Emotion Recognition：Galvanic Skin Response

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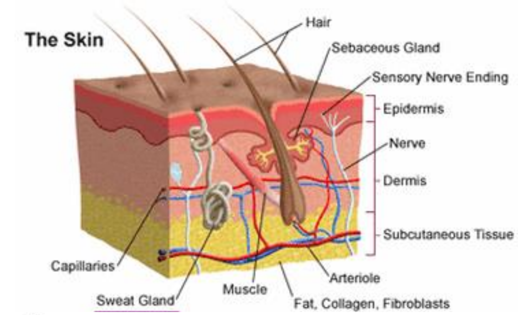
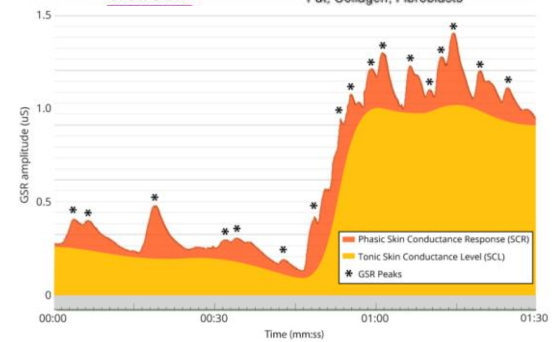
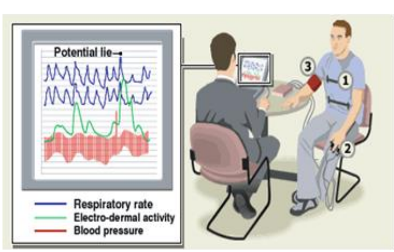
Galvanic Skin Response (GSR)

- Introduction
  - Related to sweat gland activity
  - Related to sympathetic nervous system
  - Reflect emotional arousal
  - Main components
    - Skin Conductance Response (0.5-2Hz)
    - Skin Conductance Level (0.05-0.5Hz)
  - Raw Signal 0.1-10μs
- Application[1][2]



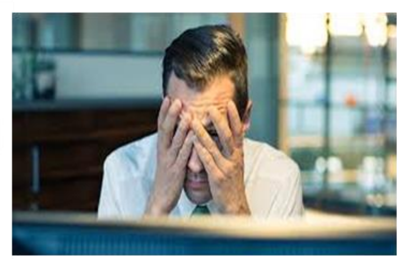


Lie detection



Anti-sleep alarm

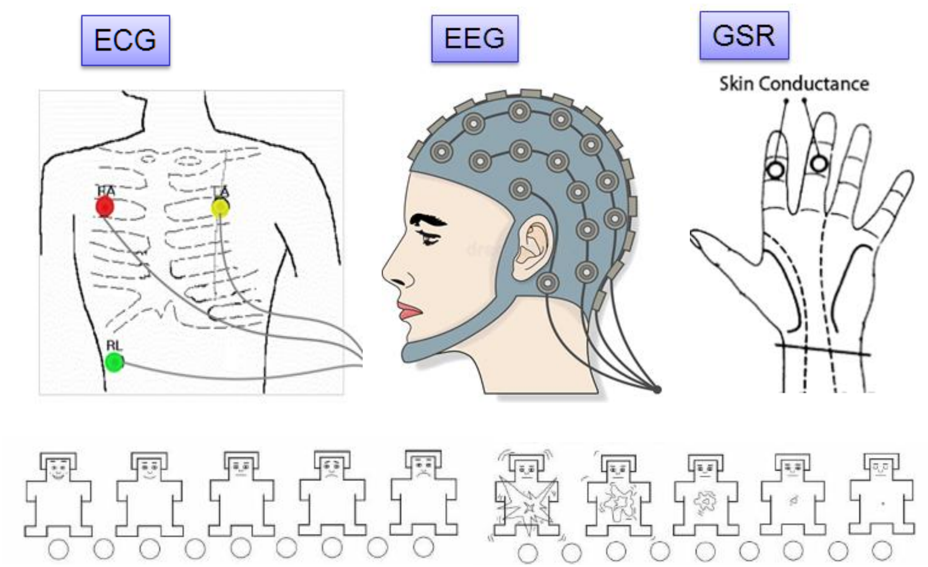
Stress detection



Emotion Recognition

Database Introduction

- DEAP[3] and AMIGOS[4] database
- Objective
  - To study the personality, mood and affective response of people engaging with multimedia content
- Experiment
  - Emotion stimuli
  - Signal collection
  - Self-Assessment
- Compare
  - 22p. 40e. vs 40p.16e.
  - Physiological signals
  - Facial expression
  - Video duration



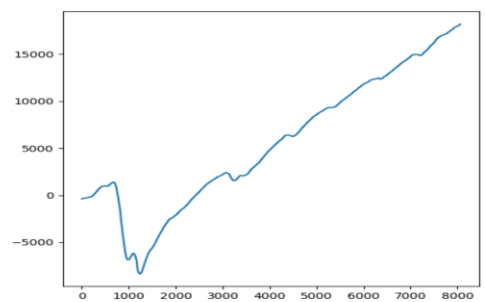
Previous Problems

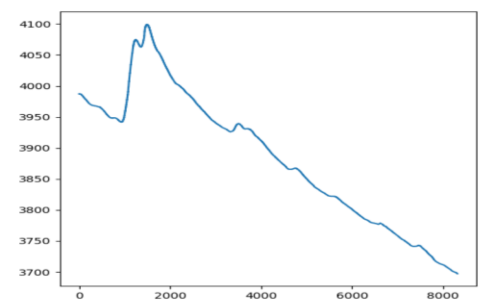
fstdiff_nu		
562	568	544
323	342	311
717	732	723
483	491	467
721	751	729
354	393	371
646	666	655
453	406	404
866	935	893
379	378	358
364	406	396
507	546	502
630	657	600
385	384	374
548	621	585
463	445	437

- AMIGOS database with different video duration
  - Learning video information
  - Feature cannot relate to the data length
  - Valence performance 80% more than Arousal

Solution：cut backward data into the same length

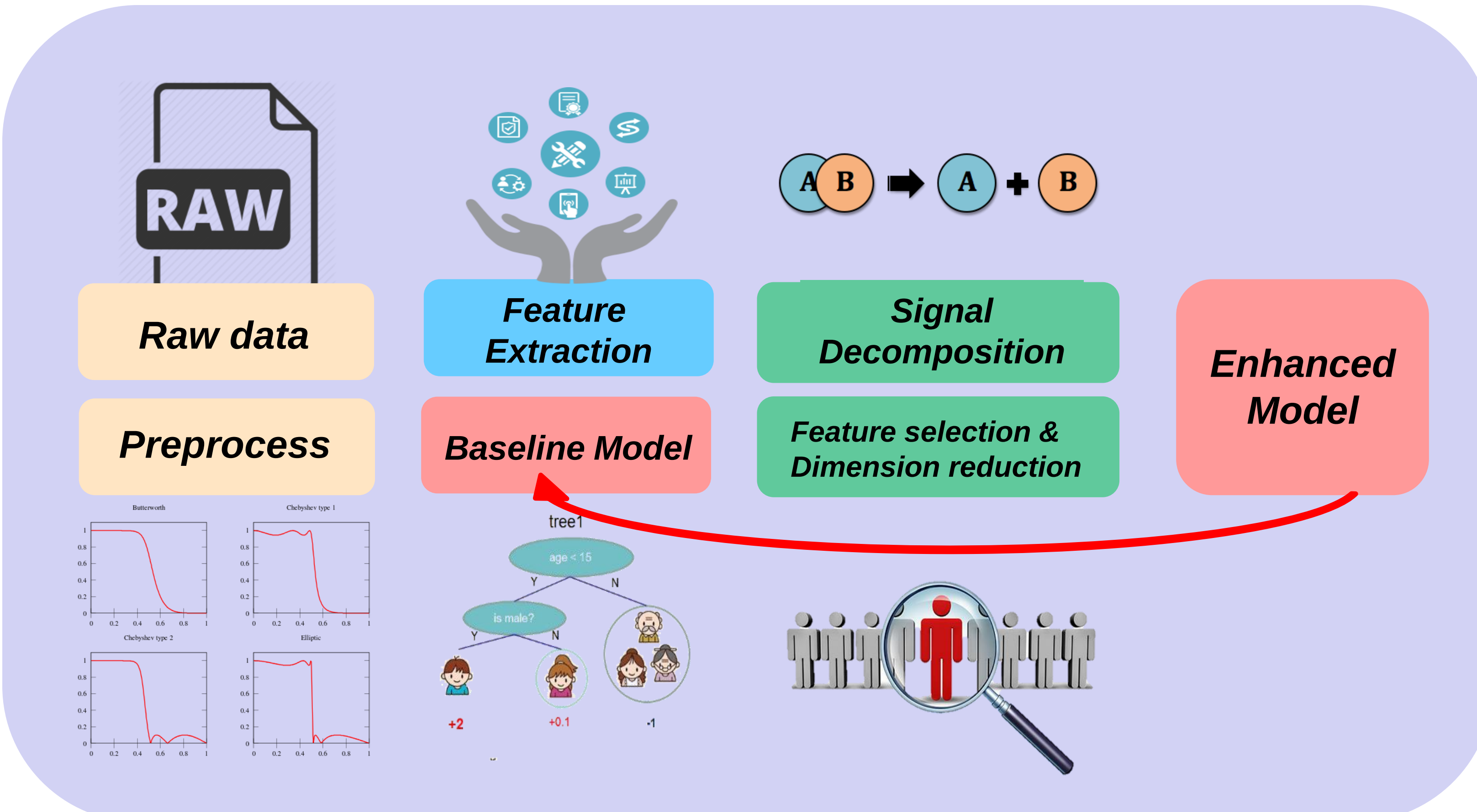
- DEAP database with wrong GSR signal morphology
  - From official website
  - Negative GSR value
  - Extreme GSR value
  - 3s baseline remove

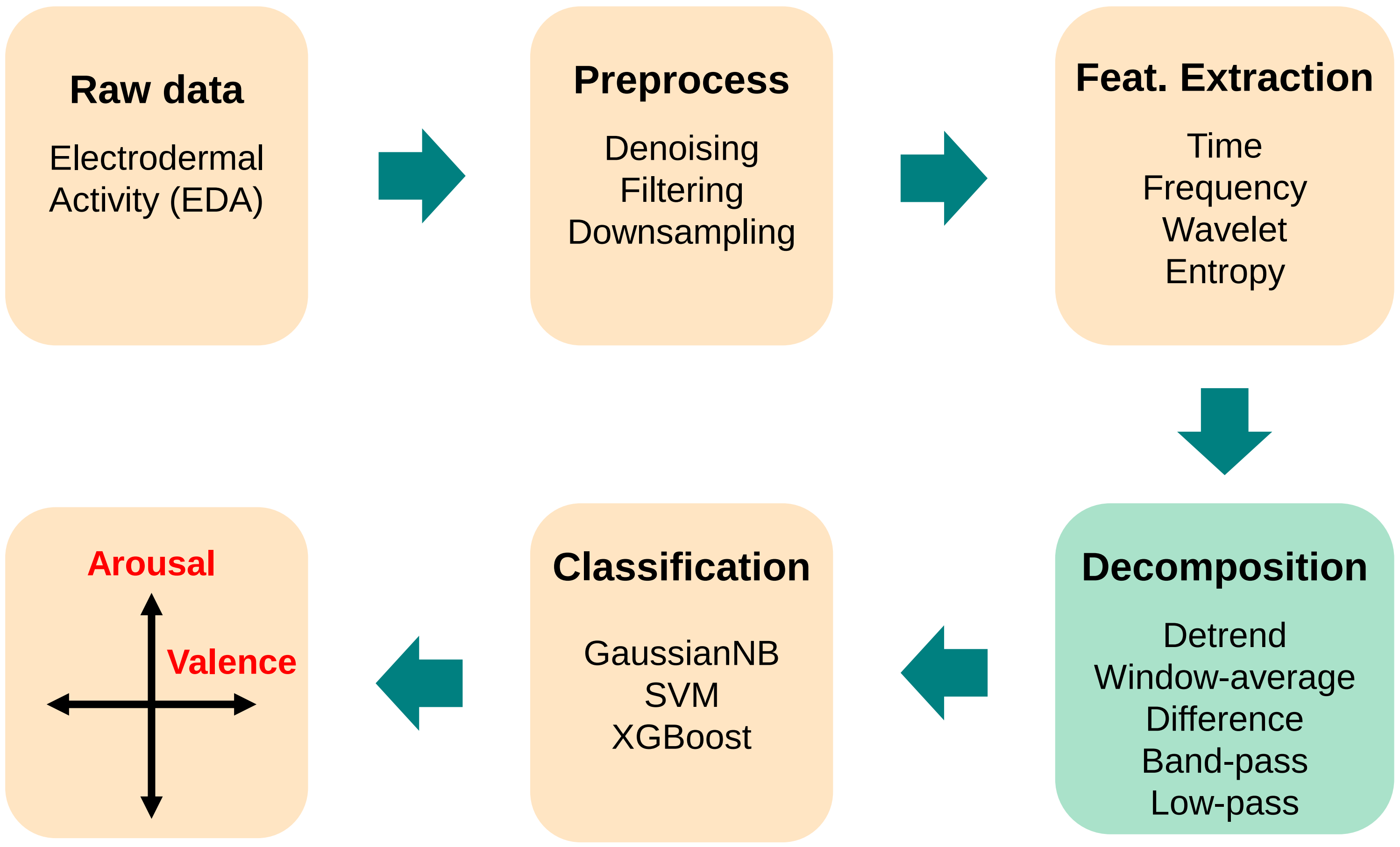




Solution：data extraction from original .bdf(raw) data

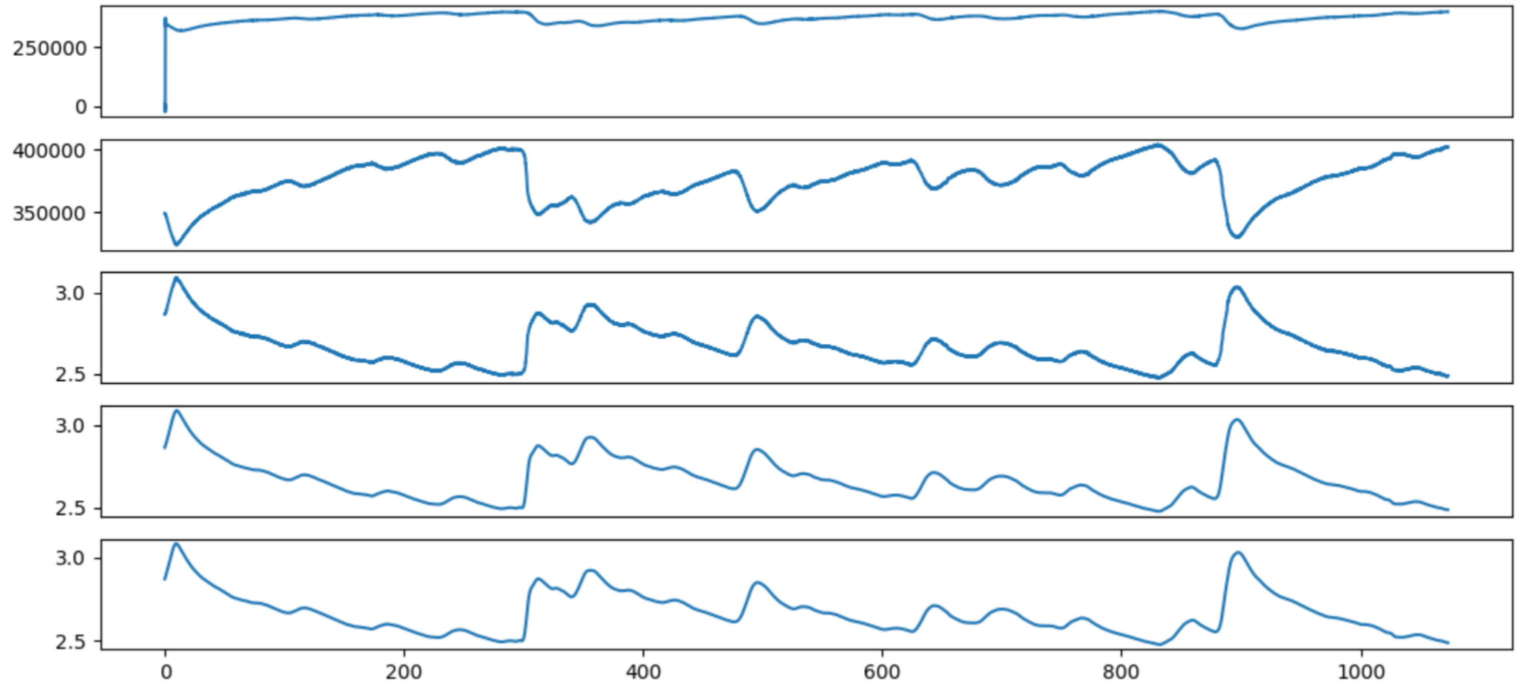
Flow Chart


RAW
Raw data
Preprocess
Butterworth
Chebyshev type 1
Chebyshev type 2
Elliptic
Feature Extraction
Baseline Model
tree1
age < 15
Y
N
is male?
Y
N
+2
+0.1
-1
A B
A
B
Signal Decomposition
Feature selection & Dimension reduction
Enhanced Model


Raw data
Electrodermal Activity (EDA)
Preprocess
Denoising
Filtering
Downsampling
Feat. Extraction
Time
Frequency
Wavelet
Entropy
Decomposition
Detrend
Window-average
Difference
Band-pass
Low-pass
Classification
GaussianNB
SVM
XGBoost
Arousal
Valence

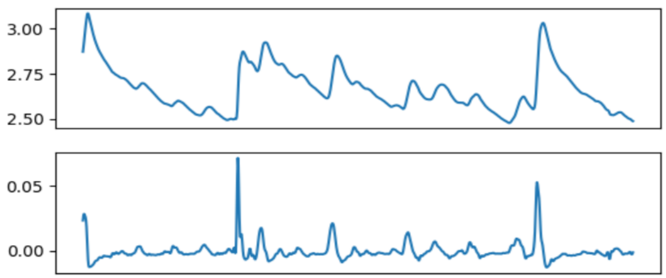
Data Pre-process

- Remove GSR artifacts
- Conductance measurement (μs)
- Low-pass filter (2Hz) and downsample (128Hz→16Hz)

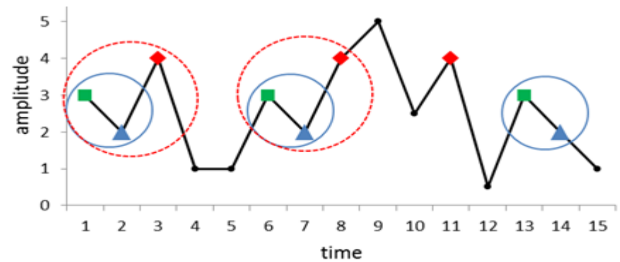


Baseline Feature Extraction

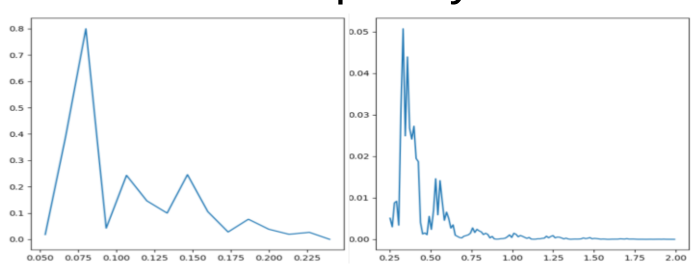
- Time Domain[5][6]
  - Difference and peak number
  - Statistics time feature



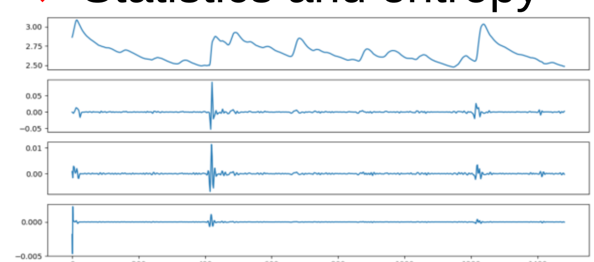
- Entropy Domain[7][8][9][10]
  - Info., Ap. entropy
  - RCMSE, RCMPE



- Frequency Domain[11][12]
  - Power spectral density
  - Statistics frequency feature

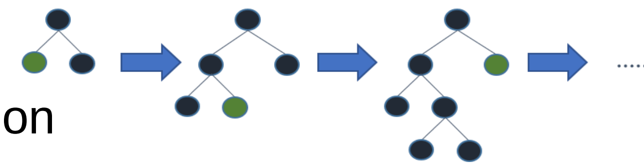


- Wavelet Domain[13]
  - Different filter level
  - Statistics and entropy

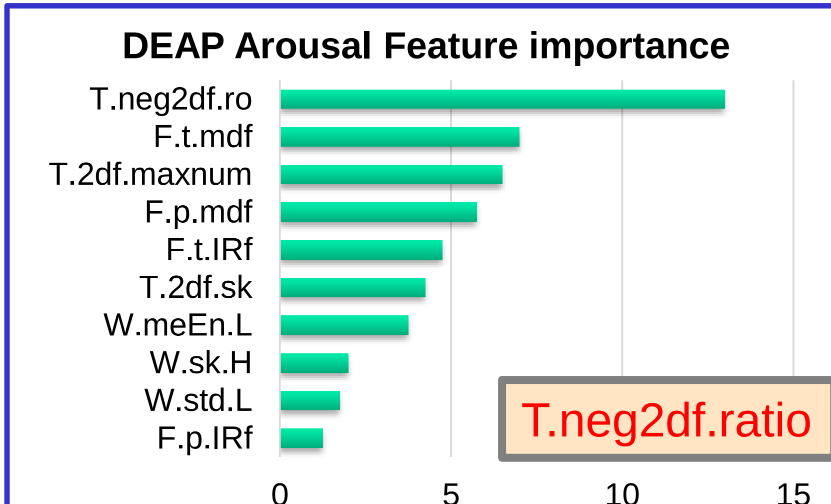


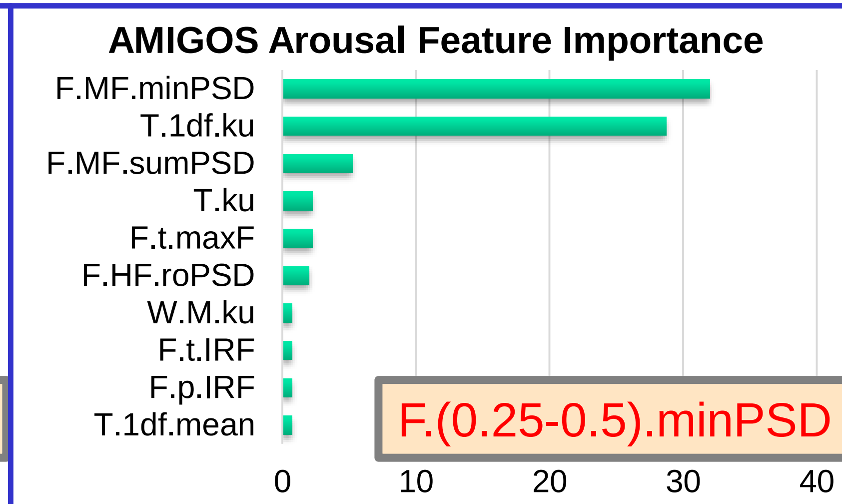
Baseline Performance

- XGBoost[14]
  - Evaluation metrics = cross entropy loss
  - Grid-search parameter on cross validation



DEAP/AMIGOS	Arousal	Valence	Arousal	Valence
F1-Score	60.84%	42.70%	57.24%	50.20%

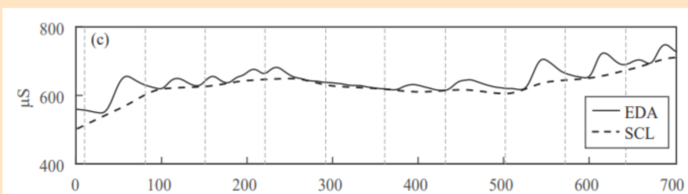




GSR Decomposition

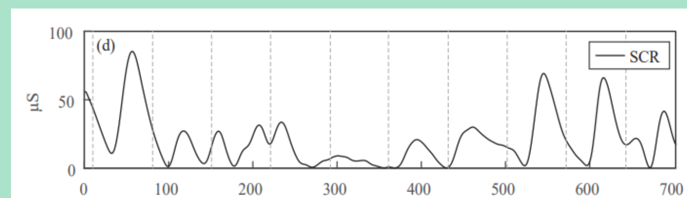
EDA = *SCL* + *SCR* + *Noise + Artifacts*

Skin Conductance Level (SCL)



- Slow varying tonic activity
- Individual Dependent
- $\leq$ 0.5 Hz

Skin Conductance Response (SCR)

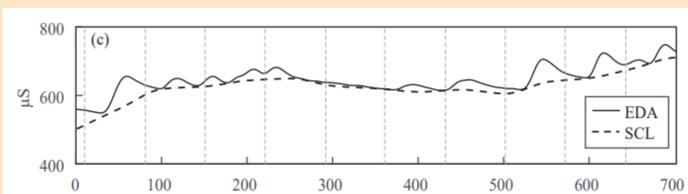


- Fast varying phasic activity
- Reflect stimulus-specific responses
- Individual Independent
- 0.5 Hz to 2 Hz

Decompose GSR into SCL and SCR will give us more info.

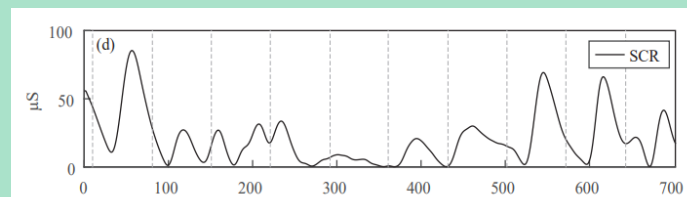
EDA = *SCL* + *SCR* + *Noise + Artifacts*

Skin Conductance Level (SCL)



- Slow varying tonic activity
- Individual Dependent
- ≤ 0.5 Hz

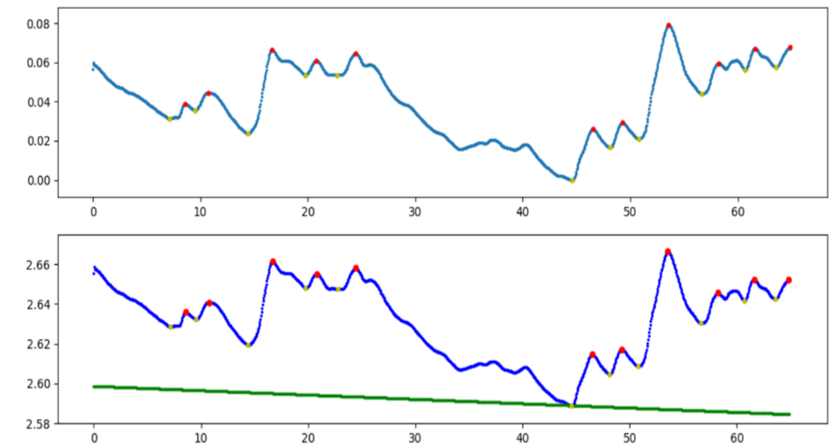
Skin Conductance Response (SCR)



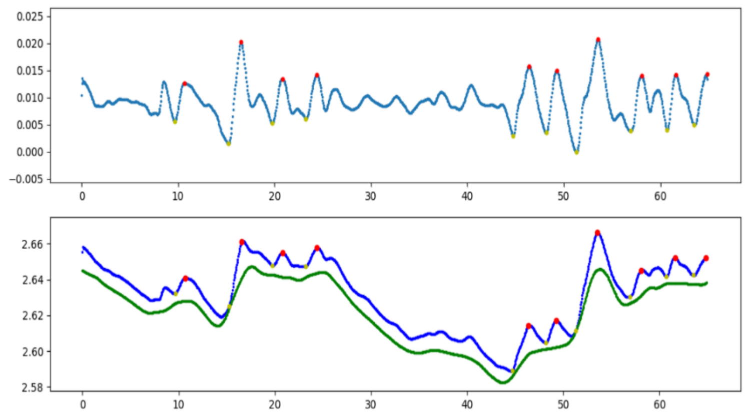
- Fast varying phasic activity
- Reflect stimulus-specific responses
- Individual Independent
- 0.5 Hz to 2 Hz

GSR Decomposition: Traditional Analysis(1/2)

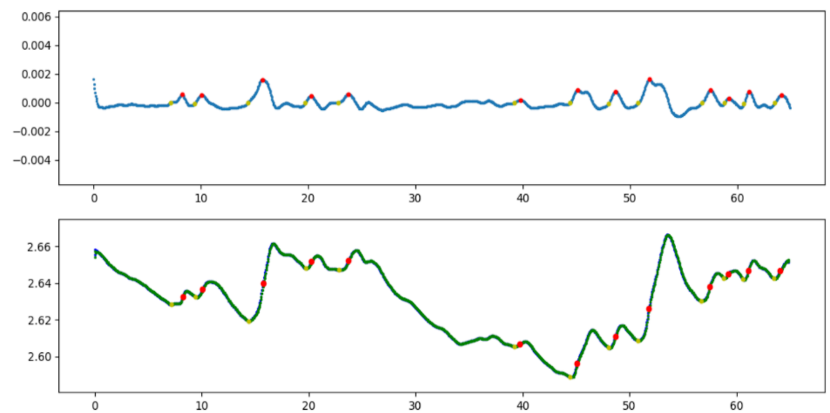
- Detrend[15]
- Window mean[16]
- Difference[17]
- Band-pass phasic (3)[15]
- Low-pass tonic (2)[18]



Detrend

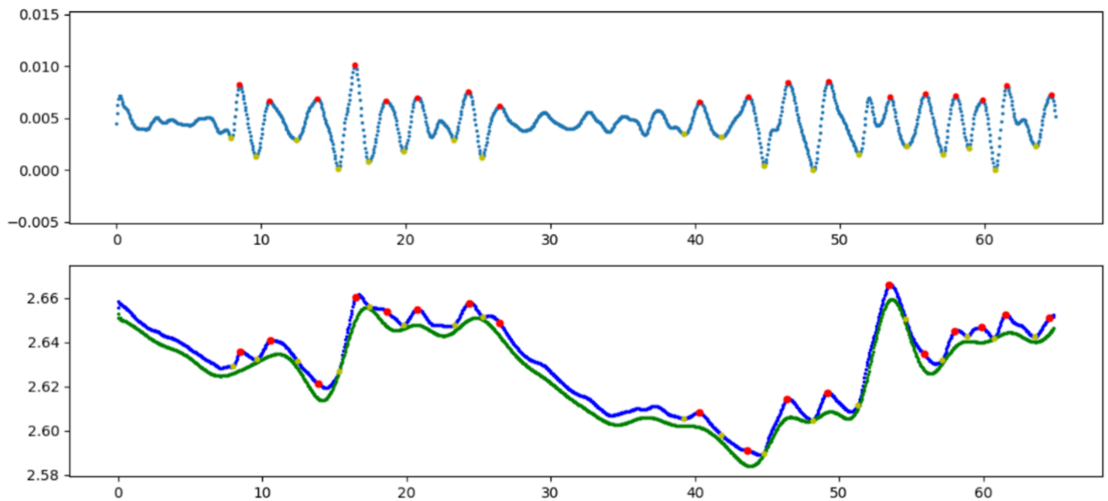


Window mean



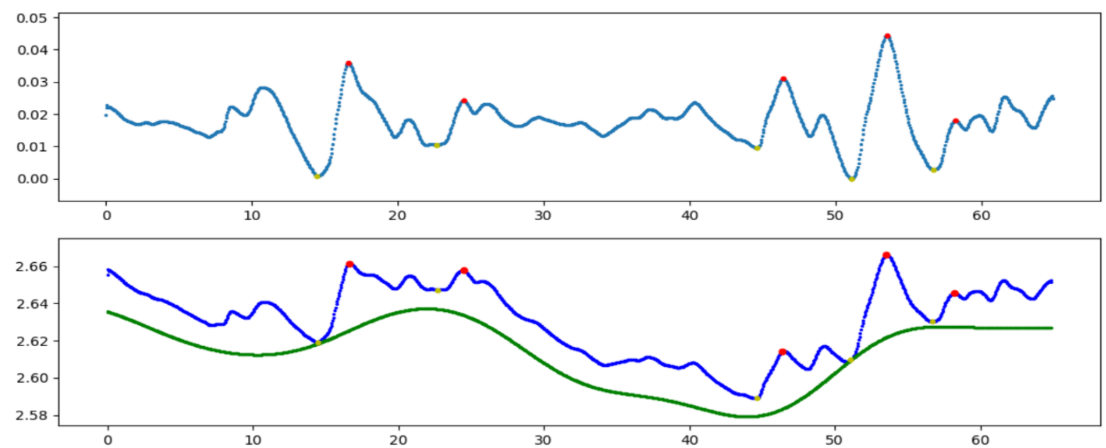
Difference

GSR Decomposition: Traditional Analysis(2/2)



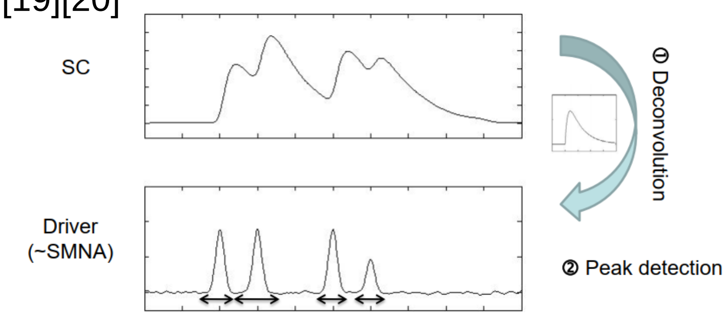
- Band-pass phasic
  - 0.5-2 Hz
  - 0.3-2 Hz
  - 0.1-2 Hz

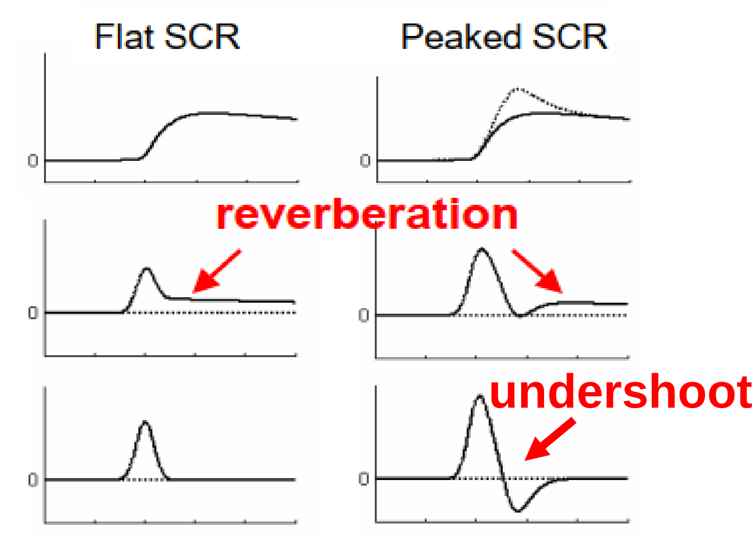
- Low-pass tonic
  - 0.2 Hz
  - 0.08 Hz

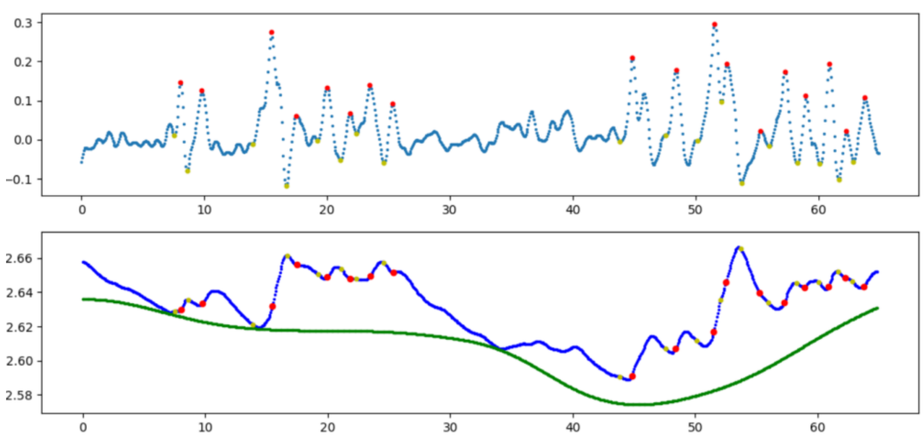


GSR Decomposition: Deconvolution Analysis(1/2)

- Continuous Decomposition Analysis[19][20]
  - $\mathrm{GSR} = \mathrm{SMNA} \otimes \mathrm{IRF}$
    - $\mathrm{SMNA} = \mathrm{Driver}_{\mathrm{tonic}} + \mathrm{Driver}_{\mathrm{phasic}}$
    - $\mathrm{IRF(t)} = \mathrm{Bateman\ Function}$
  - Reconstruct loss function
    - Reverberation
    - Undershoot

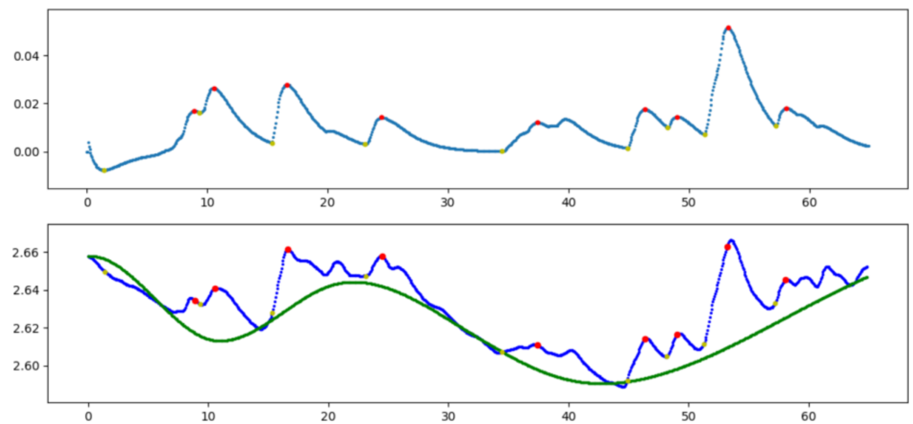


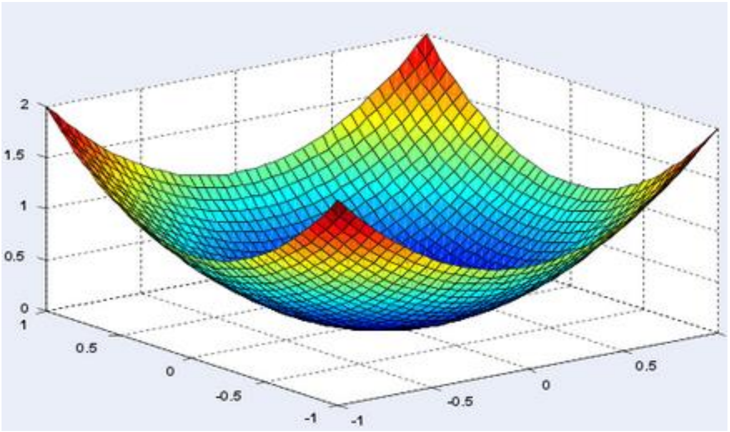




GSR Decomposition: Deconvolution Analysis(2/2)

- Optimization approach to EDA – cvxEDA[21]
  - Convex function for local minimize = global minimize
    - $y = Mq + Bl + Cd + \varepsilon$
  - Convex assumptions
    - Sparse and non-negative SCR
    - Linear time invariant
    - Subject-specific IRF
    - Phasic superimpose to tonic
  - Convex loss function
    - $[q, l, d] = argmax_{qld}\ P[q, l, d \mid y]$
    - Independence of q, l, d
    - $\frac{1}{2}\|Mq + Bl + Cd - y\|_2^2 + \alpha\|Aq\|_1 + \frac{\gamma}{2}\|l\|_2^2$

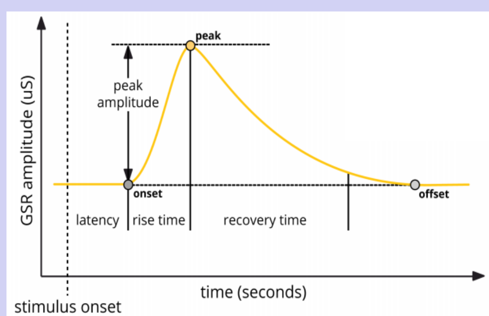


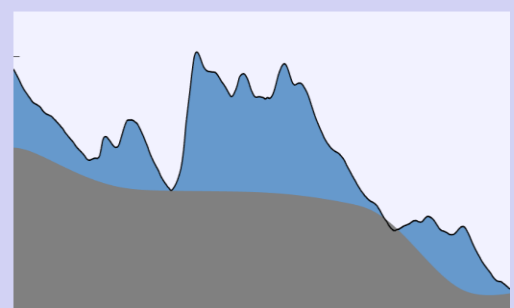


Enhanced Feature Extraction

Phasic | **Tonic**

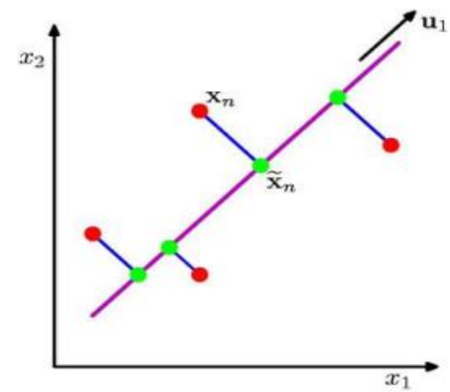
- Time Domain
  - Difference and peak number
  - Statistics time
- Frequency Domain
  - Power spectral density
  - Statistics frequency
- Entropy Domain
  - Info., Ap. entropy
  - RCMSE, RCMPE
- Wavelet Domain
  - Different filter level
  - Statistics and entropy
- SCR Domain
  - Peak amplitude
  - Peak magnitude
  - Rising time
  - Recover time



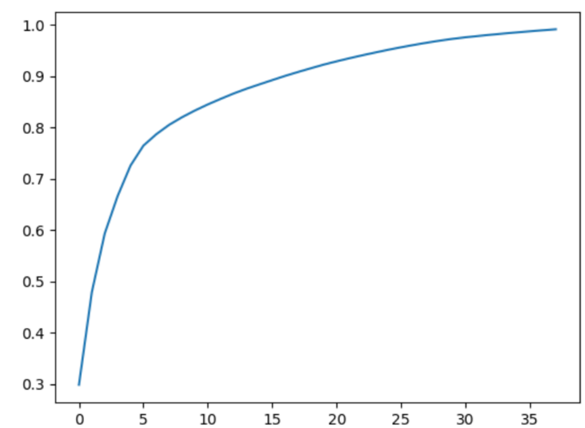


Principal Component Analysis (PCA)

- Feature number (2694) > Data number (880/640)
- Project R^D data onto a uncorrelated R^M space
- Unsupervised & linear dimension reduction
- Evaluate eigenvectors and eigenvalues
  - Maximize variance
  - Minimize reconstruction error

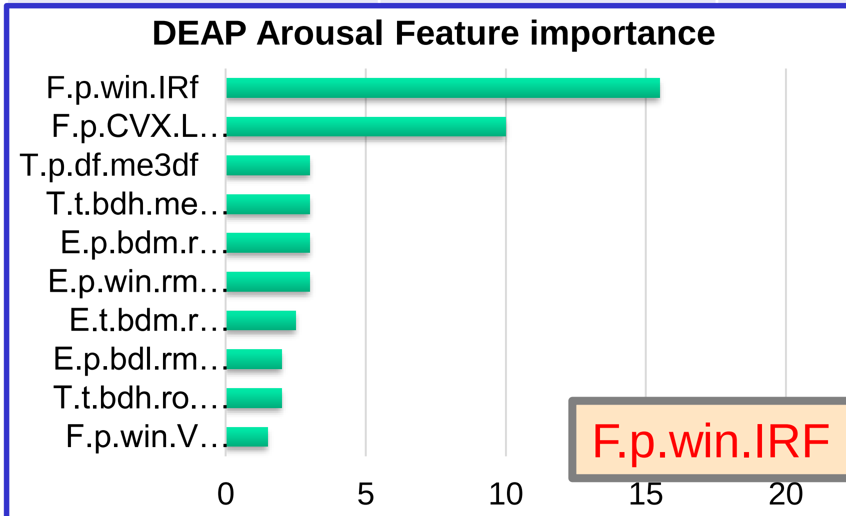


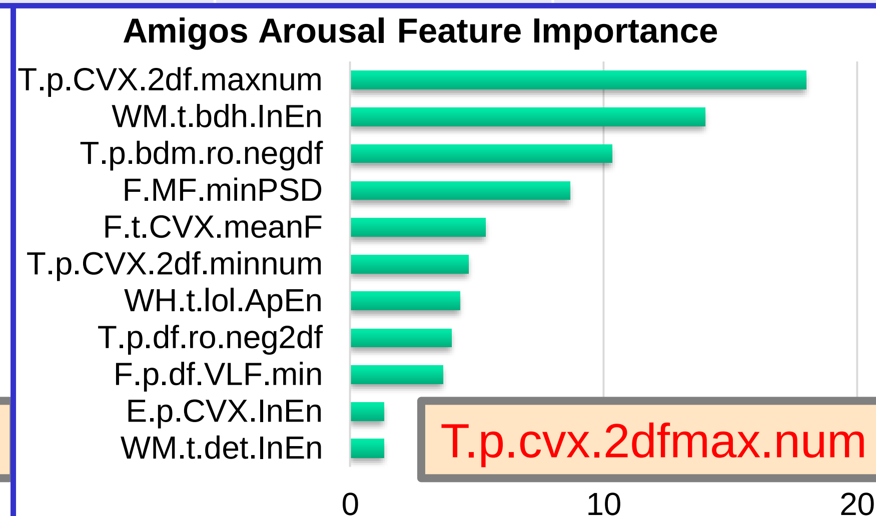
Variance = 0.99	DEAP	AMIGOS
Baseline (134)	39	38
Tradition (256)	89	81
CDA (256)	86	83
cvxEDA (256)	80	82
Fusion (2694)	363	270



Enhanced Performance

Arousal	DEAP		AMIGOS	
	Non-PCA	PCA	Non-PCA	PCA
Baseline	60.84%	61.97%	57.24%	56.76%
Traditional	62.93%	62.78%	60.23%	59.42%
CDA	59.77%	61.28%	58.48%	58.29%
cvxEDA	57.48%	63.57%	56.55%	58.31%
Fusion	60.79%	64.42%	56.78%	56.83%



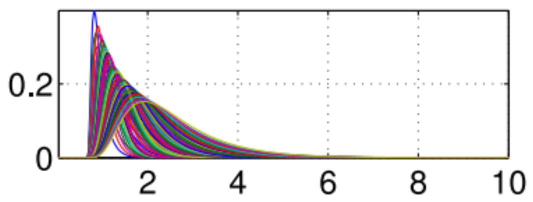


Conclusion

- Arousal has high correlation with GSR signal
- Phasic activity has more information than tonic activity
- PCA can enhance performance from maximized variance
- Frequency domain features has higher feature importance

Future Work

- Implement fusion database
- Implement other GSR decomposition
  - Sparse coding features
- Use Image emotional stimuli experiment database



Reference

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