Computer the extended core

$$\mathcal{T} := \mathcal{D} \times_2 \mathbf{U}_f^T \times_3 \mathbf{U}_c^\dagger \quad (16)$$

- (5) Centering: validation and test data is centered by subtracting the mean of the real training data.

- (6) Test data decomposition of a centered \mathbf{d}_{test} :

$$\mathbf{d}_{\text{test}} \simeq \mathcal{T} \times_2 \mathbf{r}_f^T \times_3 \mathbf{r}_c^T \leftarrow \text{Multilinear Projection}(\mathcal{T}, \mathbf{d}_{\text{test}})$$

- (7) Finding linear SVM decision boundaries using validation set

- (8) classifying all $\mathbf{d}_{\text{test}} \in \text{test set}$
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Feature & Result

- Evaluate the decision boundaries
- Frames in the range 2980-5000, the accuracy is around 82 %. Otherwise, could be considered noise
- The range 2980-5000 class is more separable linearly.

$U_c \in \mathbb{R}^{2 \times 3}, U_f \in \mathbb{R}^{5040 \times R_f}$							R_f	TN/140	TP/140	ACC
1	721	1441	2161	2881	3601	4321	1-5040	98	101	0.7107
							1-720	107	93	0.7143
							721-2160	100	90	0.6786
							2161-3600	112	122	0.8000
							3601-5040	113	98	0.7536
							4321-5040	111	89	0.7143
							2161-5040	117	112	0.8179
							2980-5000	118	112	0.8214
							2881-5040	117	103	0.7857