# A Multimodal Method to Detect DeepFake Videos

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# Overall Project Goals

- Multimedia forgery threats
- DeepFake: face-swapping
- Our aim: learning-based deepfake video detection


https://www.youtube.com/watch?v=_q16aJTXVRE&t=87s

# Specific Aims

**Multimodal framework**

- Visual-audio features
- Deepfake video detection

**Performance**

- Comparable to state-of-the-art techniques on DFTIMIT and DFDC datasets

**Comparison**

- With different architectures and results
- Why their performance differ?

# Current State of the Art

**DeepFake detection categories**

- Intra-frame visual artifacts
- Inter-frame inconsistencies
- Multimodel features

# Current State of the Art: unimodal

## Approaches

- Intra-frame visual artifacts: DNN during face wrapping [1], discontinuity of head pose [2]
- Inter-frame inconsistencies: [3][4] combine CNN and LSTM for detection

## Limitations

- Low performance
- Various unutilized features
- Vulnerable to manipulated audio

# Current State of the Art: multimodal

**Mittal et al.[5]: congruence between emotions**

- Double Siamese network
- Extract features and vectors from emotion and audio respectively

**Hosler et al.[6]:**

- LSTM network: predict emotions from Low-level Descriptors
- Train real-fake detector from predicted emotion

# Novelty

## Multimodal architecture

- Measure similarities
- Use similarities

## Investigate losses

- Different combinations affect performance

## LSTM

- Combine with bimodal architecture
- Evaluate the results

## Performance

- Of different frameworks
- On DFTIMIT and DFDC datasets

# Importance

**Framework designs**

- Inspiration on audio-visual frameworks

**LSTM**

- Insight on its influence on similarity measurement

**Datasets**

- Deeper understanding on DFTIMIT and DFDC

## Datasets

**DFTIMIT**[11]

- 32 different people from VIDTIMIT[14]
- Manipulated with FS-GAN[13]
- Real audio channel
- Choose HQ over LQ
- Each video: 512*384 resolution, 25 fps, ≈4s duration

**DFDC**[12]

- Undisclosed manipulations
- Audio/visual/audio-visual
- Each video: 30 fps, ≈ 10s duration

**Principle of data selection**

- Requirement: audio and visual channels
- DFTIMIT:
  - Frontal angles
  - 3 out of 32 subjects
  - Correct learning outcome
- DFDC:
  - Computational limitation
  - Same size
  - Different folders

# Technical Approach

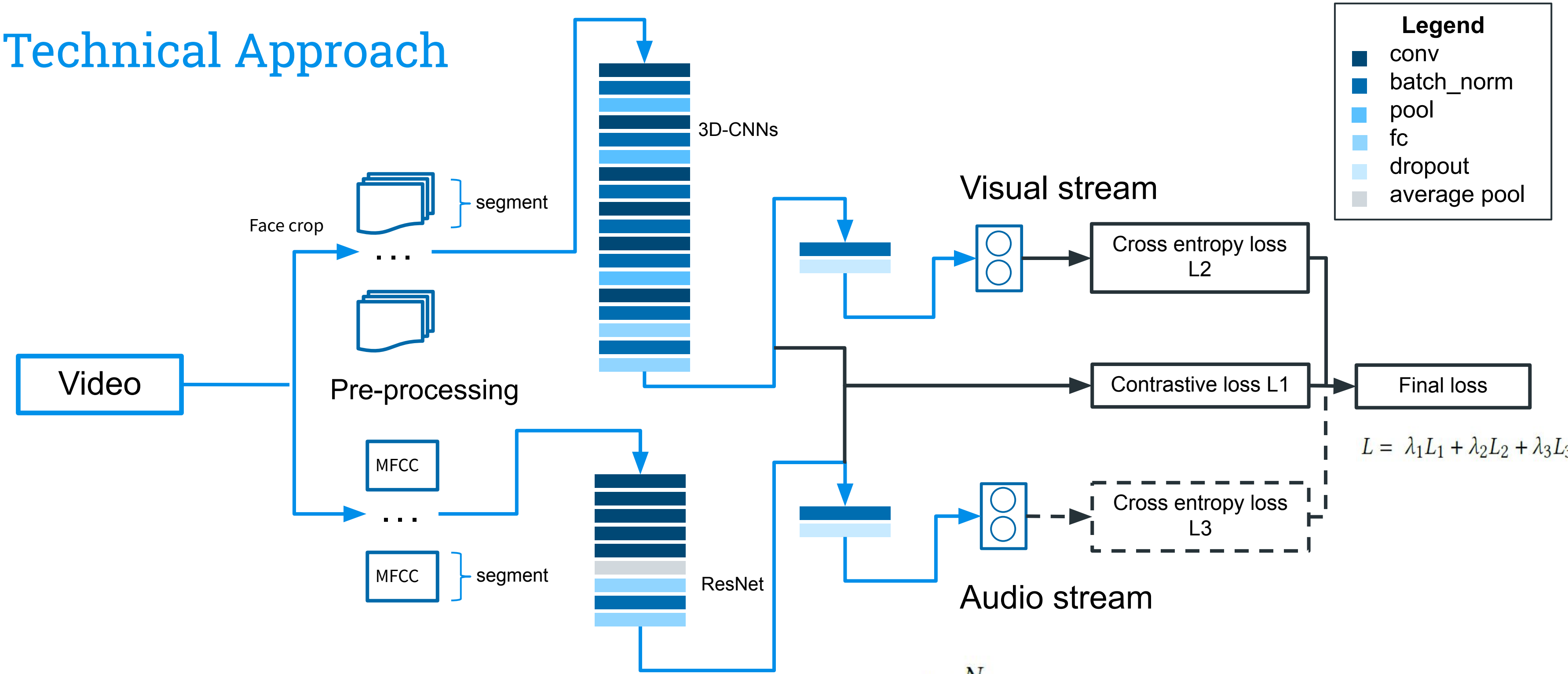
## Transition from midterm presentation

- Initially, Emotions Don’t Lie[5]
- Prob 1: Require the inputs of a real and fake video pair
- Prob 2: Framework too complicated

## Inspirations

- Directly model the similarity between visual and audio features
- Contrastive loss from Chung and Zisserman et al.[7]
- Imposition of cross-entropy loss from Chugh et al.[8]
- Extract visual features using 3D-CNNs[9]
- Extract audio MFCC[10] features using ResNet architectures

# Technical Approach




$$L = \lambda_1 L_1 + \lambda_2 L_2 + \lambda_3 L_3$$

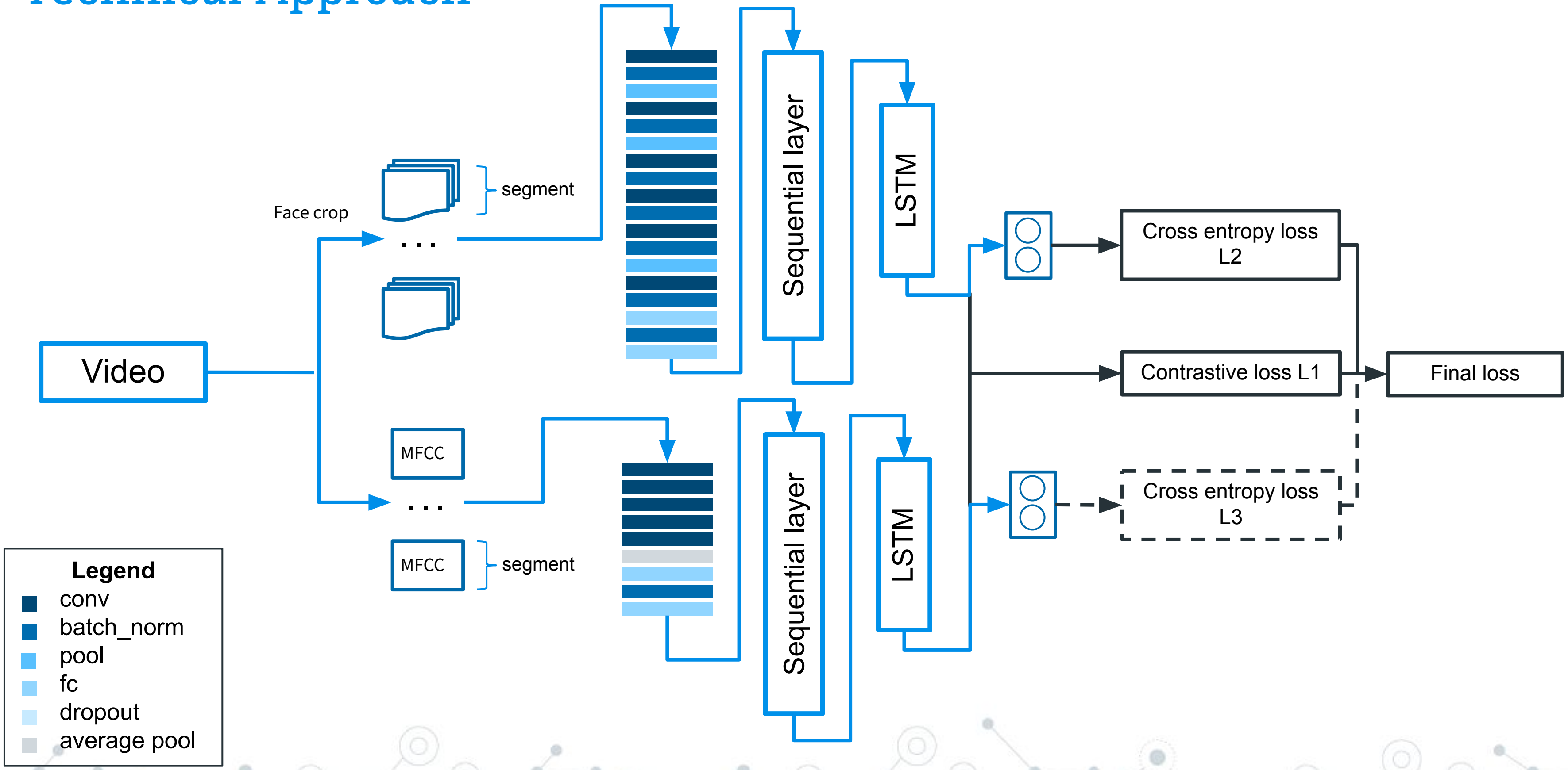
$$L_1 = \frac{1}{N}\sum_{i=1}^{N}(y^i)\,(d_t^i)^2 + (1-y^i)\,max(margin - d_t^i, 0)^2$$

$$d_t^i = \|f_v - f_a\|_2$$

$$L_2 = -\frac{1}{N}\sum_{i=1}^{N} y^i \log \hat{y}_v^i + (1-y^i)\log(1-\hat{y}_v^i)$$

$$L_3 = -\frac{1}{N}\sum_{i=1}^{N} y^i \log \hat{y}_a^i + (1-y^i)\log(1-\hat{y}_a^i)$$

# Technical Approach



# Platform

## Preprocessing

- 1-second segments (FFMpeg)
- S3FD to crop faces
- Python_speech_features for MFCC features

## Training and testing

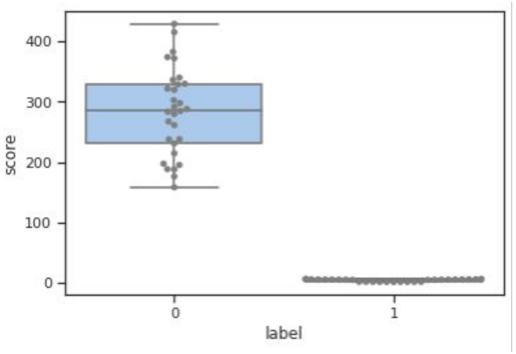
- PyTorch to build the network

## Runtime environment

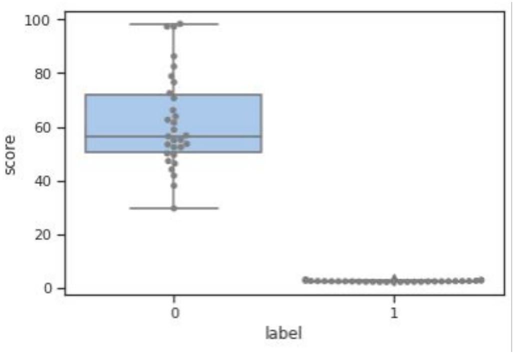
- Google CoLab using one GPU

# Evaluation

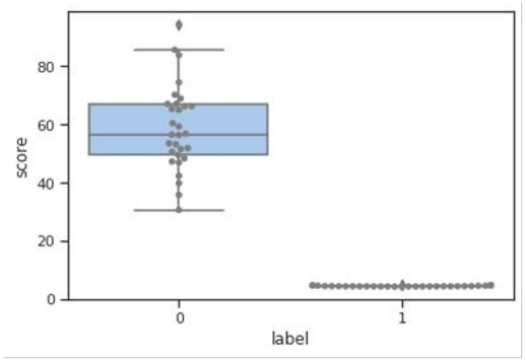
Results for DFTIMIT




L1+L2+L3



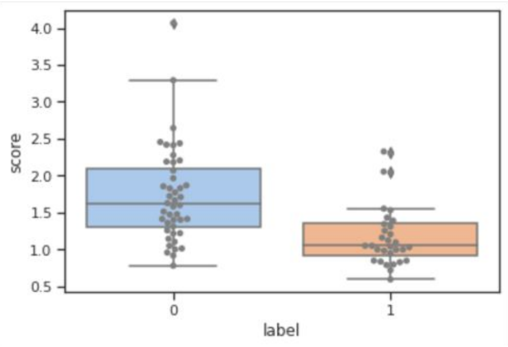

L1+L2




Only L1

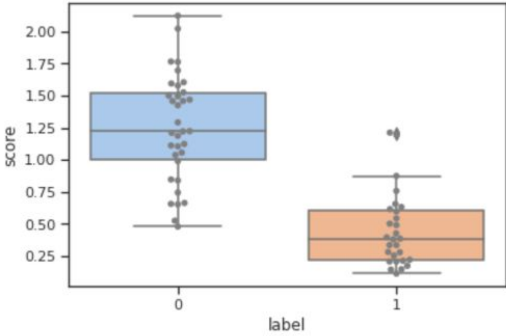
# Evaluation

Results for DFDC



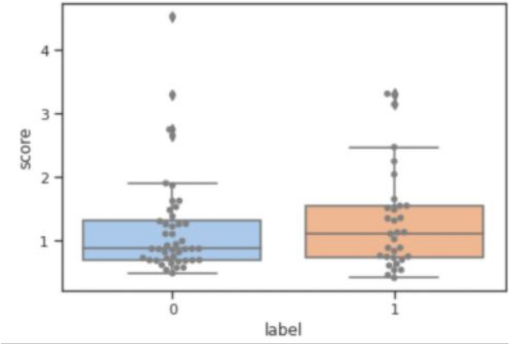

AUC:0.72

L1+L2+L3




AUC:0.83

L1+L2

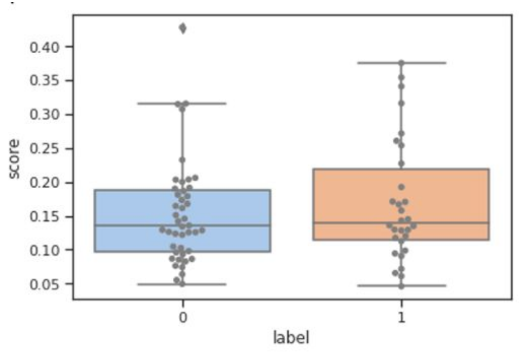


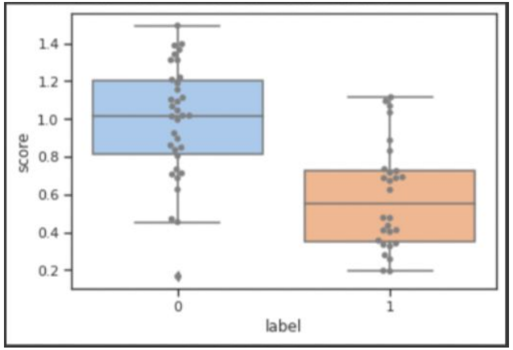

AUC:0.49

Only L1

# Evaluation

Results for DFDC (LSTM)




AUC:0.44

L1+L2+L3

AUC:0.78

L1+L2

# Evaluation

| | Capsule[15] | HeadPose[2] | VA-MLP[16] | FWA[1] | Siamese-based[5] | AV-dissonance[6] | Our method |
|---|---|---|---|---|---|---|---|
| DFDC | **53.3** | **55.9** | **61.9** | **72.7** | **84.4** | **90.55** | **83.19**<br>**77.52(LSTM)** |
| DFTIMIT-HQ | **74.4** | **53.2** | **62.1** | **93.2** | **94.9** | **96.8** | **99.9** |
| Modality | **V** | **V** | **V** | **V** | **AV** | **AV** | **AV** |

# Discussions

**Advantages**

- Achieved perfect performance on DFTIMIT and decent results on DFDC
- Analyzed the effects to the performance using different loss combinations

**Disadvantages**

- The size of training samples is relatively small due to computation limit
- The performance of the LSTM based network is not good as expected

## Future directions

- Test our models on bigger and more SOTA datasets
- Improve the architecture of the LSTM based network
- Try different advanced feature extraction networks and analyze the results
- Improve the techniques used in data preprocessing, e.g. face alignment, overlapping, etc.

# Team member contributions

- **Jinchen Wu:**
- Coding of entire projects
- Data cleaning
- Training and evaluating DFDC dataset
- Slides

- **Weijian Zhang:**
- Idea exploring
- Co-coding of LSTM network
- Training DFTIMIT dataset
- Training DFDC dataset using LSTM network
- Slides and report

- **Ruoye Wang:**
- Evaluating DFTIMIT dataset
- Slides and report

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# Thank you

Questions?