

Best of both worlds:

Integration of EEG and survey data for TV commercial evaluation

Mathieu Bertin ^{*1}Yasumatsu Ken ^{*1}Tanida Yasuo ^{*1}^{*1} Synergy Marketing, Inc.

Current evaluation methods of TV advertisements can be grouped into two categories. Classical methods involve a survey or interview where the viewer reports his subjective experience after diffusion of an ad. Newer methods, based on neuroscience tools, extract objective information of a viewer's brain response during the advertisement screening. We propose in this paper a statistical model for integration of those two complementary outputs.

1. Introduction

The emerging field of neuromarketing has found a strong application in the pre-testing of television advertisement. During a typical experiment, an ad is displayed to a few subjects while brain activity is recorded through various measurement techniques, Electroencephalography (EEG) being the most widely used due to its low cost and high temporal precision. The resulting activation data is then analyzed to infer the future buying behavior of the subject, and thus the efficiency of the ad.

EEG measurements complement classical methods of ad evaluation such as self-report surveys and interviews. Communications of neuromarketing firms and scientific literature have focused on comparing efficiency of both methods in accurately predicting actual buying behavior. While we agree that such research is critical for asserting the relevancy of the new neuromarketing techniques, we argue that both classical survey and EEG data offer distinct and complementary insight on how advertising is experienced by viewers. Therefore, a sound research topic is the integration those two outputs into a simple and actionable view of ad effectiveness.

As a first step in this direction, we propose in the current paper a statistical model of information integration, based on the hierarchical Bayesian framework. In particular, we focus on the evaluation of the different emotions felt during the viewing of an advertisement, and the timing of the stimulus eliciting each of them.

2. Overview of ad evaluation methods

We quickly review in this section two evaluation methods for pre-testing advertising: survey and EEG measurement. The data obtained through these methods will form the input of the model described in the following section.

2.1 Survey data

Numerous survey templates exist to evaluate TV advertising. They usually include two categories of questions:

- Numerical evaluation of the ad efficiency, for instance on a 1~5 scale. Examples include "How appealing did you find this advertisement?" and so forth.

- The properties of the ad, which can be expressed as the emotions felt during the viewing, using a multiple-answer format. Examples include "funny", "irritating", "warm-hearted".

The current paper focused on modeling emotion felt during the viewing of an ad. We will therefore consider only the later category of questions.

2.2 EEG information

EEG is the recording of electrical activity along different locations on the scalp. A wide amount of recent literature has been devoted to extract meaningful information from the raw electrical signal data. The three following signals are among the most relevant to evaluate ad efficiency:

- *Emotion arousal*: the intensity of a felt emotion has been related to the general activation of the prefrontal cortex, for instance the average of the inverse alpha activation of F3 and F4 locations in the 10-20 system [Schmidt et al., 2001].
- *Emotion valence*: pleasant and unpleasant emotions can be distinguished by measuring the asymmetry between the activation of the left and right lobe of the prefrontal cortex [Davidson, 2004]. Pleasant experiences are linked to stronger activation in the left region, and vice-versa. A meaningful signal is for instance the quotient of the inverse alpha activation of the F3 and F4 locations.
- *Long-term memory*: knowing if an ad has a long-standing effect in the viewer's memory is of paramount importance. Activation in the hippocampus and the strongly related medial temporal cortex has long been established as a good predictor of successful long-term memory encoding [Henson 2005]. The average of the inverse alpha activation of T3 and T4 locations is therefore another critical signal.

3. Model

3.1 Intuition

The basic intuition behind the proposed model is the following. Suppose, as an ideal example, that an ad contains two salient stimuli, a "funny" one at the 10th second, and a "warm-hearted" one at the 14th. The subjective strength of each stimulus depends on the tastes and the personality of each viewer. Suppose that some viewers evaluate the ad as "funny" and show a strong brain activation following the 10th second, while another group report

the ad as “warm-hearted” and react strongly after the 14th. Taking the average activation of the whole population would only show a blurry few-seconds long activation around the two stimuli. Conversely, taking the survey into consideration by analyzing brain activity of the two groups separately would help pinpointing the two stimuli, while providing an insight of how each of them is felt.

3.2 Formalization

The proposed model follows the hierarchical Bayes framework [Rossi et al., 2003]. Time is discretized on the second by second level for simplicity, and because is a usual sampling frequency of preprocessed signal on EEG devices.

We consider $K>1$ emotions, corresponding to the emotions queried on the evaluation survey, plus a “no emotion” value. We hypothesize that an ad contains a few critical stimuli, each of them linked to a given emotion. At each second, for each emotion, a stimulus can be generated following a Bernoulli process:

$$s_{t,k} \sim \text{Bernoulli}(\rho)$$

Where $s_{t,k} \in \{0,1\}$ marks the presence or absence of stimulus, t is the current time in seconds, k the corresponding emotion, and ρ the probability of stimulus generation.

We consider N viewers for a given experiment. Each viewer has a probability of being indifferent to a given stimulus, or of generating random emotions only loosely linked to the ad. We model this perception noise with a binary symmetric channel [MacKay, 2003], modified to generate the same number of false positives and false negatives:

$$P(f_{t,k,n}=0 / s_{t,k}=0) = 1 - q_n * \rho * K / (1 - \rho * K)$$

$$P(f_{t,k,n}=1 / s_{t,k}=0) = q_n * \rho * K / (1 - \rho * K)$$

$$P(f_{t,k,n}=0 / s_{t,k}=1) = q_n$$

$$P(f_{t,k,n}=1 / s_{t,k}=1) = 1 - q_n$$

Where $f_{t,k,n} \in \{0,1\}$ is the probability of experiencing a stimulus for emotion k , at time t , for the subject n . The probability of error q_n is generated for each viewer using a uniform prior:

$$q_n \sim \text{Unif}(0, 0.5)$$

After being induced by a stimulus, a felt emotion is hypothesized to last a few moments, with a fixed probability of extinction at each following second. Therefore, the currently felt emotion is given by:

$$P(e_{t,k,n} = 0 / f_{t,k,n} = 1) = 0$$

$$P(e_{t,k,n} = 1 / f_{t,k,n} = 1) = 1$$

$$P(e_{t,k,n} = 0 / f_{t,k,n} = 0, e_{t-1,k,n} = 0) = 1$$

$$P(e_{t,k,n} = 1 / f_{t,k,n} = 0, e_{t-1,k,n} = 0) = 0$$

$$P(e_{t,k,n} = 0 / f_{t,k,n} = 0, e_{t-1,k,n} = 1) = \pi$$

$$P(e_{t,k,n} = 1 / f_{t,k,n} = 0, e_{t-1,k,n} = 1) = 1 - \pi$$

Where $e_{t,k,n} \in \{0,1\}$ encodes if emotion k is felt at time t by the viewer n , and π is the probability of extinction. We assume that emotions are felt on at a time by each viewer. In the case where multiple stimuli of different emotions are generated at the exact same time for a given subject, only one emotion is felt, chosen randomly between the stimuli. If at a time t no other emotion is felt, the emotion “no emotion” is set to 1.

The EEG signal is preprocessed to extract M significant information, such as the 3 dimensions arousal/valence/memory described in the previous section. The different signals are

generated from the currently felt emotion using a normal distribution:

$$x_{t,m,n} \sim \sum_{k \in \{1, \dots, K\}} \text{Normal}(\mu_{m,k}, 1) * e_{t,k,n}$$

Where $m \in 1, \dots, M$ is the index of the EEG signal. The mean of the normal distribution $\mu_{m,k}$, is derived from previous studies on the relationship between EEG activation and reported emotion. Here we consider the arousal/valence classification of emotions [Lang, 1995]. For instance, the emotion “funny” has high positive arousal and valence, while “irritating” has positive arousal and negative valence. For emotions and EEG information where no obvious value is available, such as the “long-term memory” dimension, a normal prior is assumed:

$$\mu_{m,k} \sim \text{Normal}(0, 1)$$

Finally, every emotion felt during the course of the ad is related in the survey:

$$r_{m,n} = \text{OR}_{t \in \{1, \dots, L\}} f_{t,k,n}$$

where $r_{m,n} \in \{0,1\}$ shows whether the subject n has described the ad as inducing emotion m or not.

From the evidence (x, r) obtained from EEG and survey data during an experiment, numerical methods such as MCMC can infer the most probable timing and related emotion of each salient stimulus in a commercial.

4. Conclusion

We proposed a model for EEG and survey data integration. The model offers a framework to easily incorporate knowledge from previous research on emotion and EEG signal, and can generate new insight on how an advertisement is felt by each viewer.

The model output, namely the characteristics of the salient stimuli of a given ad, is not directly observable by other methods. Therefore, an important remaining issue is how to evaluate its pertinence and accuracy, a challenge shared by other models of brain data integration [Yoshioka et al., 2008].

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