Using EEG for Emotion Experience Design in TV Commercials

by **Jordan** Deja

0 3 1 6 2020

the two types of people listening to my talk...

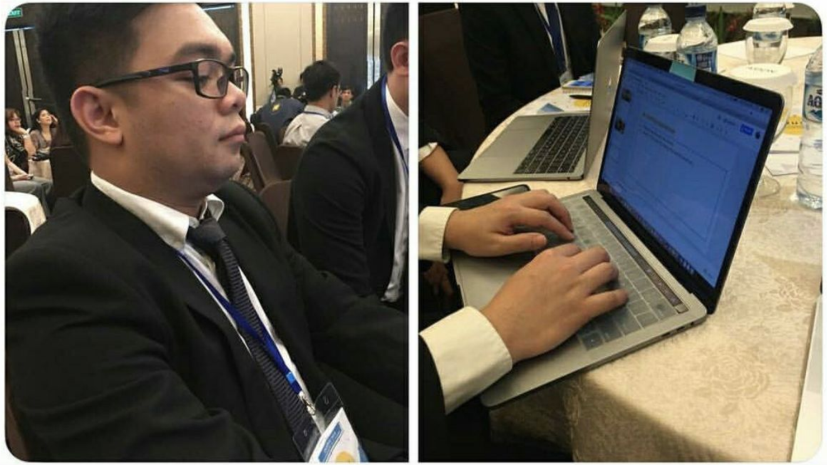
cramming professor meme

Google Search | I'm Feeling Lucky

Google offered in: Filipino Cebuano

Blaise Cruz
@finelined_

If you think you're good at cramming, my prof makes his slides and prepares his presentation for an international conference IN THE CONFERENCE ITSELF




NERD

DeepDive: combining marketing and science using brainwaves and AI

in partnership with

NUWORKS
INTERACTIVE

TV Commercials and the industry

- TVC airtime is paid by the second; usually expensive
- Most TVC’s are from 30 to 45 seconds in length
- Most dandruff commercials would include the “scalp” scene
- Marketing teams do qualitative testing through structured interviews after TVC viewing
- Each interview lasts around 30 to 45 minutes per respondent.
- Conversion is measured directly-attributable sales from TVC’s

On viewing experiences

- Filipinos usually watch as a family
- Current TVC’s in the PH setting elicit certain emotions which we call “feels”
- Most product conversions take place after watching TV commercials
- TV Commercials are more likely to appear on shows during prime time

Four ideas to take from this report

warc

1

BIG BUDGETS DELIVER BIG PROFITS

Judges of this year's Creative Effectiveness Awards deliberately focused on campaigns that could show they had delivered a profit for their brands. This emphasis, which was less pronounced in 2015, has had an impact on the types of campaign doing well in the competition. The result, Jury President Andrew Robertson adds, is a far more 'traditional' set of winners than in some previous years – big brands with big budgets showing high financial returns from their advertising. The Grand Prix winner from UK retailer John Lewis, built around a Christmas TV ad, is a case in point.

2

ONLINE LEADS BUT TRADITIONAL MEDIA OVERPERFORM

Arguably, the stronger focus on profit ROI in this year's competition has favoured more tried-and-tested campaign models. Digital media, in particular social media, continue to feature heavily in the campaign mix. Social media is the most widely used channel in the mix, and is also the most widely used lead channel. However, it was a remarkably strong year for 'traditional' channels. TV was the second-biggest 'lead' medium – and TV-led campaigns significantly overperformed among the shortlist and winners. It was also a strong year for radio, outdoor and cinema. It appears that digital-led campaigns, particularly those on a low budget, were less likely to have evidence of a profit ROI.

3

EMOTION WORKS WHEN IT AIDS MEMORABILITY

Emotion is once again a widely used creative approach among the winners and shortlisted entries, reflecting the power of emotional appeal to drive business results. A neuroscientific analysis of the Grand Prix winner suggests one reason emotion is so important. The study found that the John Lewis ad's emotional peak coincided with a strong response in terms of memory encoding. In other words, emotional appeal and memorability work together in effective advertising.

4

'REAL-TIME' EFFECTIVENESS IS AN EMERGING CHALLENGE

Effectiveness in this competition is still largely backward-looking – the success of a campaign is measured after it has run. However, as one judge pointed out, the challenge is increasingly not just being able to prove effectiveness retrospectively, but to identify real-time effectiveness indicators that allow marketers to optimise campaigns as they're running. One way this can work is evident in a Gold-winning campaign from The Economist. This campaign was built around online content and programmatic technology. By seeing what types of content were working with the target audience in real time, it was able to evolve the strategy during the campaign.

Emotion works when it aids memorability

The study by John Lewis found that the ad's emotional peak coincided with a strong response in terms of memory encoding. In other words, emotional appeal and memorability work together in effective advertising.

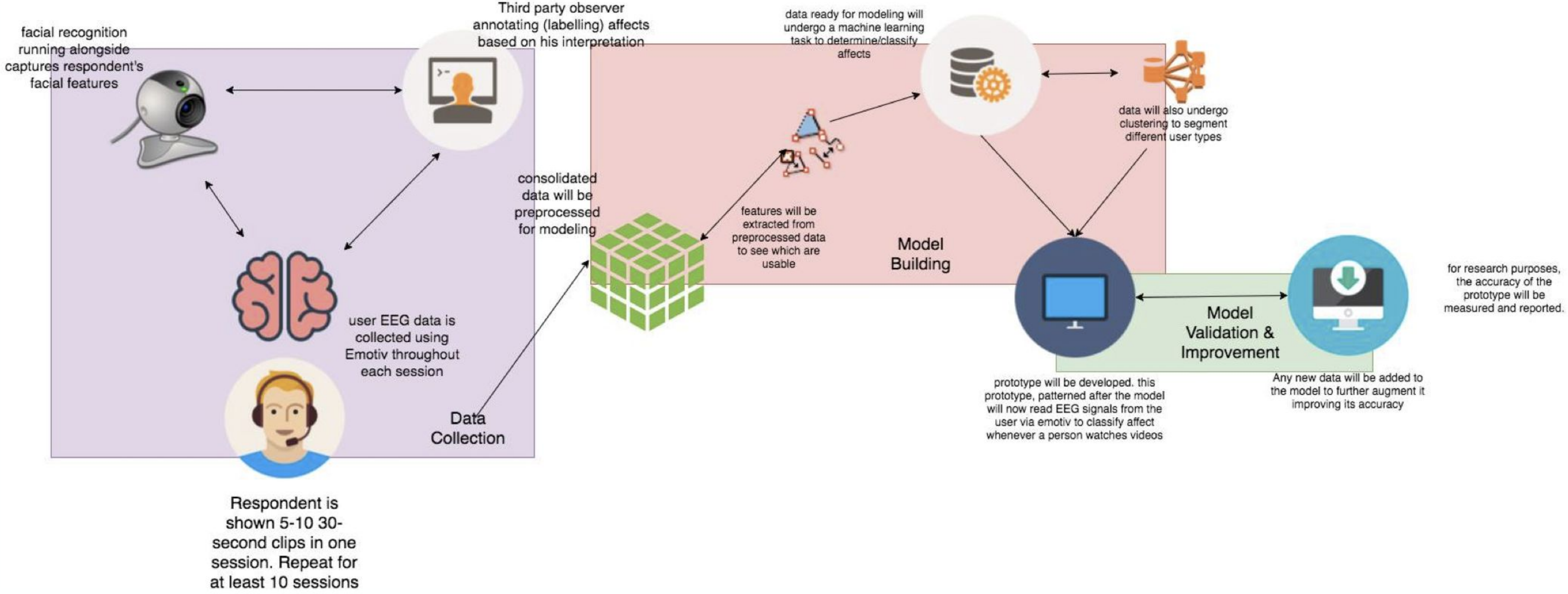
How might we use EEG emotion models to measure TV viewer experience?

How might we train a computer model to help us determine if a certain scene elicits the intended emotion?

How might we extract patterns and observations from these viewer experiences to turn them into actionable insights?

Objectives

- Build a data set from EEG data to model emotions such as (1) calm, (2) disgust, (3) excited, (4) kilig, (5) angry and (6) neutral
- Use emotion models to measure if certain scenes in a video elicits such emotions to its viewers
- Interpret these data into actionable insights that producers and business can use for their commercial campaign (**data-inspired creativity**)


facial recognition running alongside captures respondent's facial features
Third party observer annotating (labelling) affects based on his interpretation
data ready for modeling will undergo a machine learning task to determine/classify affects
data will also undergo clustering to segment different user types
consolidated data will be preprocessed for modeling
features will be extracted from preprocessed data to see which are usable
Model Building
user EEG data is collected using Emotiv throughout each session
Data Collection
Model Validation & Improvement
for research purposes, the accuracy of the prototype will be measured and reported.
prototype will be developed. this prototype, patterned after the model will now read EEG signals from the user via emotiv to classify affect whenever a person watches videos
Any new data will be added to the model to further augment it improving its accuracy
Respondent is shown 5-10 30-second clips in one session. Repeat for at least 10 sessions

Two Phases

Model Building

- Data Collection
- Emotion Labelling/Detection
- Data Cleaning
- Model Training
- Model Implementation

Affective Testing

- Individual Viewing Sessions
- Structured Interviews
- Post-Interview Discussions
- Insights Analysis

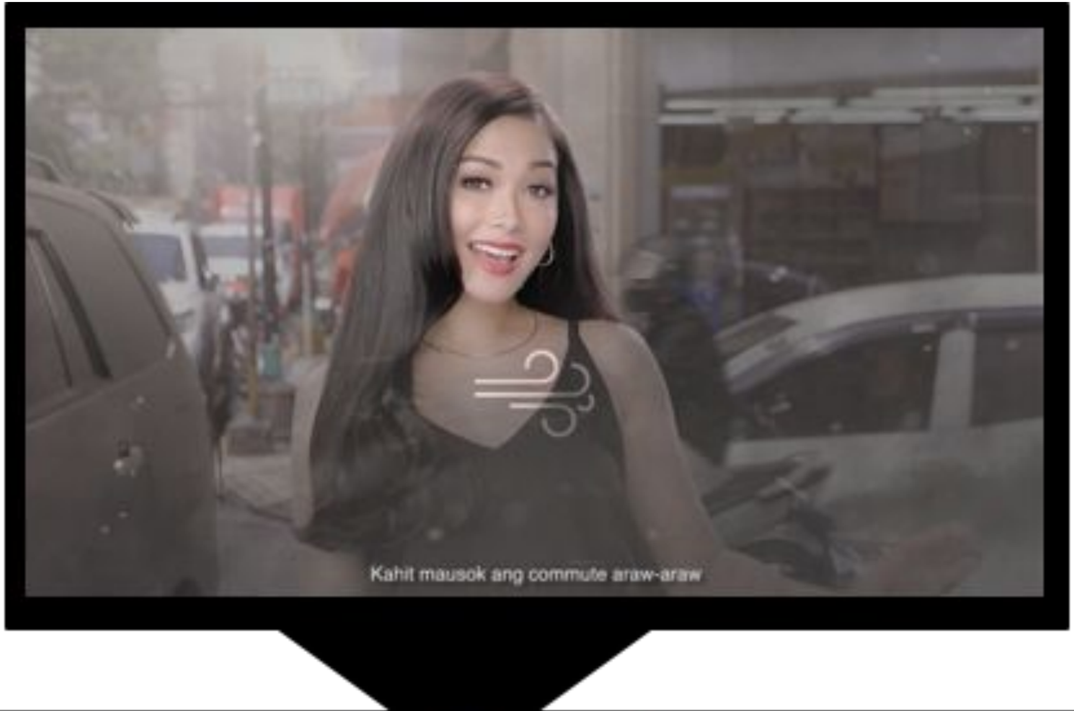
Model Building

- Participants were asked to watch video clips that showed “calm”, “exciting” and “disgusting” scenes

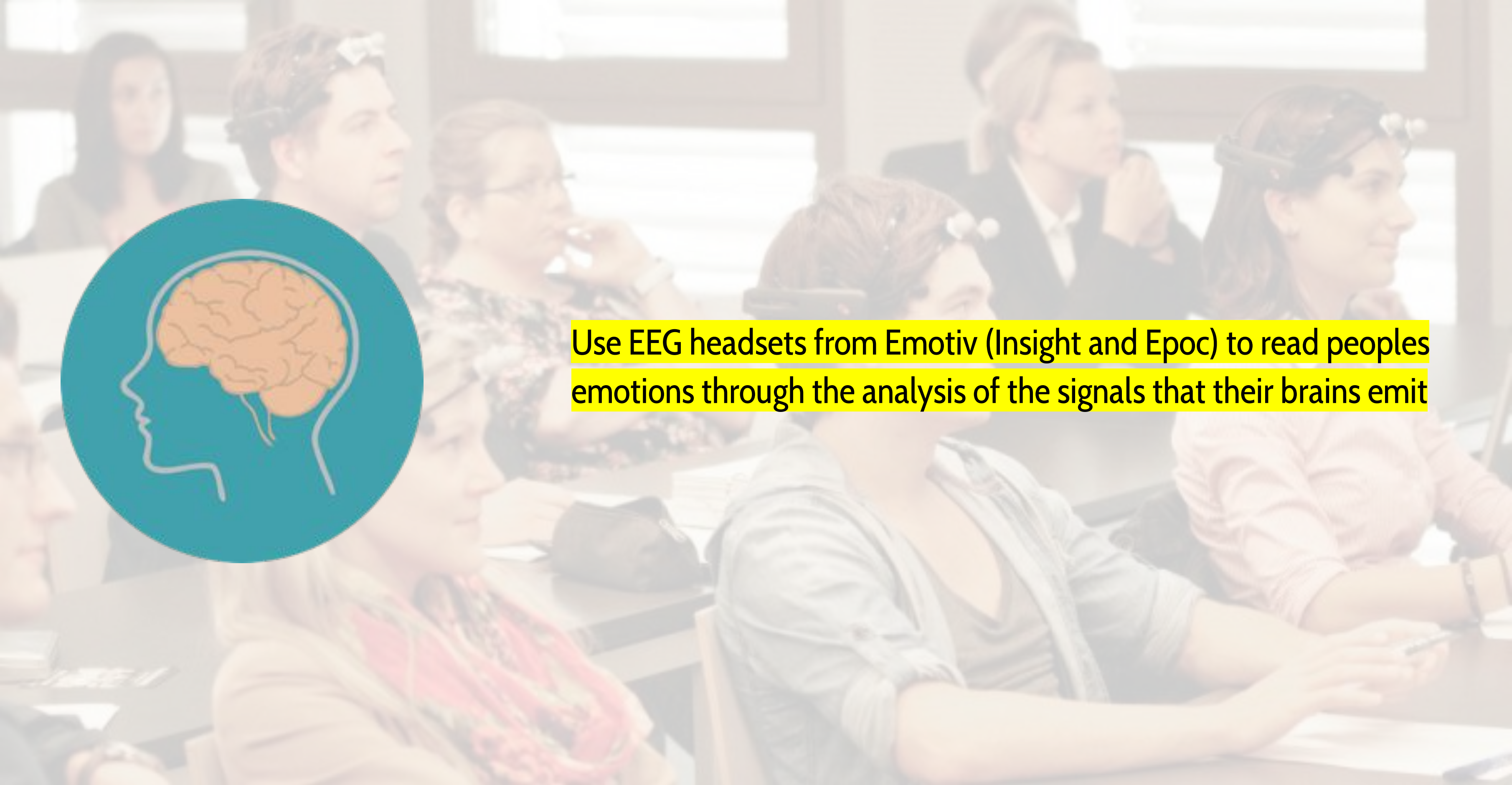
Participants

- 10 males aged 18-31 recruited for model building
- 30 males aged 18-31 recruited for affective testing
- Half of testers were users of a specific shampoo product
- The other half of testers were not


EMOTIV



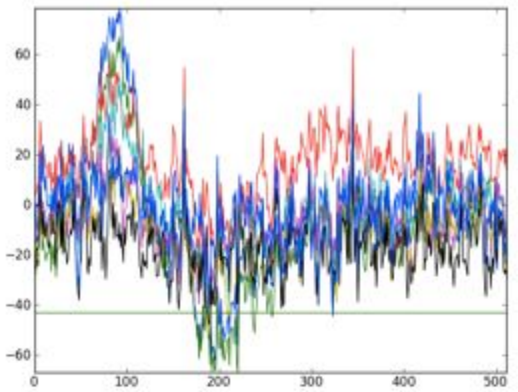
Emotion detection through facial recognition



Use EEG headsets from Emotiv (Insight and Epoc) to read peoples emotions through the analysis of the signals that their brains emit

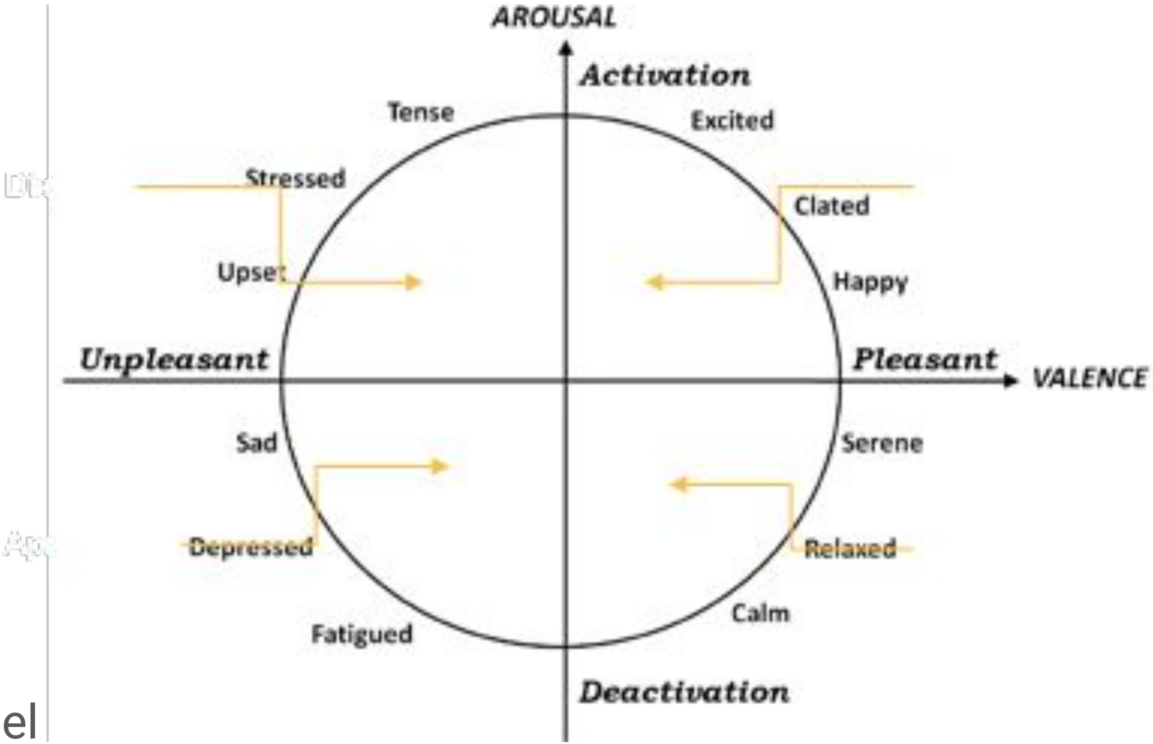
Researchers manually encode and annotate moment by moment emotion responses of participants during tests

Emotion was labelled using three approaches: (1) capturing EEG signals, (2) use of facial recognition and (3) observer coder



Using EMOTIV’s Xavier, we get to look at the raw signals and process them from the five signals namely Pz, AF3, AF4, T7 and T8

In this study, we got to label based on 3 affects/emotions: Calm, Excited and Disgust (to cover at least positive and negative arousal and valence values)



Plutchik’s wheel

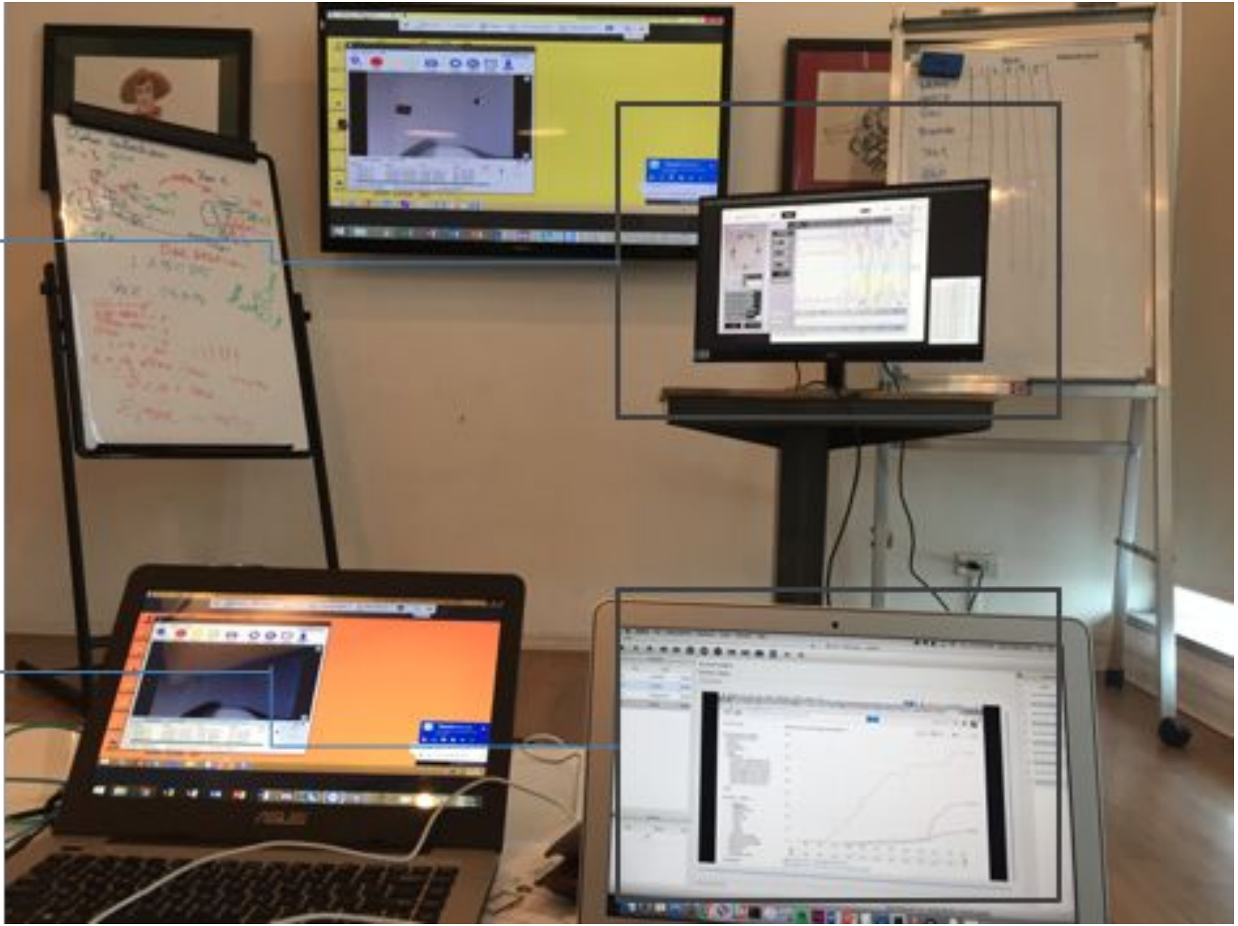
Tools Used in Model Creation Initial Data Collection:

Emotiv Xavier – Output for raw EEG visualization

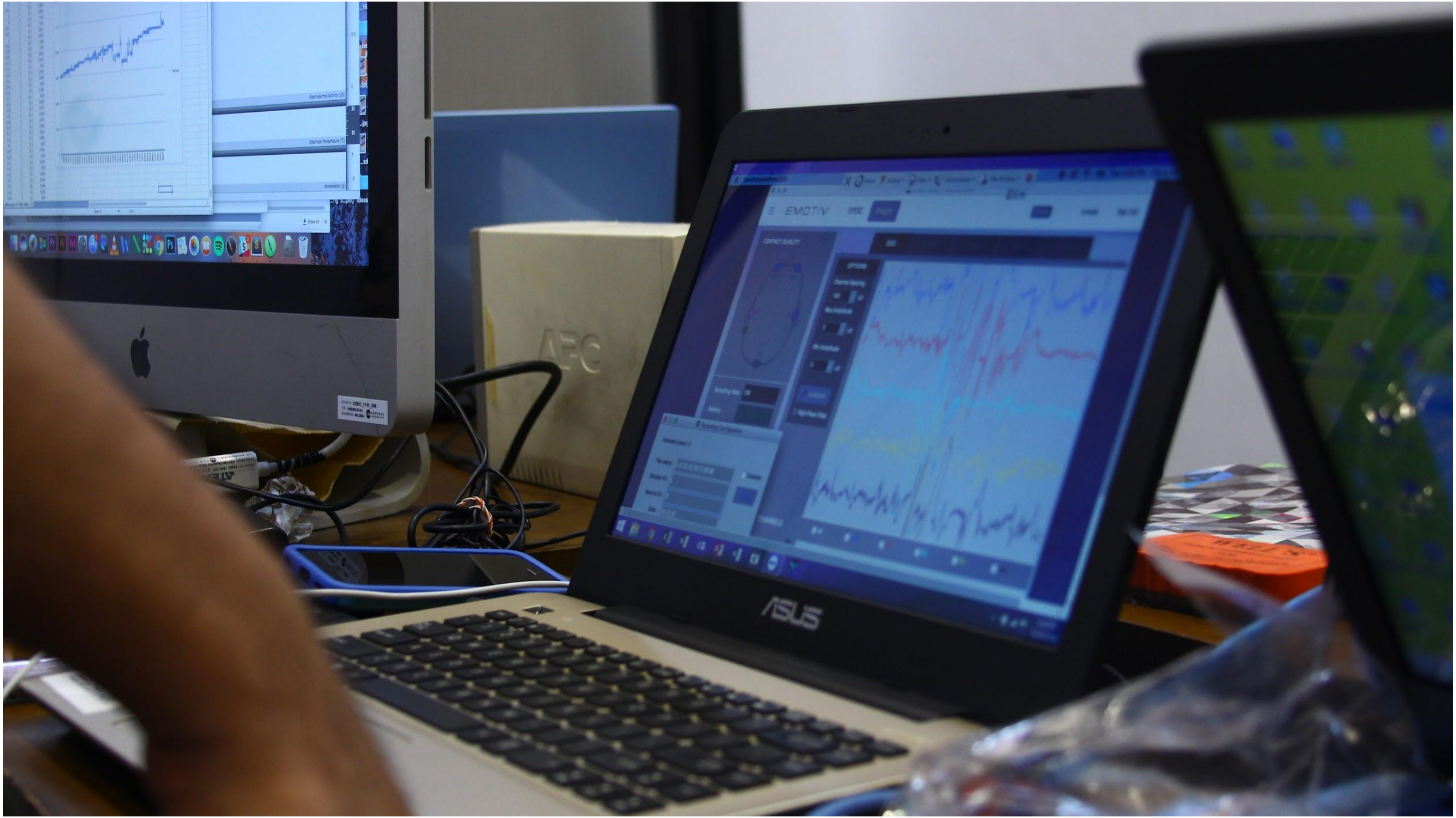
NuWorks EEG Reader/Interpreter – Data reader in partnership with DLSU COMET

BORIS – **B**ehavioral **O**bservation **R**esearch **I**nteractive **S**oftware from the University of Turin, Italy.

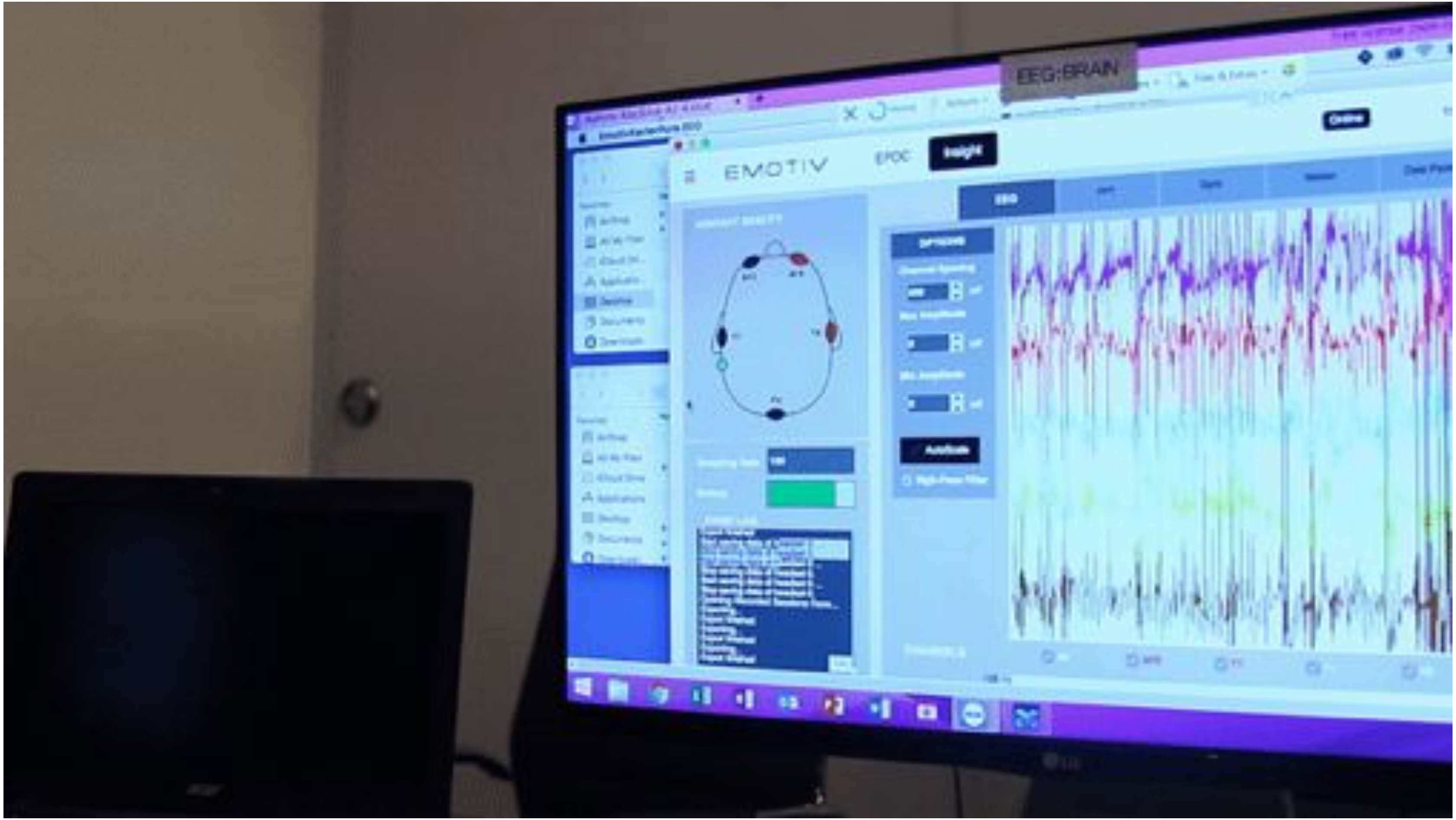
An event logging software for video/audio coding that is open-source

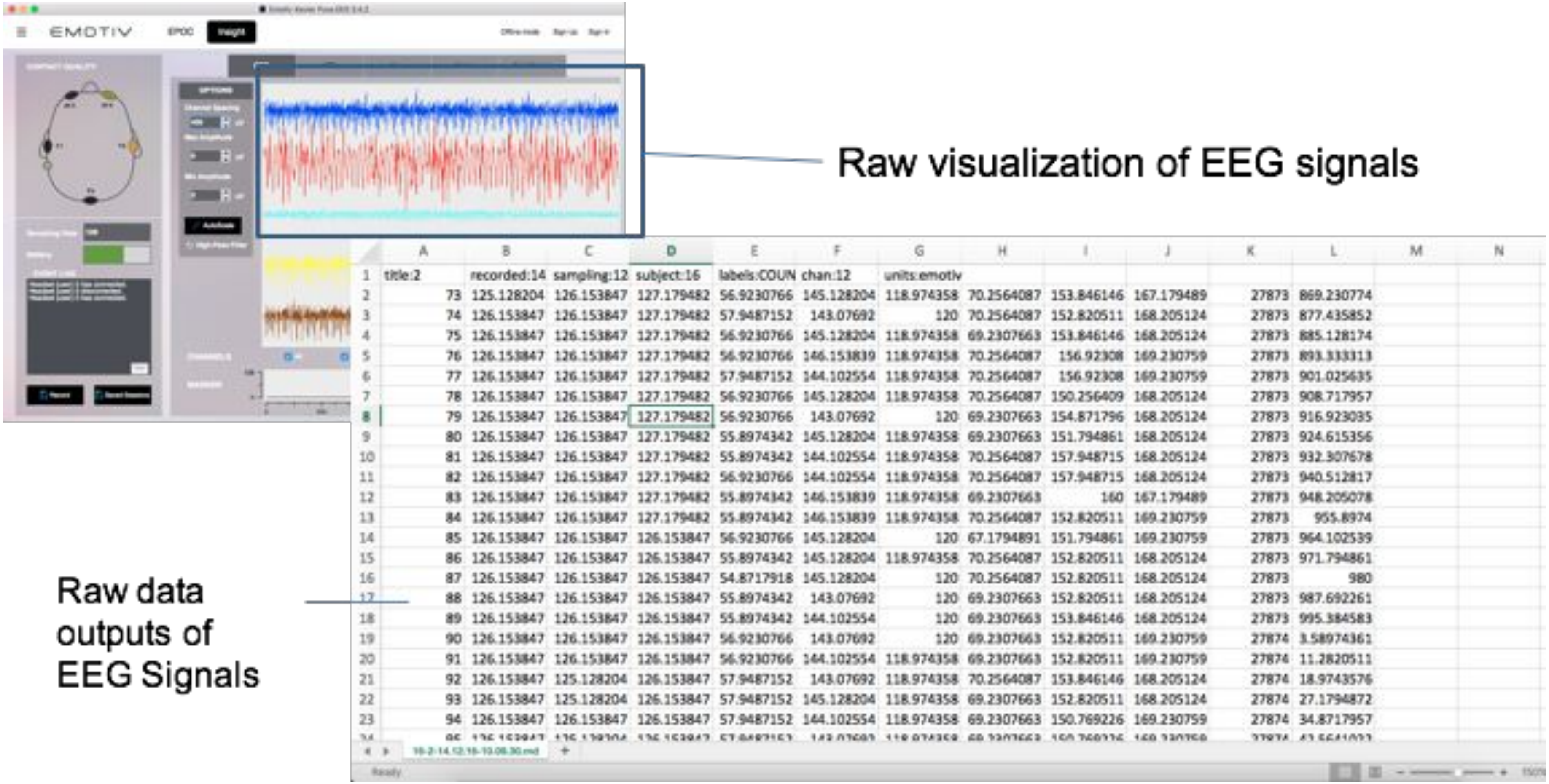



STORYTECHING
TELLING HUMAN STORIES THROUGH CREATIVE TECHNOLOGY
HIKVISION DS-2CD2020F-IW
Live View
Playback
Log
01-02-1970 Fri 01:50:25


EMOTIV
ASUS


NO GSR
NO GSR

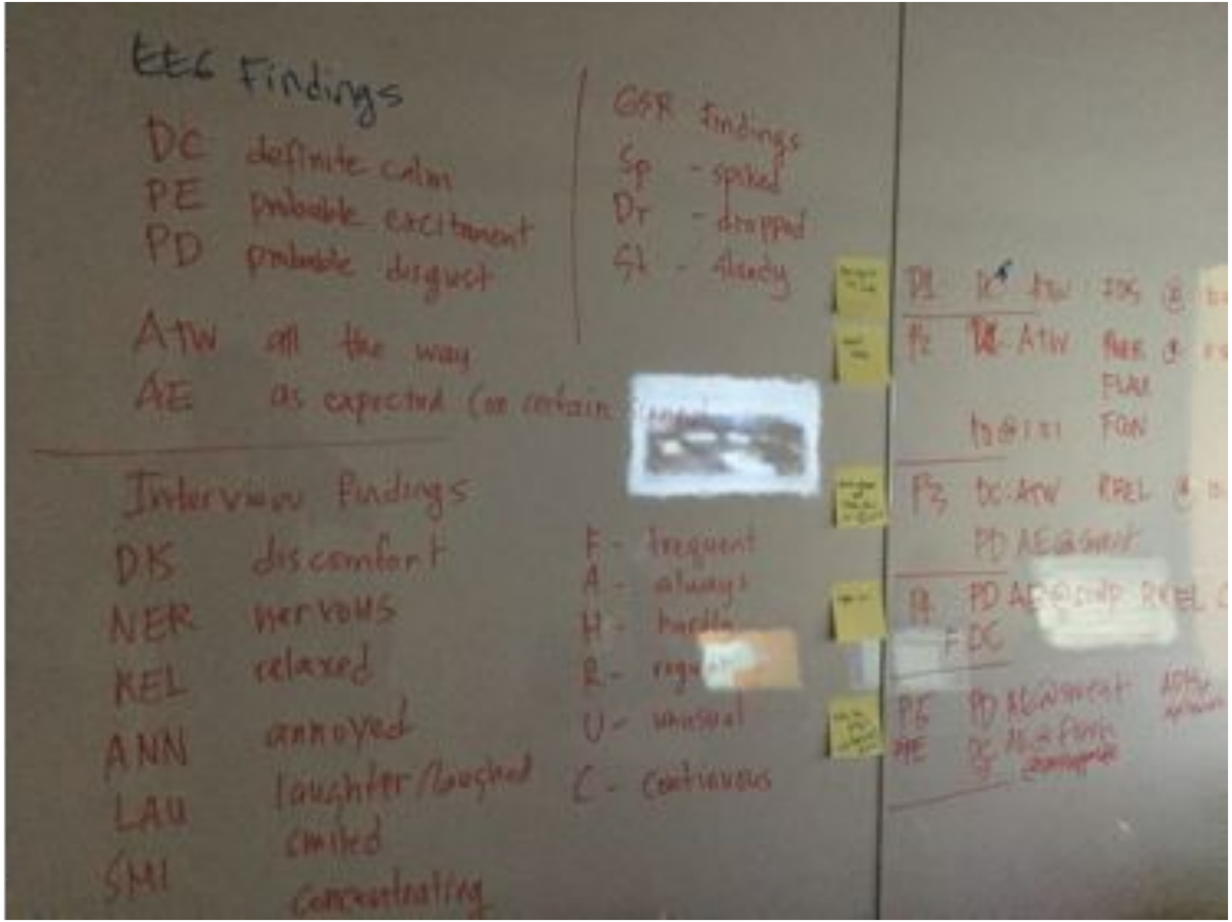

EEG:BRAIN
EMOTIV
EPOC
Insight



	A	B	C	D	E	F	G	H	I	J	K	L
1	title:2	recorded:14	sampling:12	subject:16	labels:COUN	chan:12	units:emotiv					
2	73	125.128204	126.153847	127.179482	56.9230766	145.128204	118.974358	70.2564087	153.846146	167.179489	27873	869.230774
3	74	126.153847	126.153847	127.179482	57.9487152	143.07692	120	70.2564087	152.820511	168.205124	27873	877.435852
4	75	126.153847	126.153847	127.179482	56.9230766	145.128204	118.974358	69.2307663	153.846146	168.205124	27873	885.128174
5	76	126.153847	126.153847	127.179482	56.9230766	146.153839	118.974358	70.2564087	156.92308	169.230759	27873	893.333313
6	77	126.153847	126.153847	127.179482	57.9487152	144.102554	118.974358	70.2564087	156.92308	169.230759	27873	901.025635
7	78	126.153847	126.153847	127.179482	56.9230766	145.128204	118.974358	70.2564087	150.256409	168.205124	27873	908.717957
8	79	126.153847	126.153847	127.179482	56.9230766	143.07692	120	69.2307663	154.871796	168.205124	27873	916.923035
9	80	126.153847	126.153847	127.179482	55.8974342	145.128204	118.974358	69.2307663	151.794861	168.205124	27873	924.615356
10	81	126.153847	126.153847	127.179482	55.8974342	144.102554	118.974358	70.2564087	157.948715	168.205124	27873	932.307678
11	82	126.153847	126.153847	127.179482	56.9230766	144.102554	118.974358	70.2564087	157.948715	168.205124	27873	940.512817
12	83	126.153847	126.153847	127.179482	55.8974342	146.153839	118.974358	69.2307663	160	167.179489	27873	948.205078
13	84	126.153847	126.153847	127.179482	55.8974342	146.153839	118.974358	70.2564087	152.820511	169.230759	27873	955.8974
14	85	126.153847	126.153847	126.153847	56.9230766	145.128204	120	67.1794891	151.794861	169.230759	27873	964.102539
15	86	126.153847	126.153847	126.153847	55.8974342	145.128204	118.974358	70.2564087	152.820511	168.205124	27873	971.794861
16	87	126.153847	126.153847	126.153847	54.8717918	145.128204	120	70.2564087	152.820511	168.205124	27873	980
17	88	126.153847	126.153847	126.153847	55.8974342	143.07692	120	69.2307663	152.820511	168.205124	27873	987.692261
18	89	126.153847	126.153847	126.153847	55.8974342	144.102554	120	69.2307663	153.846146	168.205124	27873	995.384583
19	90	126.153847	126.153847	126.153847	56.9230766	143.07692	120	69.2307663	152.820511	169.230759	27874	3.58974361
20	91	126.153847	126.153847	126.153847	56.9230766	144.102554	118.974358	69.2307663	152.820511	169.230759	27874	11.2820511
21	92	126.153847	125.128204	126.153847	57.9487152	143.07692	118.974358	70.2564087	153.846146	168.205124	27874	18.9743576
22	93	126.153847	125.128204	126.153847	57.9487152	145.128204	118.974358	69.2307663	152.820511	168.205124	27874	27.1794872
23	94	126.153847	126.153847	126.153847	57.9487152	144.102554	118.974358	69.2307663	150.769226	169.230759	27874	34.8717957

Raw visualization of EEG signals

Raw data outputs of EEG Signals

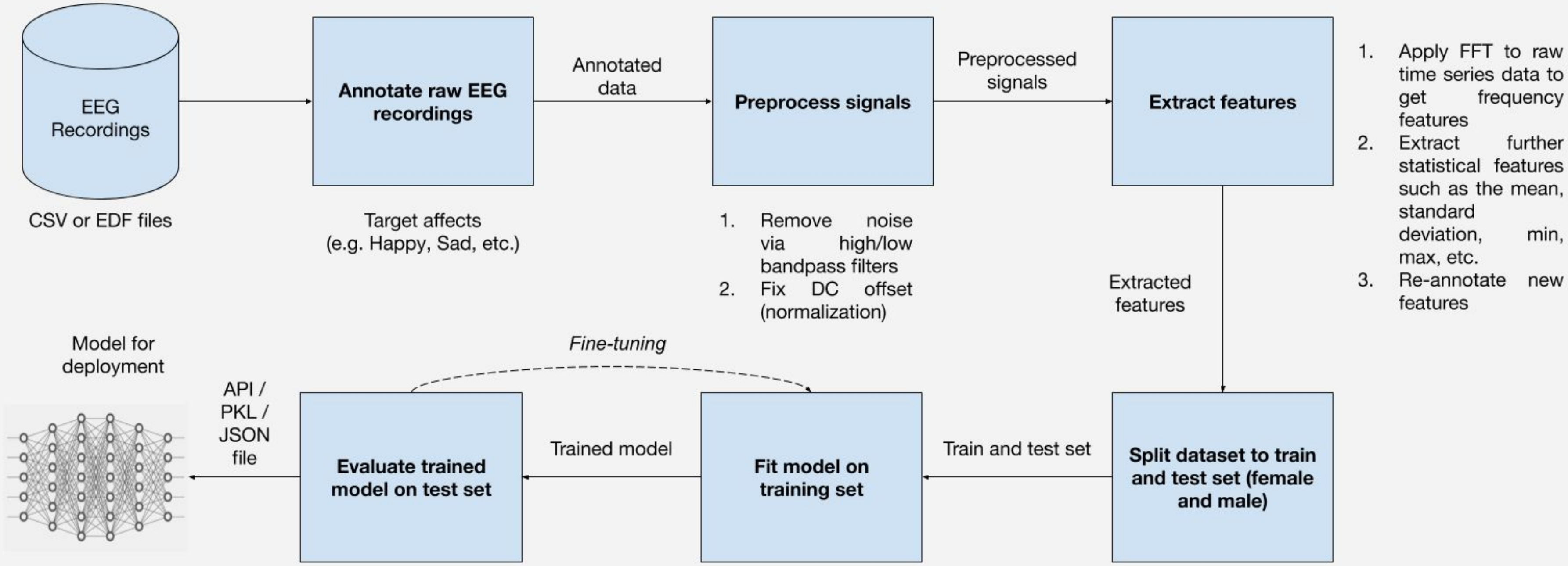


How we annotated user responses during affective testing

2GIRLS
GSR findings
Interview findings
NO GSR
only early GSR


2GIRLS
P6
DC@COOL
DC:ATW@V1
GSR FLAT
arousal increase @"dandruff"
valence drop @V2 (15s)
P7
DC@V1 ATW
P9
DC ATW
definite relieved @clean
DC@V2
PD@dirt V3
DC@ATW V1
almost flat/jagged

NuWorks DeepDive Model Improvement



Results: Insights from User emotions during testing

- We were able to identify which scenes had high/low valence and arousal values based from the EEG data of participants in the affective testing stage
- We could confirm how certain visual elements can be tagged with certain affects
- User insights from EEG can be used to accelerate the Rapid Content Prototyping stages in the Media Production


Bedroom
SRC TC: 03:13:47:19
A003C019_161202_R212.mov


Motor Bike
SRC TC: 01:18:27:03
A001C034_161201_R212.mov


Dancing
SRC TC: 02:01:18:08
A002C001_161202_R212.mov


Dandruff Guy
SRC TC: 01:31:49:16
B001C015_161202_R20B.mov

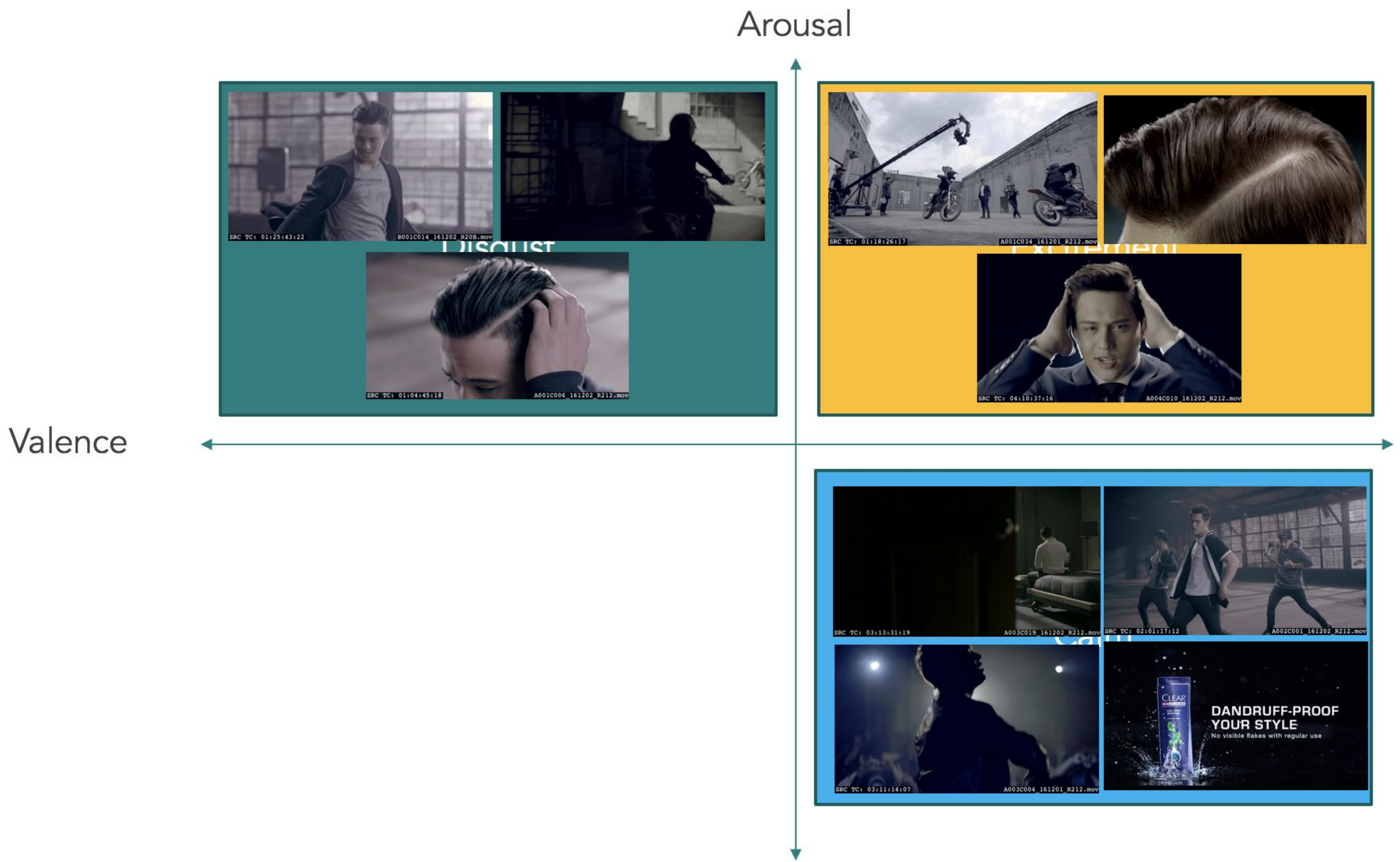

Dandruff Close Up
SRC TC: 01:04:45:22
A001C006_161202_R212.mov

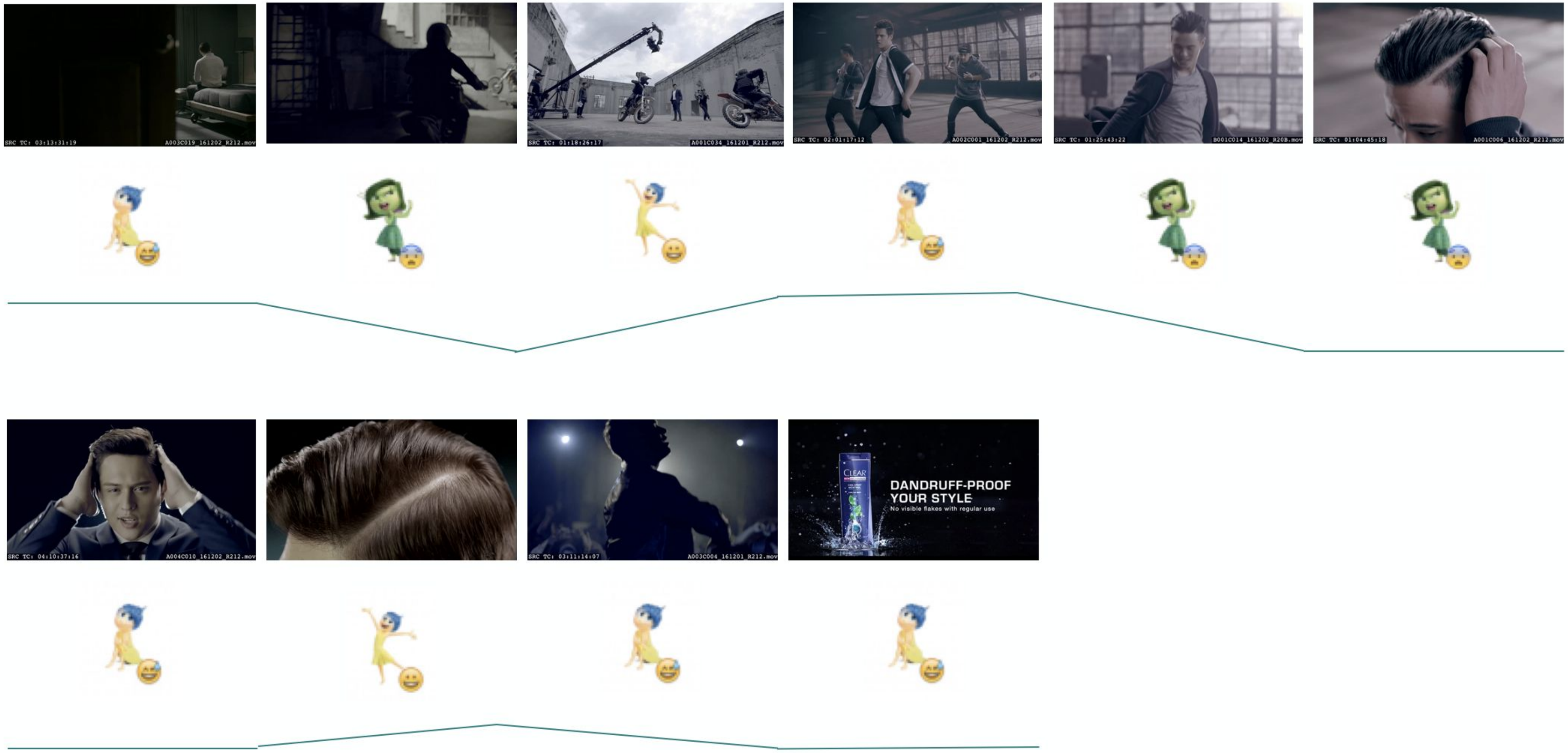

CLEAR
DANDRUFF-PROOF
YOUR STYLE
No visible flakes with regular use


Party / Singing
SRC TC: 03:13:01:16
A003C004_161201_R212.mov


Clean Scalp


Nothing to Hide


Arousal
Valence
DANDRUFF-PROOF
YOUR STYLE
No visible flakes with regular use


CLEAR
DANDRUFF-PROOF
YOUR STYLE
No visible flakes with regular use

Sample scene analysis: Bike scene

Avg. Valence: 1.024 (high)

Avg. arousal: 0.512 (high)

Affect: Possible Excitement

Pocket recommendation: **keep**

Notes: confirms interest for bicycles

EEG values display 30% spike of values on arousal for the next 3 seconds from this scene

Sample scene analysis: Enrique dance

Avg valence:1.01 (high)

Avg arousal: 0.481 (low)

Affect: Definite Calm

Pocket recommendation: **dont**

Notes: EEG values 2 seconds before and 2 seconds after hardly changed (also for most selected scenes from 15s videos)

Sample scene analysis: scalp scene

Avg. Valence: 0.998 (low)

Avg. Arousal: 0.5101 (high)

Affect: Probable Disgust

Pocket recommendation: **keep**

Notes:

Some participants remembered dandruff on this scene even there was none as this was unedited


UNSTOPPABLE
DANDRUFF-FREE FRESHNESS
no visible flakes with regular use


no visible flakes with regular use

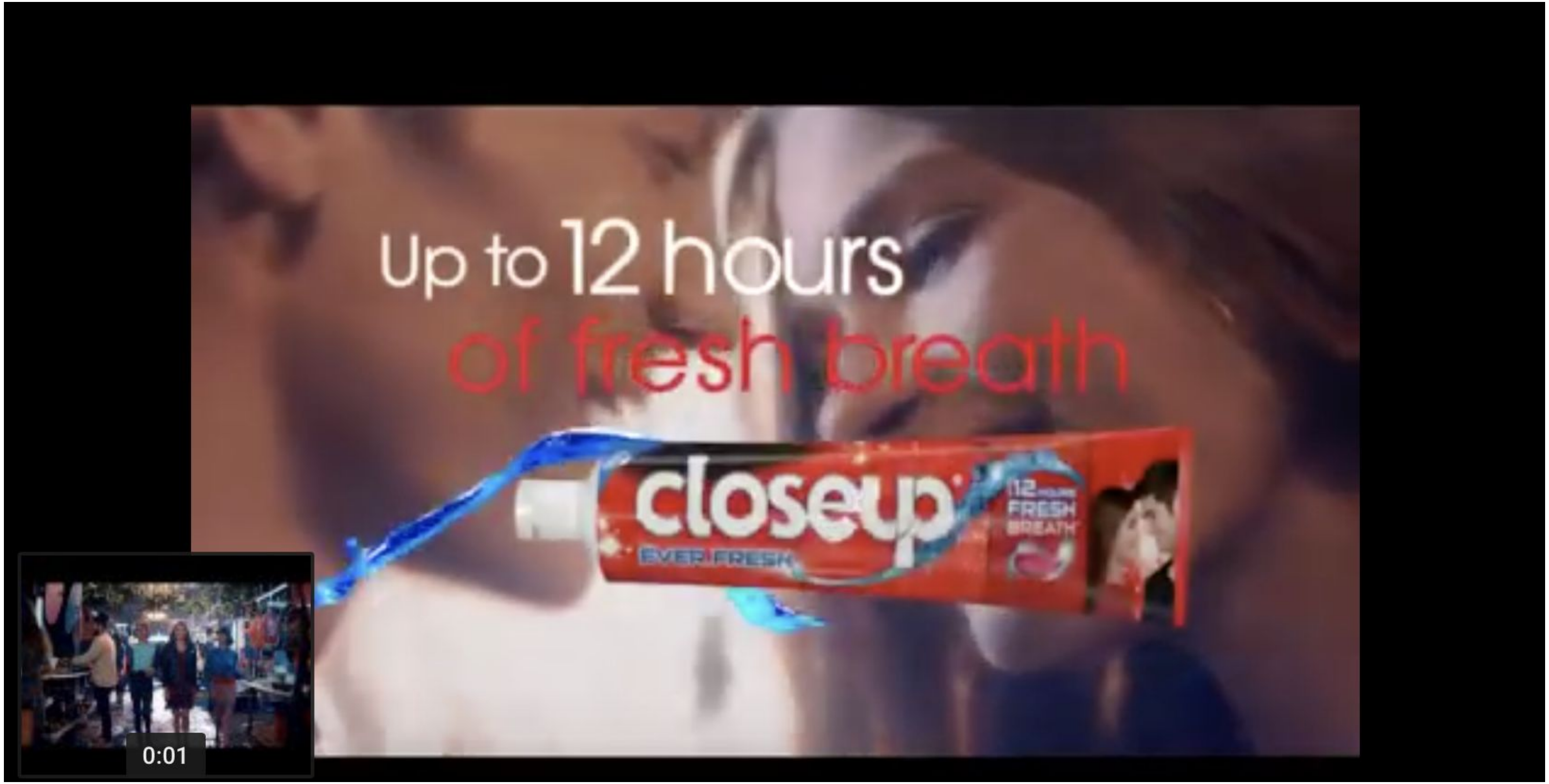
Conclusion

- We were able to produce a model that can detect 3 affects from EEG data of users during their viewing experiences
- Quals by marketing were augmented by the implemented model especially on cases where interviews failed to extract certain insights
- Rapid Content Prototyping process in Ad Agencies are expedited with the use of our model
- Certain visual elements can be associated with emotions (but these can be very culturally-specific)

Future Work

- Increase the number of affects it can detect from 3 to 7
- Increase participant number for model building
- Cover unusual affects like “kilig”
- Design affective experiments towards measuring conversion rate in advertising

CloseUP #CloserThanEver Indonesia vs Philippines



“Kilig” scene which is only shown in the PH version


Planes **dont flap** their wings to fly, but
birds **dont take off** from trees either...


A car can **run faster** than a cheetah but it can **never climb** a tree..

Resources:

- Check out https://github.com/jrdndj/techtalkslides
- Website: https://jrdndj.github.io

Using EEG for Emotion Experience Design in TV Commercials

by **Jordan** Deja

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