



Apathy diagnosis by analyzing **facial dynamics** in videos

S L Happy

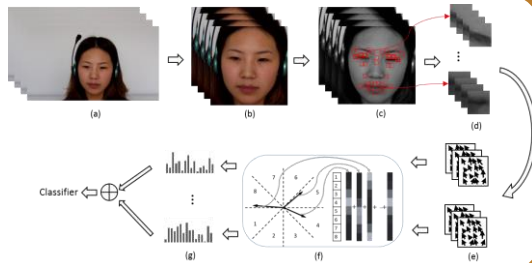
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and Francois Bremond

STARS team, **INRIA** Sophia Antipolis

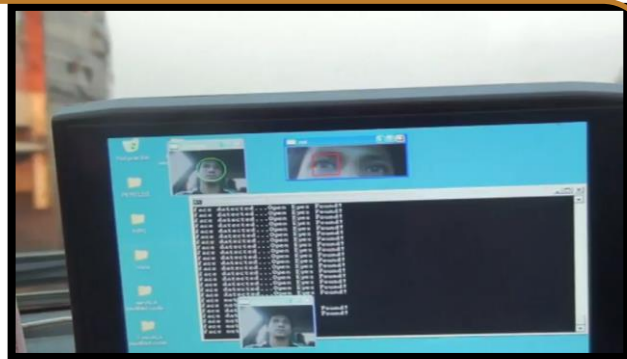
2nd April 2019

My research

(Emotion recognition)



(Driver drowsiness detection system)



(Cancer Cell cytoplasm segmentation)



Original
(Hyperspectral image classification)

Adapted

(Activity recognition)



Apathy

- Apathy is a symptom of the majority of neurocognitive, neurodegenerative, and psychiatric disorders
- Quantitative reduction of activity in behavioral, cognitive, emotional, or social dimensions
- Symptoms:
 - **reduced emotional response**
 - lack of motivation
 - change of behavior
 - **limited social interaction**

Apathy



Non-Apathy



Challenge

Activity classification

Boxing



Pull up



Playing Guitar



Typing



Apathy classification

Apathy



Control



Apathy





Control



Objective

- Assisting clinicians in the **apathy diagnostics** based on facial behavior analysis
- Given the facial **videos**, **predict** whether the patient is **apathetic** or **not**.

("tell me a positive/negative event of your life in one minute")

 Positive narration  Negative narration

Apathy

Yes

No

Yes

⋮

⋮

⋮

???

Part 1: Feature Regression Classification

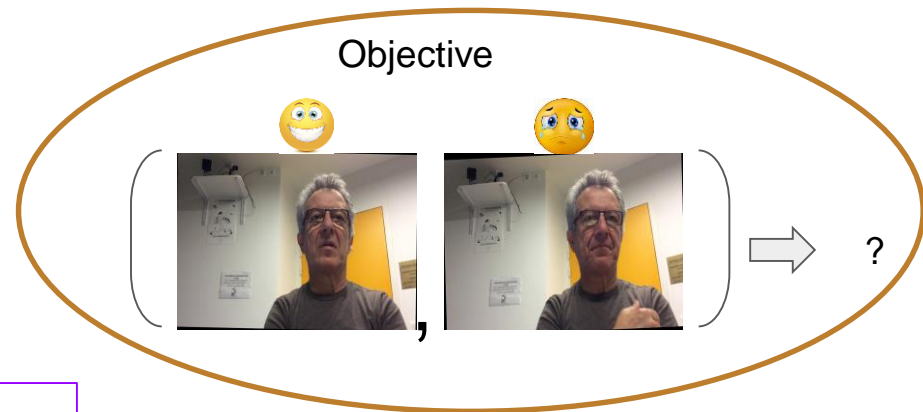
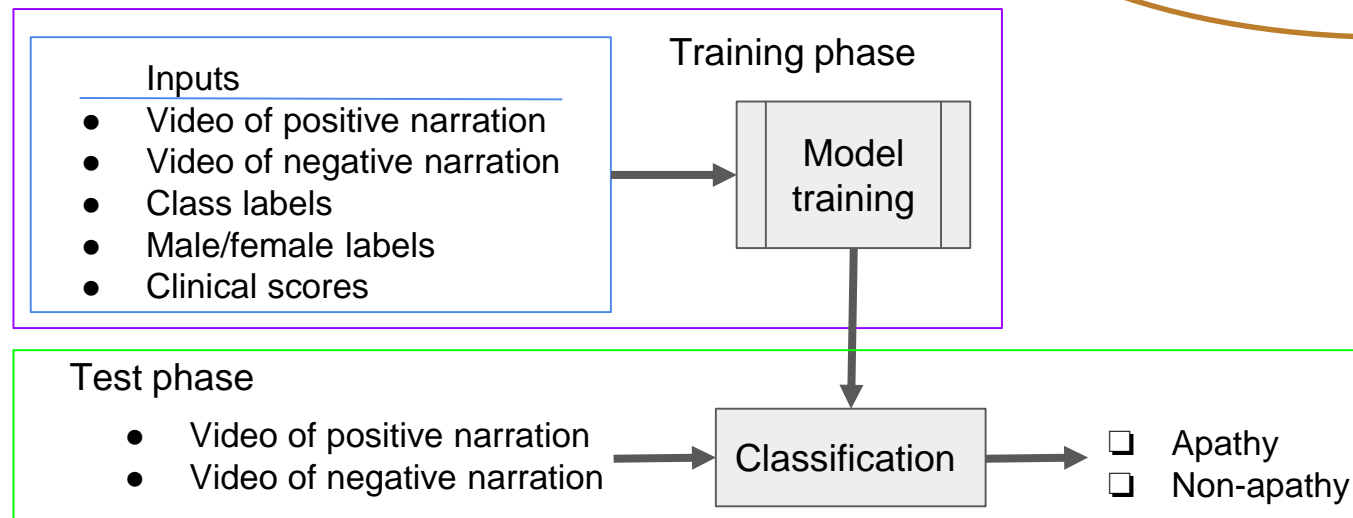
Data

- Total subjects: 45
- The patient-clinician interview involves
 - the collection of demographic details
 - Age, **gender**, ...
 - a standardized neuropsychological assessment
 - Mini mental state examination (**MMSE**)
 - Neuropsychiatric apathy inventory (**NPI-apathy**)
 - a short **positive and negative** experience **narration** (tell me a positive/negative event of your life in one minute)

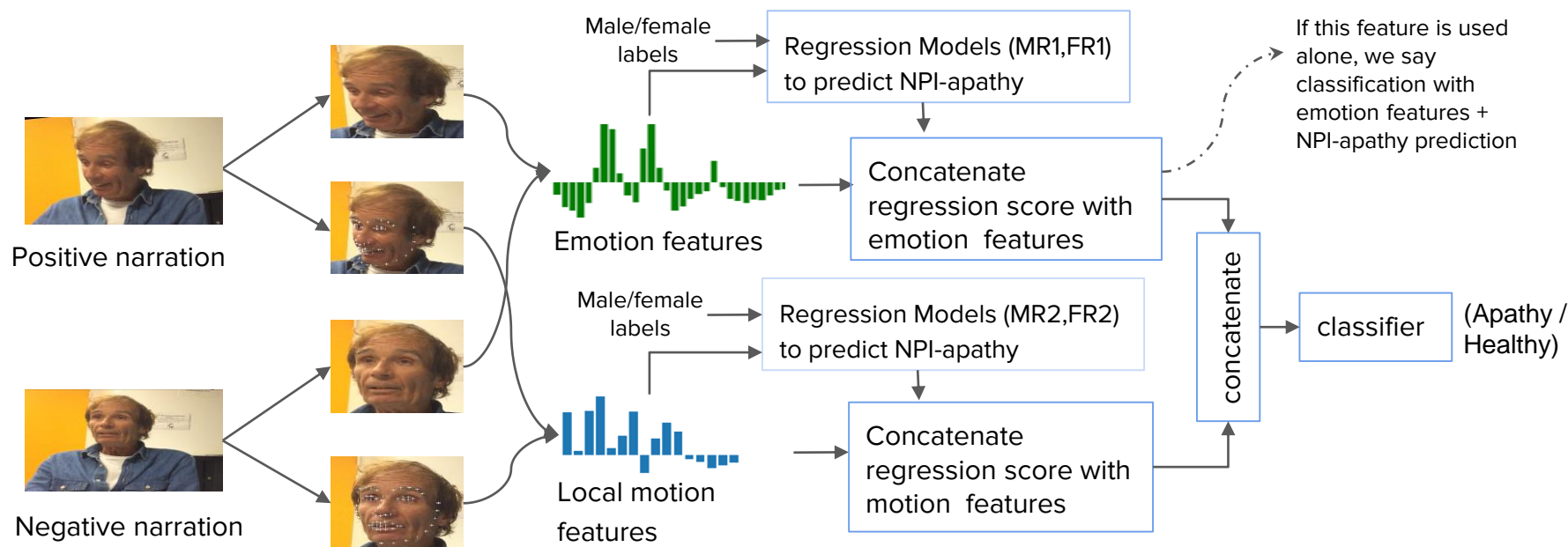
Demographic data of patients

	Number of Patients	Age	MMSE	NPI-Apathy
Apathy	18	73.5 (7.7)	22.6 (3.1)	6.2 (2.6)
Control	27	71.7 (8.8)	25.4 (3.6)	0.4 (0.8)

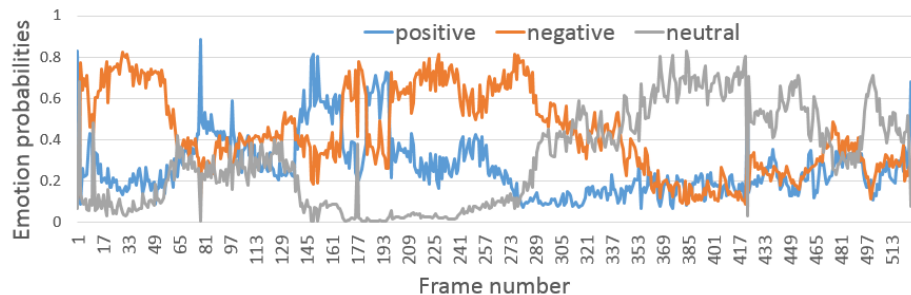
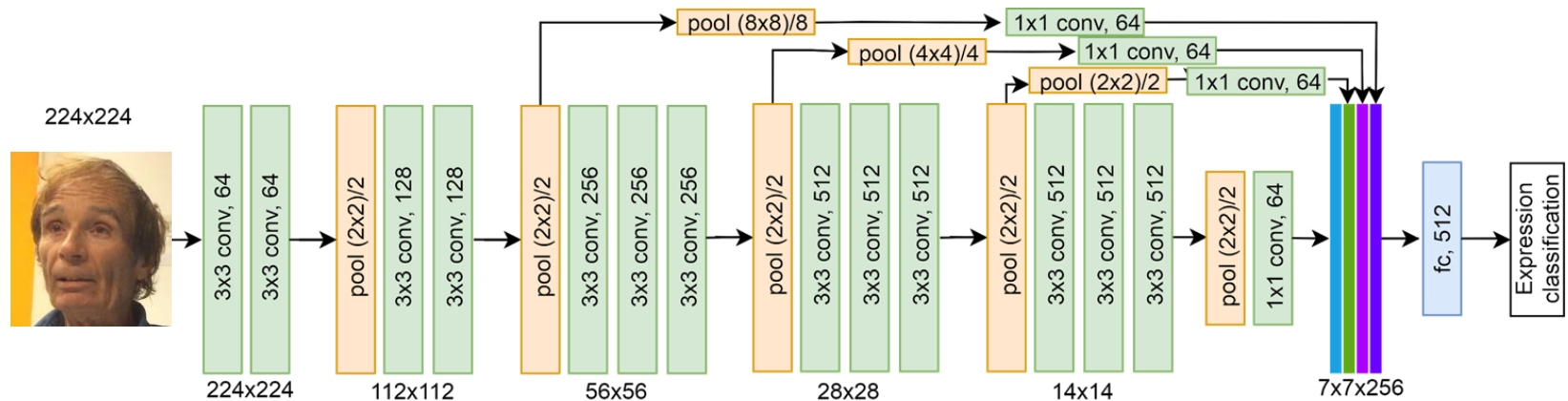
Overall Framework



Detailed Framework



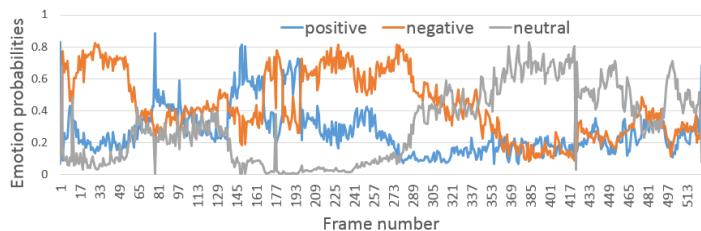
Emotion Recognition



Emotion Feature



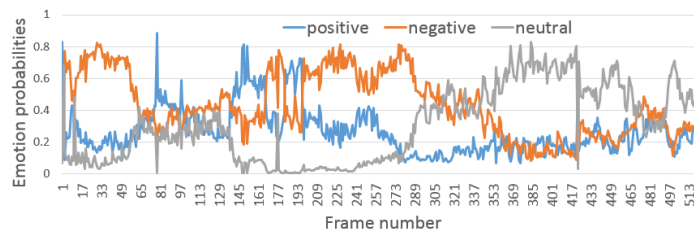
Positive narration



[Histograms of each emotion , Duration of each emotion ,

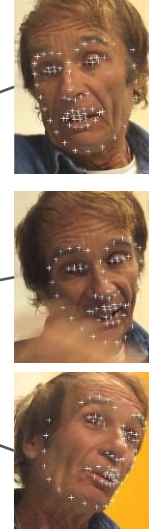
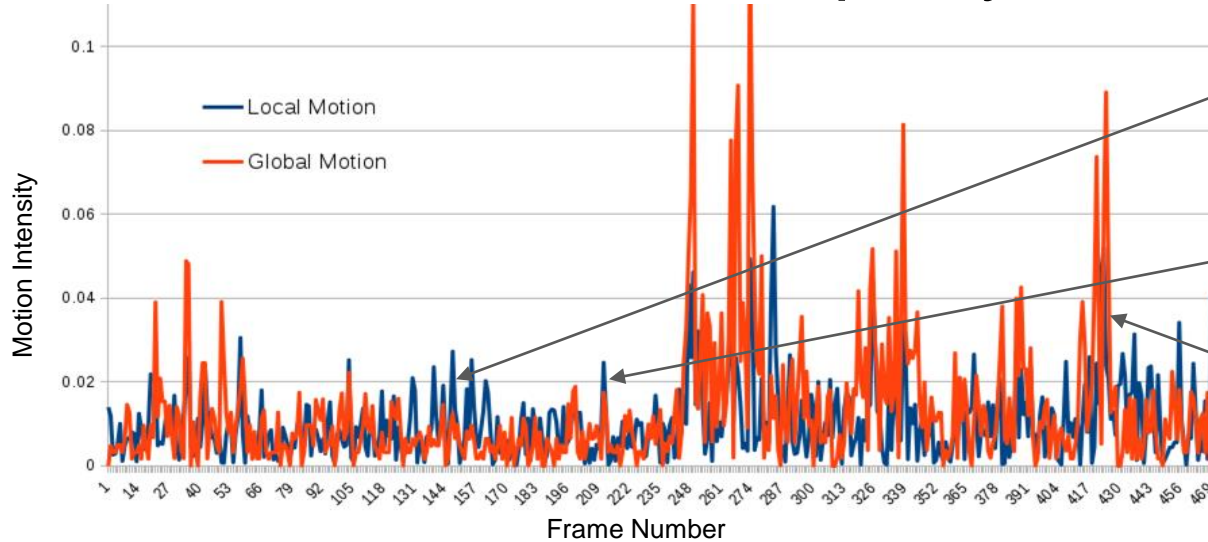


Negative narration



[Histograms of each emotion , Duration of each emotion]

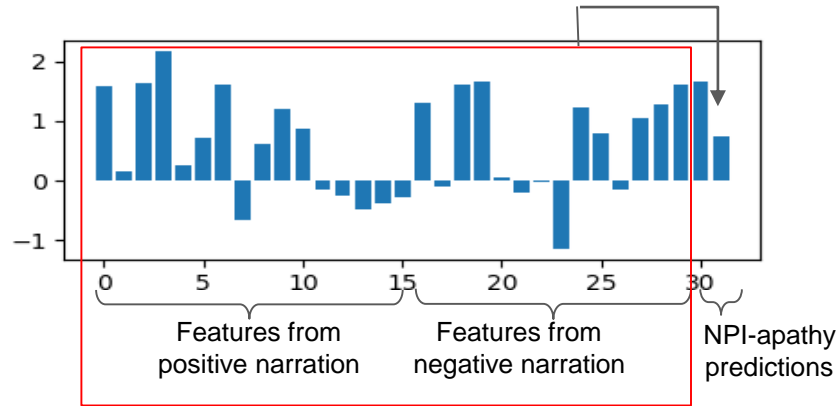
Facial movement-based apathy inference



- **Global** motion: **head movement** in successive frames
- **Local** motion: movement of **facial parts**, such as **lips, eyebrows, cheeks**, etc.
 - Computed by removing the global motion information from the interior facial landmarks

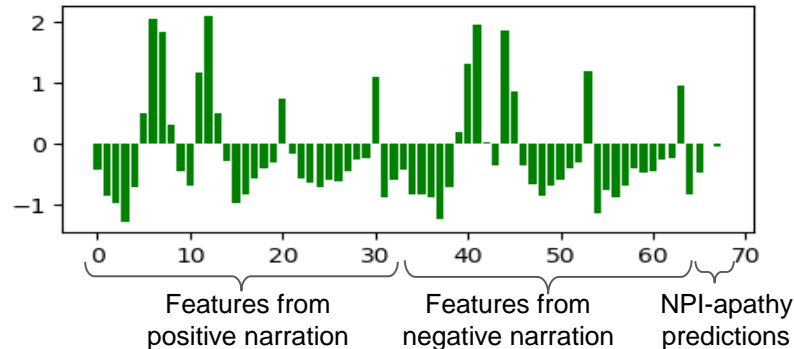
Emotion and Motion features

Motion features



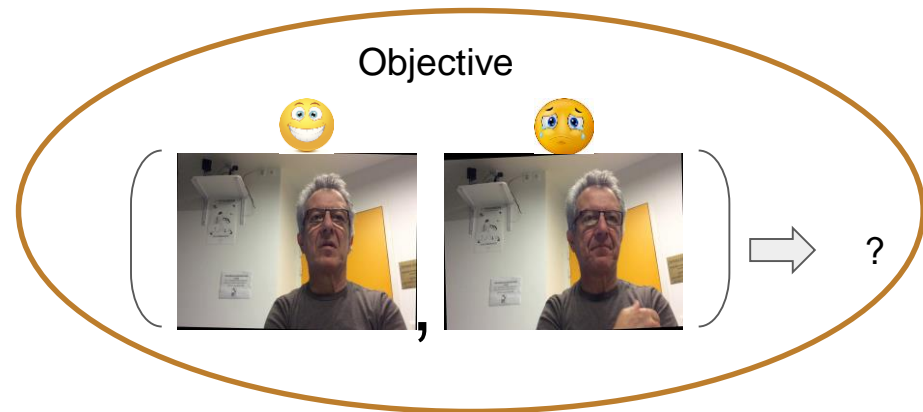
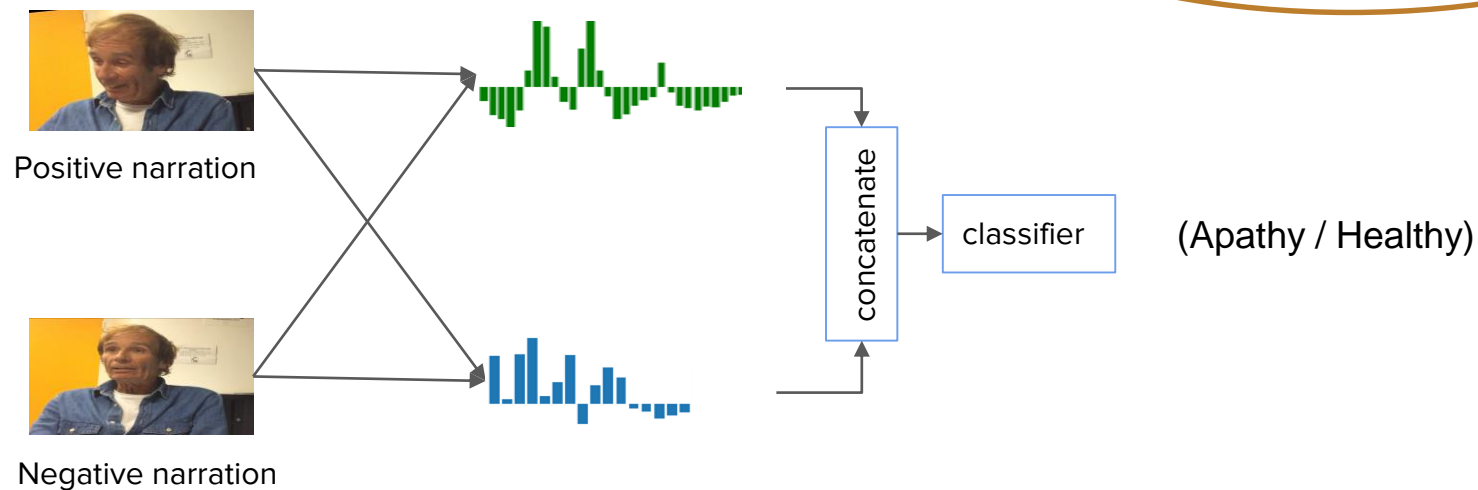
- *Movement of facial parts* in successive frames are represented in a histogram.

Emotion features



- The *expressions* in all frames are represented in a histogram.

Simplified Test Framework



LOSO performances

without pos-neg
concatenation

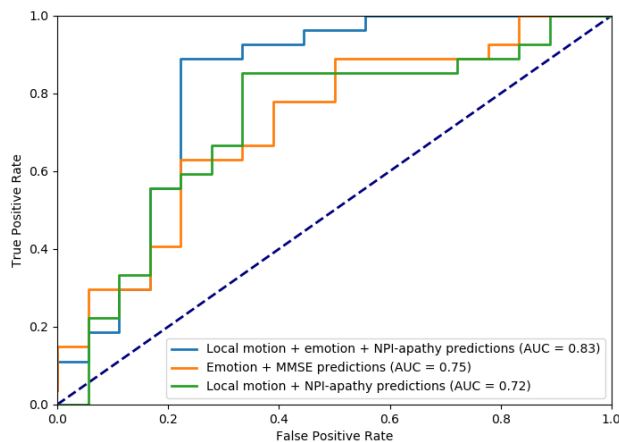
with pos-neg
concatenation

Features used	Accuracy	F1-score	AUC	Accuracy	F1-score	AUC
Local Motion Features	58.88	0.505	0.527	57.77	0.555	0.558
Global Motion Features	56.66	0.516	0.523	55.55	0.537	0.537
Local + Global Motion Features	51.11	0.458	0.467	62.22	0.602	0.601
Emotion features	52.68	0.532	0.518	64.44	0.622	0.620
Emotion features + Local Motion Features	53.86	0.526	0.552	77.77	0.757	0.75
Emotion features + Local + Global Motion Features	54.57	0.532	0.537	71.11	0.68	0.676

LOSO performances with pos-neg concatenation

Features used	Accuracy	F1-score	AUC
Local Motion Features + NPI-apathy prediction	73.33	0.722	0.722
Global Motion Features + NPI-apathy prediction	77.77	0.765	0.768
Local + Global Motion Features + NPI-apathy prediction	68.88	0.676	0.678
Emotion features + MMSE prediction	77.77	0.757	0.75
Emotion features + NPI-apathy prediction	66.66	0.649	0.648
Emotion features + Local Motion Features + MMSE prediction	68.88	0.675	0.675
Emotion features + Local Motion Features + NPI-apathy prediction	84.44	0.836	0.833
Emotion features + Local and Global Motion Features + MMSE prediction	68.88	0.660	0.657
Emotion features + Local and Global Motion Features + NPI-apathy prediction	77.77	0.757	0.75

ROC and Confusion matrices



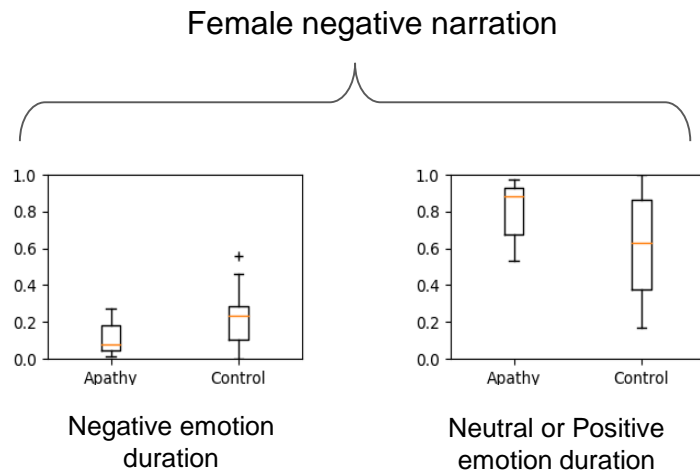
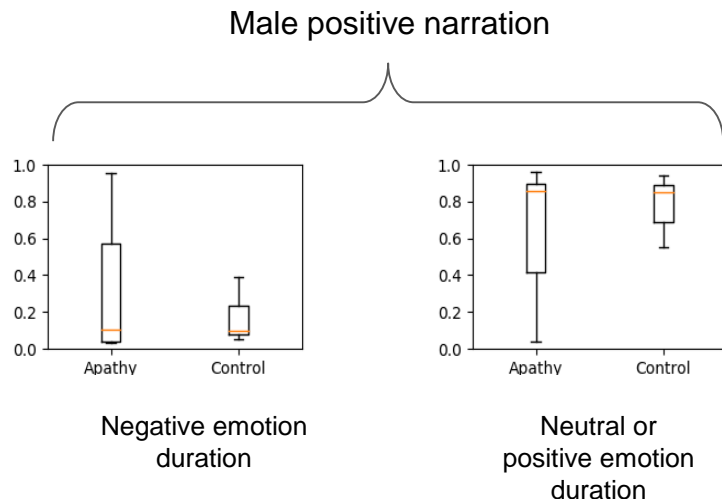
Motion and emotion features combined

True label	Predicted label	
	Control	Apathy
Control	24	3
Apathy	7	11

Motion and emotion features along with NPI-apathy prediction

True label	Predicted label	
	Control	Apathy
Control	24	3
Apathy	4	14

An observation



- During **positive** narration, **male** subjects with **Apathy** showed both **positive and negative emotions**, whereas the **control group** showed **more positive expressions compared to negative expressions**.
- During **negative** narration, **female** subjects with **Apathy** showed **less negative emotion** compared to the control group.

Summary

- **First** to classify apathy based on **facial behavior** analysis
- Observation cues:
 - variation of facial **expressions**
 - facial **movements**
- **Regression** models to estimate the clinical scores
- Accuracy: 84%

To be presented at:

S L Happy, Antitza Dantcheva, Abhijit Das, Radia Zeghari, Philippe Robert, and Francois Bremond, "Characterizing the State of Apathy with Facial Expression and Motion Analysis," in *IEEE International Conference on Automatic Face & Gesture Recognition*, 2019 (FG-19).

Download here: <https://goo.gl/zXFi38>

Part 2: using Multi-task Learning

Multi-task learning (MTL)

[joint learning, learning to learn, and learning with auxiliary tasks]

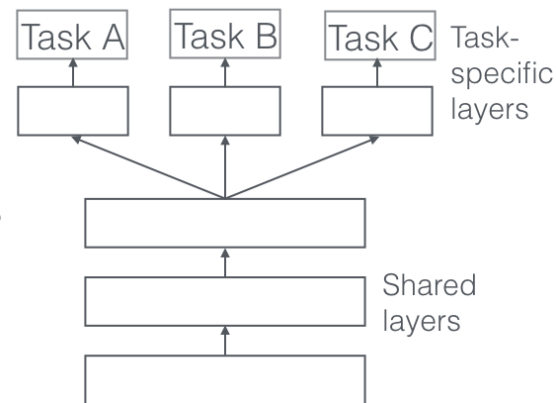
- MTL promotes sharing of model parameters to exploit the shared information across multiple tasks

Advantages:

- Knowledge transfer
- Learns general representation of all tasks
- Learns the relevant and irrelevant features for different tasks
- Joint learning results in a good regularization
- Ignores the data-dependent noise

Limitations:

- **Negative transfer**: sharing parameters with unrelated and dissimilar tasks

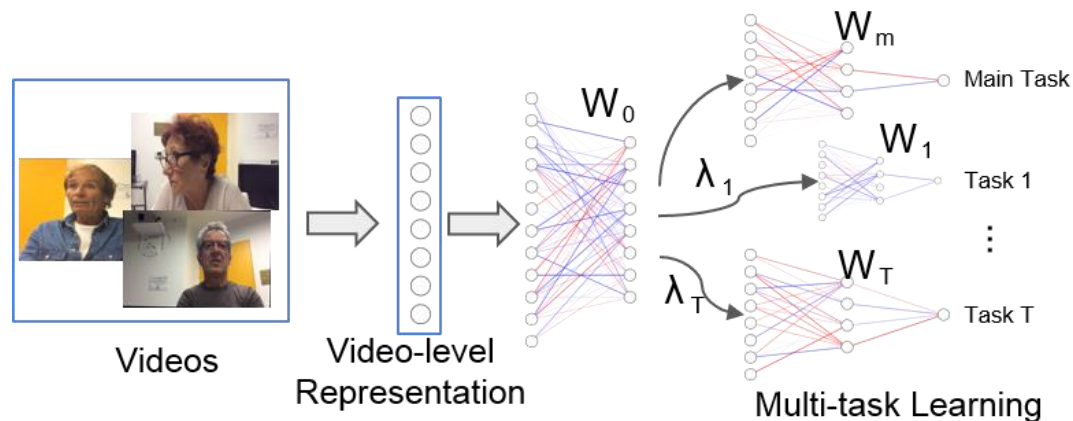


Experiment setting

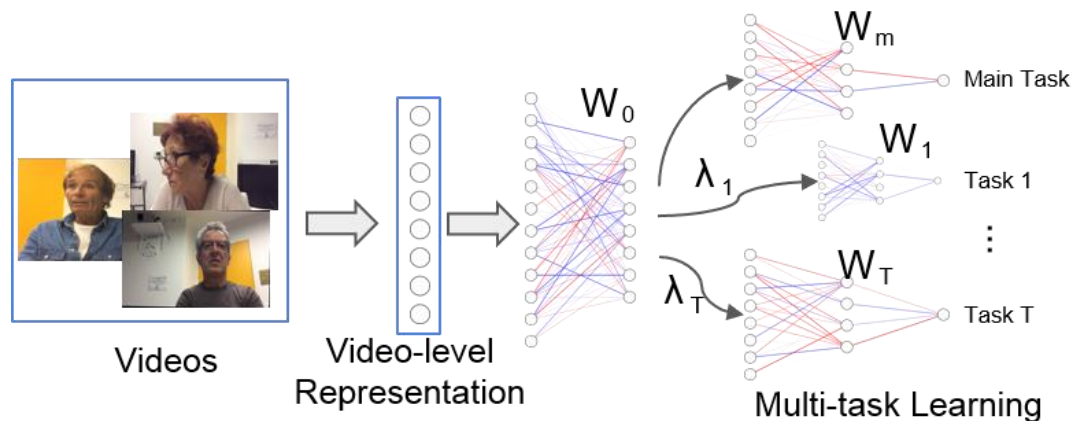
- Main task
 - Apathy classification
- Auxiliary regression tasks
 1. MMSE
 2. NPI-apathy
 3. NPI-anxiety
 4. NPI-depression
 5. NPI-total
 6. clinical dementia score (CDR)
 7. IA-affect
 8. IA-initiative
 9. IA-interest

 } NPI inventory

 } apathy inventory



Multi-task Learning



$$\arg \min_{\mathbf{W}_0, \mathbf{W}_m, \{\mathbf{W}_t\}_{a=1}^T} \sum_{i=1}^N \mathcal{L}(y_i^m, f(\mathbf{x}_i; \mathbf{W}_0, \mathbf{W}_m)) + \sum_{a=1}^T \sum_{i=1}^N \lambda^a \mathcal{L}(y_i^a, f(\mathbf{x}_i; \mathbf{W}_0, \mathbf{W}_a))$$



$$\arg \min_{\mathbf{W}} \mathcal{L}^m + \sum_{a=1}^T \lambda^a \mathcal{L}^a$$


(Choose λ based on prior knowledge)

Objective

- MTL:
$$\arg \min_{\mathbf{W}} \mathcal{L}^m + \sum_{a=1}^T \lambda^a \mathcal{L}^a$$
- Our Objective (MTL+):
$$\arg \min_{\mathbf{W}, \{\lambda^a\}_{a=1}^T} \mathcal{L}^m + \sum_{a=1}^T \lambda^a \mathcal{L}^a$$
- (avoid negative transfer) learn the relatedness of the auxiliary tasks to the main task
- avoid trivial solution $\lambda^a = 0, \forall a$ (nullifying loss incurred by auxiliary tasks)

Proposed Method

- Initialize $W_{i,j} \sim U[-\sqrt{1/n}, \sqrt{1/n}]$ and $\lambda^a = 1, \forall a$
- Weight update by back propagation (several epochs)


$$\mathbf{W} \leftarrow \mathbf{W} - \eta_1 \frac{\partial \mathcal{L}}{\partial \mathbf{W}}$$

- Penalize λ^a intermittently in the same manner


$$\lambda^a \leftarrow \lambda^a - \eta_2 \mathcal{L}^a \quad (\text{because } \frac{\partial \mathcal{L}}{\partial \lambda^a} = \mathcal{L}^a)$$

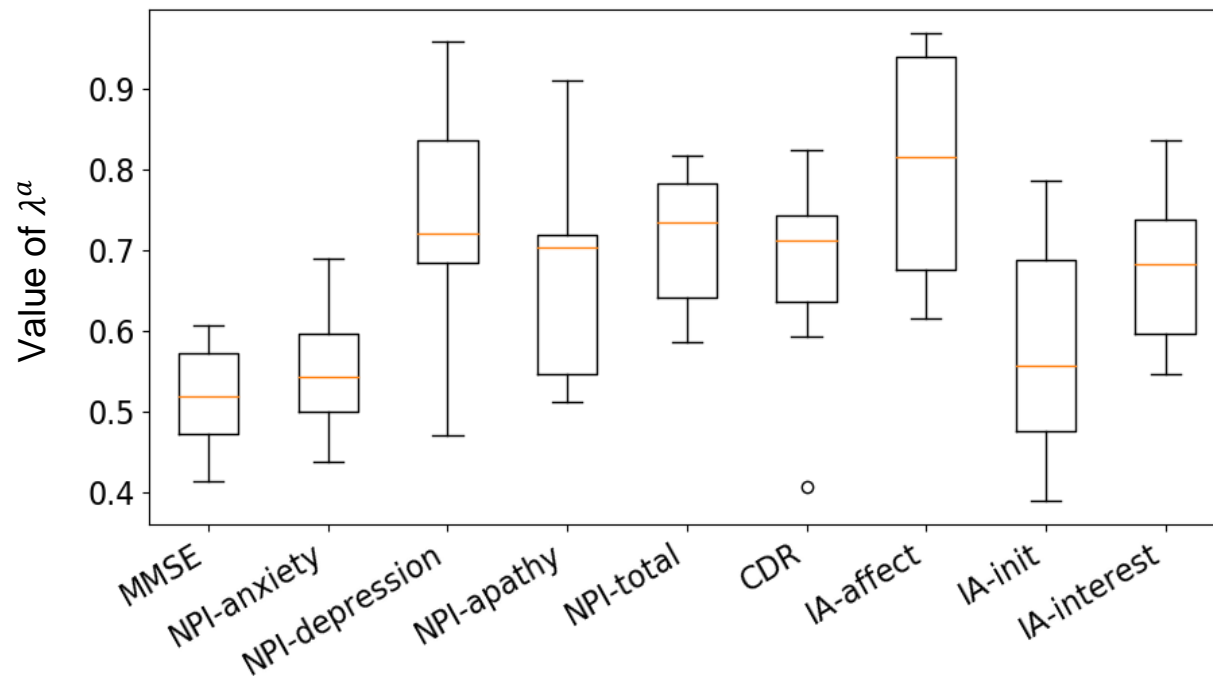
- 
- Stopping criteria (to avoid over-fit the main task)

$$\frac{k \cdot \text{med}_{j=t-k}^t E_{val}^a(j)}{\sum_{j=t-k}^t E_{val}^a(j) - k \cdot \text{med}_{j=t-k}^t E_{val}^a(j)} > \epsilon$$

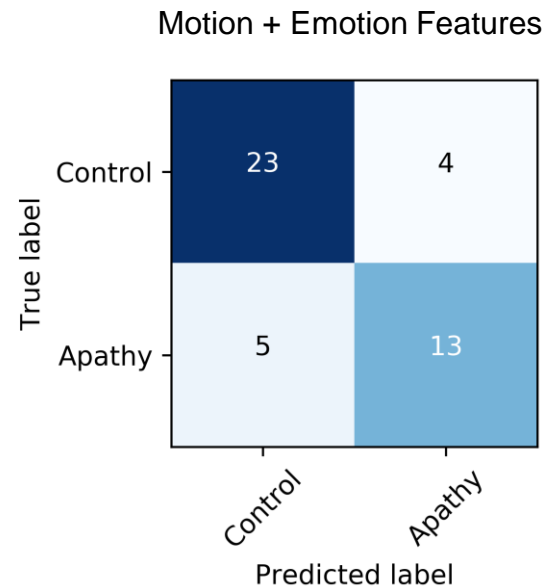
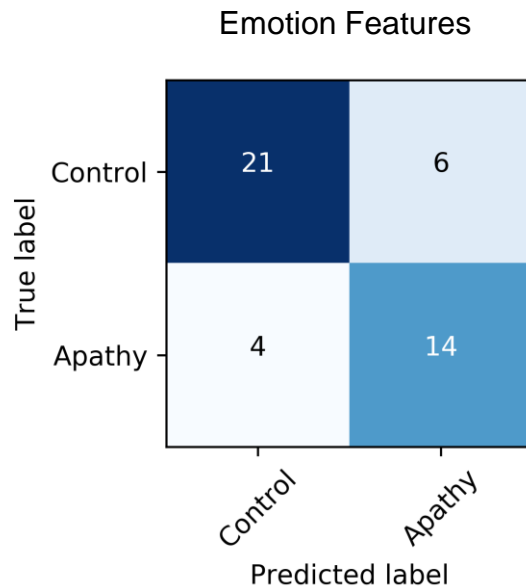
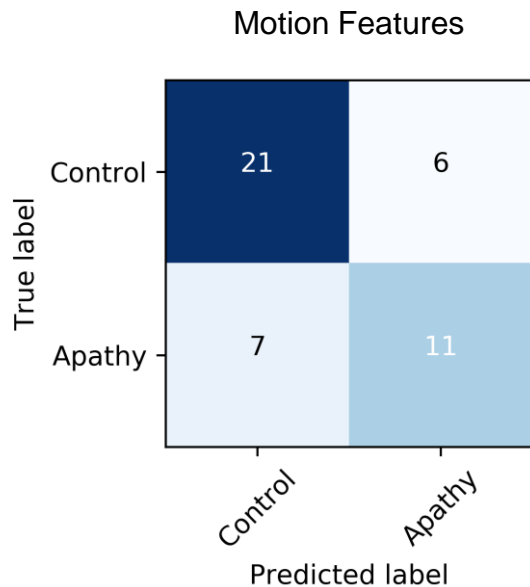
Performance

Features used	Accuracy	F1-score
MTL with Motion Features	62.22	0.582
MTL with Emotion features	66.66	0.638
MTL with Emotion + Motion Features	71.11	0.716
MTL+ with Motion Features	71.11	0.679
MTL+ with Emotion features	77.77	0.776
MTL+ with Emotion + Motion Features	80.00	0.786

How much are the tasks related?



Confusion Matrices



Summary

- Less accurate than the previous model
 - Probably due to less sample size, deep learning models could not learn well
 - Could improve the model performance with more data
- Learns the relatedness of different tasks/channels

Accuracy	80%
F1-score	0.786
Precision	0.825
Recall	0.816

Thank you