INTRODUCTION

NAILS: Neurally Augmented Image Labelling Strategies

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- · The Insight Centre for Data Analytics
- · Dublin City University
- · <u>Topic:</u> P300 signals for image labelling

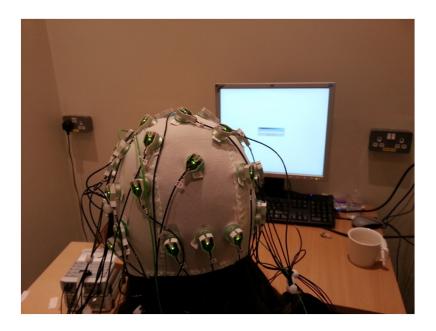
OVERVIEW

- · Overview
- · Examples on EEG, P300 & ERPs

- · Our Task & Data Plan
- · Schedule & Plan

QUICKLY: EEG

 EEG (Electroencephalography) recording systems come in many forms





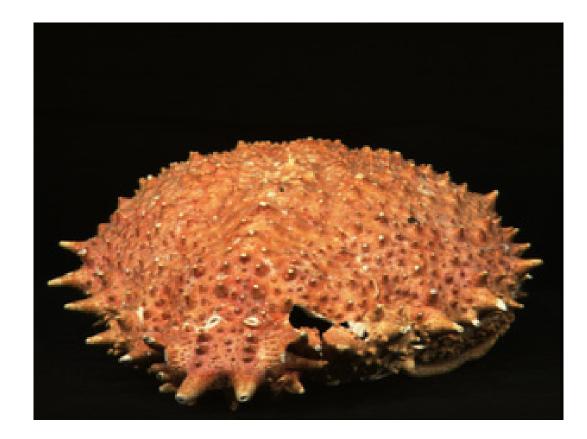


- · This concept is best introduced with an example
- Find the image of a can of coke in the following stream of images:











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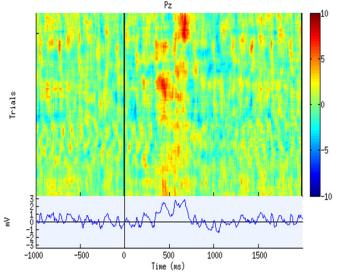


• Everybody noticed it?



P300 RESPONSE

- There is nothing special about the can of coke, I could have told you to look out for the cup instead or used entirely different images
- This works because you do not know when the can of coke will appear and as a result when it does, your attentior orientates to it (sort of like going through television stations)

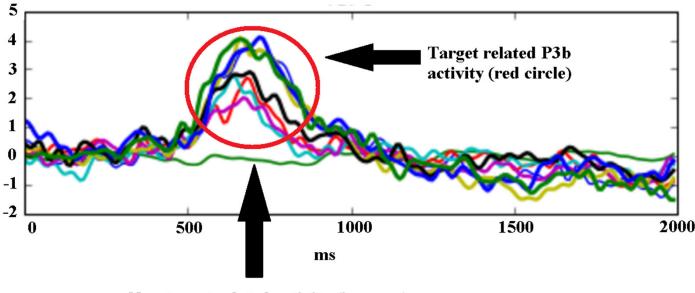


ANOTHER EXAMPLE (RSVP)

exp	L,py 🔞
247	
248	····#·using·a·distractor··shape·so·no·letter·distractor
249	····selected_targets_letter.=-BASE_LETTER_ALPHABET[:]
250	<pre>random.seed(cfg_SEED_POINT ++ SUB_ID)</pre>
251	····random.shuffle(selected_targets_letter)
252	····selected_targets_letter_1targ =- [·selected_targets_letter.pop(wi(0))·]
253	···· selected_targets_letter_4targ = [selected_targets_letter.pop(wi(0)) for t_ in range(4)]
254	···· selected_standards_letter =- selected_targets_letter
255	
256	
257	
258	win.close() with the second se
259	$\dots \dots $
260 261	<pre>leb = LifelogExpBlock.LifelogExpBlock(cfg_lifelog_pickle_path, cfg_lifelog_img_dir ,SEED_PAR_ID=SUB_ID, \</pre>
261	
262	
263	im_stims, stim_ordering = leb.prepareStimPresentation_0t8(target_ids=target_ids, distractor_ids=distractor_ids)
265	the stand of the fing a real property of the sector of sector and sector
265	print-im_stims
267	vis_triager==TriagerMaker()
268	deails == leb.presentation(im.stims, stim_ordering, stim_time=stim_time, txt_logger=txt_logger, vis_trigger.=.vis_trigger.=.udp_trig_er.=.udp_trigid_str.=.k, .test_run=cfg_TES
269	if k not in results_forPickle.kevs(): results_forPickle[k] = []
270	results_forPickle[k].append(details)
271	handlePickle()
272	
273	······return details
274	
275	
276	···· def·LLrand(k_, ·target_ids·=-[], ·distractor_ids·=-[],SEED_0FFSET=0):
277	······win.close()
278	$\cdots \cdots k = "\{0\} = \{1\} = \{2\}".format(k_{-}, len(target_ids), len(distractor_ids))$
279	··········leb = LifelogExpBlock.LifelogExpBlock(cfg_lifelog_pickle_path, cfg_lifelog_img_dir ,SEED_PAR_ID=SUB_ID, \
280	<pre>SEED=cfg_SEED_POINT+SEED_OFFSET, win_func=setupMainWindow, show_dists=cfg_SHOW_DISTS, `\</pre>
281	max_diff=1)
282	······im_stims, stim_ordering = leb.prepareStimPresentation_rand(·target_ids=target_ids, distractor_ids=distractor_ids)
283	print-im_stims
284	vis_trigger = TriggerMaker()
285	details =-leb.presentation(im_stims, stim_ordering, stim_time=stim_time, txt_logger=txt_logger, vis_trigger.evis_trigger, udp_trigger.evidp_trig, id_str.e.k, test_run =-cfg_
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 . RN0 	002293_2118BT_20150224_163503E': <psychopy.visual.image.imagestim 0x13af7fb0="" at="" object="">, 'B00002103_2118BT_20150224_161502E': <psychopy.visual.image.imagestim 0x68892130="" at="" object="">,</psychopy.visual.image.imagestim></psychopy.visual.image.imagestim>

P300: A LIFELOG EXAMPLE

 We've done this where participants are required to search a stream of visual data for certain targets images/concepts



Non-target related activity (in green)

P300-RSVP STRATEGY

· What this type of approach takes advantage of:

 The speed of human visual recognition/processing i.e. we can often present these images at a very fast rate (example given) via RSVP (Rapid Serial Visual Presentation)

• The on-the-fly capability of defining search tasks for users (within some constraints)

- For NTCIR-13 we will release a dataset from 10 experiment participants preforming a number of search tasks
- The images used will be derived from the Places 2¹
 dataset and the ImageNet² dataset











Places 2 dataset made available from MIT , ²ImageNet Stanford vision lab

- The experiment for each participant will involve 8 search tasks
- i.e. *"Find photos of cats amongst the following stream of images"*
- \cdot Each search task is broken into 3 blocks (24 blocks total)
- \cdot Each block contains 450 images presented at 5 Hz

 45 (10%) of these are targets (relevant) and 405 (90%) are non-targets(non-relevant)

- The aim for participating organisations will be to successfully predict from neural and behavioural (key press) which images are relevant (target) or non-relevant (non-target) for the relevant search query
- Participating organisations will be provided with training/validation data: 2 of 3 blocks for each search task

- During the evaluation period participating organisations will benchmark their prediction models using an online REST API (with some time-based limitations)
- We will provide raw/pre-processed feature vector for both neural / behavioural data for each image (-X task X subject) and must submit a prediction (0, 1)
- Accuracy will be assessed across all predictions for subjects X search – tasks on a withheld test set

TYPES OF SEARCH TASKS

- · *Search-tasks will be modelled around those in ILSVRC
 - Four scene-centric search-tasks from Places2 i.e. find images of 'art_gallery', 'nursing_home', 'oilrig', 'television_room'
 - Four object-centric search tasks from ImageNet i.e. find images of 'cat', 'car', 'mushroom', 'desert'

Exact search tasks will be identified during a piloting phase identifying those which a human is capable of sufficiently doin

TYPES OF DATA

- Data will be available in raw and numerous pre-processed formats to participants to lower the barrier to entry for those unfamiliar with processing EEG signals
- Neural-data feature vectors will include raw, bandpassed, wavelet, ICA, and other common feature transformations on which ML methods can be applied

TYPES OF DATA

- Example pipelines will be provided in python enabling participating organisation to leverage an already working (naive) solution to get started right away
- Before the evaluation period begins code examples will be provided showing participants how to interact with the online evaluation system

SCHEDULE & PLAN

- Next Steps:
 - Internal DCU ethics application to begin conducting experimentation (*July 2016*) - Approved (August)
 - Pilot experiments validating RT & neural responses (Sep 2016 Oct 2016)
 - Collection of final experimental dataset (*Oct 2016 Nov 2016*)
 - Dataset release (*Jan 2017*)

CONCLUSION

- We can better understand the types of search-tasks where detection of neural events are useful
- Amplify insights and perspectives on labelling-behaviour of users (i.e. nuance and state-of-mind)
- Will help to develop state-of-the-art methods for such tasks
- Will help to understand the connection between behavioural and neural responses when performing an image search-task in this way

THANK YOU

- Further information will be available as the task structure develops at:
 - <u>ntcir-nails.computing.dcu.ie</u>
- If any further queries please feel free to: <u>ghealy@computing.dcu.ie</u>