LEARNING AFFECTIVE MEANINGS THAT DERIVES THE SOCIAL BEHAVIOR USING BIDIRECTIONAL ENCODER REPRESENTATIONS FROM TRANSFORMERS

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ABSTRACT

Predicting the outcome of a process requires modeling the system dynamic and observing the states. In the context of social behaviors, sentiments characterize the states of the system. Affect Control Theory (ACT) uses sentiments to manifest potential interaction. ACT is a generative theory of culture and behavior based on a three-dimensional sentiment lexicon. Traditionally, the sentiments are quantified using survey data which is fed into a regression model to explain social behavior. The lexicons used in the survey are limited due to prohibitive cost. This paper uses a fine-tuned Bidirectional Encoder Representations from Transformers (BERT) model to develop a replacement for these surveys. This model achieves state-of-the-art accuracy in estimating affective meanings, expanding the affective lexicon, and allowing more behaviors to be explained.

1 INTRODUCTION

Consider talking to your mentor for some advice about how to behave with your colleague. Your mentor probably starts asking questions about the culture in the workspace and may continue asking about the identity of the person. These questions could be about institutional constraints such as being the manager, or they could be personality sentiment such as being nice or active. Knowing this information, your mentor may have some initial recommendations, but you adapt your behavior after observing the reactions from the colleague. This is a descriptive scenario for a daily interaction. Affect Control Theory (ACT) quantifies the variables in this scenario and produces equations for simulating human behavior in social interactions.

ACT was introduced in the 1970s (Heise, 1977) and has been validated in more than 100 social science projects (Robinson & Smith-Lovin, 2018). ACT has been used in interdisciplinary applications such as Human-Computer Interactions (Robillard & Hoey, 2018), finding how language cultures affect social response (Kriegal et al., 2017), and modeling identities and behaviors within groups (Rogers & Smith-Lovin, 2019). More recently, Mostafavi (2021) introduced ACT to estimate and track emotional states during online messaging. For example, chatbots can use the ACT framework to understand the emotional state of the customer in real time and adapt their behavior accordingly. While the potential uses of ACT are understanding emotional changes during online messaging (Mostafavi, 2021), real life applications are limited due to the vocabulary size of affective dictionaries.

ACT uses a three-dimensional affective meaning space as a quantified form of sentiments (Heise, 1977). ACT uses Evaluation [good vs. bad], Potency [powerful vs. powerless], and Activity [active vs. passive] (EPA) space introduced by Osgood et al. (1957) as a semantic differential form of affective meaning. These affective lexicons represent the word of interest within cultural and social boundaries (Robinson & Smith-Lovin, 1992). Fontaine et al. (2007) found that EPA scores are the first three principal components after reducing dimensionality on 144 features representing the main components of emotions.

∗https://moeenm.github.io
Historically, surveys are used to quantify the affective meanings within a cultural group. To compensate for unreliability in the survey, most EPA surveys are designed so that each word is scored by at least 25 different participants. Thus, finding the affective meaning for 5000 words requires over 125,000 ratings and 400 hours of respondent time (Heise, 2010). Because ACT also requires EPA estimates for social interactions, EPA surveys must also include participants to score a large number of additional scenarios. Due to the high cost and time required, most EPA surveys have been focused on a small number of words which has limited the applicability of ACT. As an alternative to conducting new surveys, researchers have tried supervised (Mostafavi & Porter, 2021; Li et al., 2017) and semi-supervised (Althothali & Hoey, 2017) methods on shallow word-embeddings to find affective lexicons. However, their performance on the activity and potency dimensions is poor. In this paper, we discuss the main limitations for the applicability of shallow word-embeddings. In this work, we use deep sentence-embedding to consider contextual aspects of concepts in social events. For that purpose, we show how to generate a contextual data-set describing social events to train and test a deep neural network. We use Bidirectional Encoder Representations from Transformers (BERT) embedding tuned for finding affective lexicons. The performance of our approach achieves state-of-the-art accuracy in estimating affective lexicons.

2 BACKGROUND

In this section, we start with a review of ACT and how it uses sentiment of social characters to model interactions. Then we review related works to estimate affective meanings from corpus and discuss their main limitations. Finally, we briefly review the BERT model and how we can use this model as a deep embedding space.

2.1 AFFECT CONTROL THEORY

According to ACT, every concept representing interactions is quantified in EPA space. The baseline EPA representation of words is known as sentiments. Figure 1 visualizes EPA representation of some sample words. In this plot, we can observe that “suicidal” and “nervous” both have bad, powerless, and passive meanings but “suicidal” is more negative in all three dimensions. On the other hand, “happy” is a pleasant, powerful, and active word. Note the range of EPA ratings is from -4.3 to 4.3.

ACT considers social interactions or events that include an actor that behaves toward an object. Extracting the Actor-Behavior-Object (ABO) components of an event is the first step in modeling interactions (Heise, 2010). Actor/Object in an event has an identity such as “baby” or “boss”. In some cases, the characteristics of an actor/object is part of the identity. For example, the identity of a
person is “nervous boss”. In these cases, modifiers are amalgamated to their identities. Figure 1 is a visualization of sample words in EPA space. It uses symbols to represent that a concept is evaluated as identity, behavior, or modifier.

According to ACT theory, social events make impressions on ABO characters (Robinson & Smith-Lovin, 1999). Consider an example of observing “a bossy employer argues with an employee”. This observation leads people to evaluate both the actor and the object of the interaction are less pleasant than initial thoughts. They may also feel the employer is more powerful, and the employee is more powerless than their baseline sentiments after observing this event. Being more pleasant/powerful is impression of observing and event and it means higher value in evaluation/potency.

If actor/object behaves as expected, then impression of identity does not change far from baseline, but if actor/object does something unexpected, then a large change from the baseline is expected. Deflection is the euclidean distance between the baseline sentiments of ABO characters and their impressions following an event. If the impression of an ABO event is close to initial sentiments, deflection is small, and it gets bigger when the impression of the event leaves the initial sentiments. ACT discusses that minimizing deflection is the driving force in human activity. Highly deflecting events create social and physiological distress (Goldstein, 1989). For example, if a grandmother fights with her grandchild, the grandmother and the grandchild feel distressed and prefer to do something. We may expect one side to take an action, like apologize, to bring the impression of their identities back to where they views themselves in the society. This highly deflected event is very different from two soldiers fighting in a battle. The soldiers are supposed to fight with enemies in battle, so they may not feel social pressure to change their behavior.

Heise (2013) developed a software called INTERACT. It simulates sequential interactions between two identities and finds the behavior that minimizes the deflection. It can also predict attributes and emotions during the interaction. Consider the following set of events/interactions that we simulate using INTERACT,

1. Employee greets bossy employer.
2. Bossy employer asks employee.
3. Employee replies to bossy employer.
4. Bossy employer argues with employee.
5. Employee listens to / disobeys bossy employer.

The visualization in Figure 2 shows how the impression of actor/object’s identity changed based on sequential interactions. Let’s focus on evaluation dimension for the employer. Employer has a negative baseline evaluation but after observing the first two interactions, it increases. The first two interactions include positively rated behaviors. After second interaction, impression of the employer’s identity is positively evaluated and so the next positively evaluated action, replies to, does not move it substantially. A positive behavior is expected from a positive identity. However, in the fourth interaction, the employer is evaluated to have an unpleasant identity after doing a negative behavior, argue with. For the fifth event, we have shown how the impression of different actions by the employee has significantly moved the states for both the actor and the object. The sequential interactions discussed here are similar to our mentorship example discussed the beginning. It shows how understanding the interaction dynamic can make us predict the consequences of our behavior.

ACT has rules to describe how impression of an events changes affective meaning of ABO characters. ACT uses either mathematical equations or descriptive forms to discuss these rules. The following two descriptive forms show how the identity of the actor is impressed by some events,

- **Actors** seem nice when they behave in a positive way toward others. This describes morality fact in ACT literature. Observing the evaluation dimension for the actors after he greets the object, we can find this behavior resulted in an impression of being nicer (getting larger evaluation) comparing to the state in the last step.

- **Active behaviors** make the actors seem more active. Observing the boss’s activity, he is considered more active after he argues with [active behavior] the employee.

As we have seen in the descriptive forms, events can change the impression of ABO characters. They move them toward or away from their current/initial sentiments.
To formulate the process in mathematical space, we briefly review the quantification process using surveys. The first step is quantifying the sentiments that are introduced as identity, behavior, and modifier. For this purpose, at least 25 participants rate words of interest in EPA space (Heise, 2010). In this survey, the participants rate how they feel about an identity/behavior/modifier such as “employer”. After aggregating the sentiment surveys, every concept is assigned to its baseline affective meaning. The next step is identifying contributing facts that derive the impressions of events (Robinson & Smith-Lovin, 1999). For this purpose, the participants rate ABO characters again after observing a set of events. For example, participants rate affective meaning of “employee”, “greet”, and “employer” after observing “the employee greets the employer”. As we discussed earlier, the ratings of ABO could be different from the initial basements. ACT uses regression models, known as impression change equations, to estimate these changes (Heise, 2013). Let $X = [A_e, A_p, A_a, B_e, B_p, B_a, O_e, O_p, O_a]^T$ represent the EPA values/sentiments of an ABO triple, where $\{A, B, O\}$ represent the ABO characters and $\{e, p, a\}$ the EPA components. Consider further the two-way interactions $X^2 = [A_e B_e, A_e O_e, A_e B_a, \ldots A_a O_a]^T$ and three-way interactions $X^3 = [A_e B_e O_e, A_e B_p O_p, A_e B_a O_a, \ldots A_a B_a O_a]^T$. The basic structure of an impression change equation is the linear model

$$X' = \alpha X + \beta X^2 + \gamma X^3$$

where $\alpha, \beta,$ and $\gamma$ are coefficient vectors and $X'$ represent the resulting impression after the event. Modifiers can incorporated prior to impression change by changing the baseline values/sentiments (e.g. bossy employer). Averett & Heise (1987) defined amalgamation equations similar to (2) to find the sentiments for an identity with a modifier.

$$A = \rho + \theta M + \psi I,$$

where, $A, M, I,$ represent affective meaning of actor’s identity, modifier, baseline identity and $\rho, \theta, \psi$ are vector of intercepts and coefficient matrices. Equation (2) is a weighted average of the evaluation for the modifier and the identity.

### 2.2 Finding Affective Meaning from Text

Alhothali & Hoey (2017) used graph-based sentiment lexicon induction methods to find affective lexicons associated with words. They used similarity graphs to expand affective meanings to neighbor words in four different embedding spaces. They found that using both semantics and distributional-based approaches gives the best semi-supervised result. Li et al. (2017) argued that word-embedding can represent the words' general meaning, including denotative meaning, connotative meaning, social meaning, affective meaning, reflected meaning, collocative meaning, and thematic meaning. However, ACT uses only affective meanings of the words. So word-embedding
Figure 3: Visualization of words with different affective meaning in EPA space. Circles, squares, and triangles show identities, behaviors, and modifiers. The color represents the activity dimension.

Mostafavi & Porter (2021); Li et al. (2017) used supervised methods on shallow word-embeddings to find affective meanings of the words. However, all these approaches are limited by using one representation for different meanings of a word and not considering the context.

Shallow word embeddings have only one representation for every word. On the other hand, the affective meaning of a word in identity, modifier, or behavior categories are different. For example, “mother”, “coach”, and “fool” have very different affective meanings when they are behavior or identity, but these words have only one representation in shallow embedding space. Figure 3 shows EPA values for some words that appear in different categories. We can observe how some words are mapped very differently based on their category. For example, “baby” as an identity is a pleasant and active character but is unpleasant and passive as a behavior.

To get a sense of how similar the affective meanings are between categories, we calculated the pairwise correlation of EPA values for words shared across various different categories (Table 1). We observe that, while some categories maintain high association across categories, other categories, like identity and behavior in the activity and potency dimensions have low association implying they words used in different categories represent different affective meanings. From these tables, we observe, activity and potency dimensions of common words between identity and behavior are too small to assume they represent the same affective meanings. This suggest that ACT can benefit from models that can represent contextual aspects and differentiate between different meanings of a word.

Table 1: Correlation between the affective meaning of words in identity, behavior, and modifier category of a dictionary collected in 2014 (Smith-Lovin et al., 2016).

| Identity-Modifier | Modifier-Behavior | Identity-Behavior |
|------------------|------------------|------------------|
|                  |                  |                  |
| E                | 0.93             | 0.98             | 0.73             |
| P                | 0.77             | 0.85             | 0.29             |
| A                | -0.45            | -0.27            | -0.11            |
|                  | 0.49             | 0.92             | 0.35             |
|                  | -0.39            | -0.30            | 0.30             |
|                  | -0.58            | -0.32            | 0.40             |
|                  | 0.33             | 0.67             | 0.40             |
|                  | 0.98             | 0.80             | 0.29             |
|                  | -0.27            | -0.30            | 0.30             |
|                  | -0.32            | -0.25            | 0.35             |
|                  | 0.67             | 0.67             | 0.40             |

We can observe in Table 1 that affective meanings of the words in different categories are not necessarily highly correlated. For example, there is only a 0.4 correlation between activity dimensions of words that appear both in identity and behavior categories.
Figure 4: BERTNN pipeline. Sentences describing an event are generated in the first step and pre-processed to pass to a BERT model. Then outputs corresponding to the [CLS] token is passed to a three-layer neural network to find affective meaning.

2.3 **Bidirectional Encoder Representations from Transformers**

In 2018, Google open-sourced BERT as the state-of-the-art model for a wide range of Natural Language Processing (NLP) tasks (Devlin et al., 2018). Unlike models that use previous words to predict the target word, BERT uses words on both sides of the target word in all layers. BERT gives state of the art in many challenging NLP tasks (McCormick & Ryan, 2019). BERT has been pre-trained on Wikipedia and book corpora that includes more than 10000 books. This pre-trained model knows how to represent texts. We use the base pre-trained version of BERT in this study to find the embedding of a sentence that describes one social event. To use BERT as a contextual embedding we need to perform the following processing, shown in Figure 4 (McCormick & Ryan, 2019).

1. Input variables for BERT model are two sequences of numbers known as Token and Segment IDs. By default, BERT assumes these sequences represent two sentences and two special tokens to indicate their relationship. The [CLS] token indicates the start of the first sentence, and the special token [SEP] comes at its end. We use BERT with only one sentence, but we have to use these special tokens.

2. The BERT tokenizer, known as WordPiece, tokenizes the input sentences. If the sentence tokens are in the vocabulary of the pre-trained model, they appear in the tokenized list without any modification. However, WordPiece assigns multiple tokens to a word if the word is not in its vocabulary. In that case, tokens are root vocabulary and suffix of the original word. For example, if the words “affective” and “subtext” are not included in the vocabulary, WordPiece outputs [affect, ##ive] and [sub, ##text] tokens where ## shows the two tokens came from a compound word.

3. Token IDs are indices of the tokens in the BERT tokenizer vocabulary. Segment IDs associate the tokens to one of the two sentences. Since we are passing only one sentence, the segment ID is set to 1 for all the tokens in the sentence.
The main advantage of word-embeddings derived from BERT over shallow word-embeddings is that BERT can take into account the context of a word. This means that words can be automatically given different representations when the words is used as a behavior or an identity. To take advantage of BERT word embedding, we should train it on synthetic data that represents the concepts and their category simultaneously.

3 Method

We introduce a new framework, BERTNN, that processes synthetic data, passes it to a pre-trained BERT model, and fine-tunes the result to generate extended affective meaning dictionaries. The pipeline for our method (BERTNN) is shown in Figure 4 and we discuss the details in this section.

The data used to train our model was generated from the affective dictionary described in Smith-Lovin et al. (2016). This dictionary was developed from surveys conducted between 2012-2014 and includes 929 identities, 814 behaviors, and 660 modifiers. To partition the data into training and test set, we used stratified sampling from affective dictionaries. The three categories of identities, behaviors, and modifiers in the affective dictionaries are one “strata”. We randomly sample 85% of the words in each strata for the training, 8% are selected as the test set, and the remaining 12% are used as validation set.

To generate each sample of the synthetic data, two identities, one modifier, and one behavior are randomly selected from the training set. Sentences with an Actor Behaves Modified Actor (ABMO) grammar is made (e.g., Employee greets bossy employer). In other words, each sample describes an event in ABMO grammar. We used 10000 sample events to train the regression model. After pre-processing and tokenizing ABMO sentences similar to “data pre-processing” part of the pipeline, they are sent to the pre-trained BERT model.

We used BERT pre-trained model and the outputs corresponding to [CLS] token is used as vectorized representation of the sentence. The next step is finding a mapping from the [CLS] outputs to the affective space. Mostafavi & Porter (2021) used interactions between the features for better affective predictions. We used a neural network to provide a non-linear mapping from the BERT output to the 12-dimensional ABMO values. In this neural network, the input layer is a linear dense layer. Here, we used Relu function adds required non-linearity in the network. The last layer is a dense layer that produces the 12-dimensional vector. The $L_2$ loss used in the neural networks minimized the squared error between estimated affective meaning and the target values across all 12 dimensions.

We implemented the neural network in Python using Torch package. We used AdamW with a learning rate of 5e-6 and batch size of 64. The BERT model and neural network are tuned for a few epoch. The data in the testing set is used to decide on how many iteration is good enough. The neural network output is a 12-dimension vector that is highly correlated with the affective meaning variables. We can share the code upon request. Also, the data used in this project is publicly available on the internet.

The tuning layers in our framework are trained based on the target affective dictionary. After training, this pre-trained model can predict affective meaning for new concepts.

Multiple, preferably more than 40, ABMO event that includes the concept of interest are created and pass it to the model. The affective meaning of each sentence would be the output of the network. Then the mean value of predicted affective meanings correspond to the item of the interest is found as the estimated value. For example, if “moderator” is a new identity outside the affective dictionary, we make multiple events that includes this identity as the actor or object such as, “moderator help angry client”. The events are passed to a the model of this project, then the output of actor is the predictive affective meaning for “moderator” identity.

4 Results

We compared the performance of our model with different word analogy (Kozlowski et al., 2019), regressions (Li et al., 2017), and translation matrix methods (Mostafavi & Porter, 2021) to find affective meanings (Table 2). We used RMSE, MAE, and correlation analysis to compare the result.
Table 2: Performance of several models on (Smith-Lovin et al., 2016) data. Bold indicates the best model. Our model, BERTNN, performed best in most categories.

|                | E       | P       | A       | RMSE    | Correlation | E    | P    | A    |
|----------------|---------|---------|---------|---------|-------------|------|------|------|
| **Identity**   |         |         |         |         |             |      |      |      |
| Analogy stepW. | 0.95    | 0.92    | 0.81    | 1.2     | 1.13         | 0.99 | 0.65 | 0.53 |
| Analogy regression | 0.95  | 0.95    | 0.81    | 1.22    | 1.16         | 1.00 | 0.64 | 0.48 |
| StepW Translation | 0.74  | 0.75    | 0.67    | 0.97    | 1.04         | 0.87 | 0.82 | 0.64 |
| BERTNN         | **0.55**| **0.57**| **0.51**| **0.77**| **0.76**     | 0.68 | **0.89**| **0.81**| **0.68** |
| **Behavior**   |         |         |         |         |             |      |      |      |
| Analogy stepW. | 1.17    | 0.71    | 0.68    | 1.44    | 0.90         | 0.83 | 0.73 | 0.45 |
| Analogy regression | 1.20 | 0.75    | 0.73    | 1.48    | 0.93         | 0.90 | 0.71 | 0.44 |
| StepW Translation | 0.95  | 0.67    | 0.64    | 1.21    | 0.84         | 0.82 | 0.80 | 0.52 |
| BERTNN         | **0.73**| **0.43**| **0.49**| **0.96**| **0.57**     | **0.61**| **0.87**| **0.80**| **0.79** |
| **Modifier**   |         |         |         |         |             |      |      |      |
| Analogy stepW. | 0.33    | 0.73    | 0.88    | 1.08    | 0.9         | 1.09 | 0.87 | 0.86 |
| Analogy regression | 0.56  | 0.76    | 0.92    | 1.16    | 0.93         | 1.10 | 0.86 | 0.86 |
| StepW Translation | 0.79  | 0.48    | 0.66    | 0.98    | 0.67         | 0.84 | 0.90 | 0.89 |
| BERTNN         | **0.57**| **0.48**| **0.50**| **0.74**| **0.59**     | **0.62**| **0.94**| **0.91**| **0.87** |

Table 3: Comparing estimated affective meanings for “judge” as an identity and behavior.

| Judge | Evaluation | Potency | Activity | Est. Evaluation | Est. Potency | Est. Activity |
|-------|------------|---------|----------|-----------------|--------------|---------------|
| Behavior | -1.83     | 0.71    | 0.07     | -1.91          | 0.73         | 0.08          |
| Identity  | 1.15      | 2.53    | -0.22    | 1.18           | 2.54         | -0.17         |

The test data used to compare these methods included 139 identities, 122 behaviors, and 99 modifiers came from stratified sampling discussed earlier. All the similar works used shallow embedding (Kozlowski et al., 2019; Mostafavi & Porter, 2021; Li et al., 2017). We used the publicly available code of Mostafavi & Porter (2021) and Kozlowski et al. (2019) to replicate their work and compare the result. For Li et al. (2017) we had to implement their method in Python. To further improve their methods, we added tuning layers such as adding step-wise regression to the analogy method. Table 2 shows the best result we could get from other methods. We can observe from this table that our approach reached state of the art across most of the metrics.

To evaluate how close our extended dictionaries are to the baseline affective meanings, we calculated the correlation for identity and behaviors in Tables 4 and 5. The correlation (a) between the result of the test set in our method, (EE, EP, and EA) and the EPA values from the surveys (E, P, and A) are shown. The diagonal terms are the correlation values we have seen earlier in Table 2. Also, you can find the correlation between the three dimensions from the survey data are shown in (b), and the correlation between estimated three dimensions are shown in (c). and survey results. We can observe in both tables the values in tables (b) and (c) are close. It reveals that BERTNN estimation is highly correlated with survey data and the cross-term dynamics is well estimated.

One problem with estimation from shallow-embeddings was having the same embedding for words as identity or behavior. Using the last two layers of the BERT model as embedding, we can differentiate between these two cases. In Table 4 we can observe that estimated values for “judge” are different when it is considered as identity or behavior.

Tables 4 and 5 show that diagonal terms in the correlation of estimated values and values from the survey dictionary are reasonably large. On the other hand, the off-diagonal entries from the estimation are close to the ones from the survey.

5 CONCLUDING REMARKS

A big limitation in the applicability of ACT to different contexts such as NLP tasks was the limitation of affective vocabulary collected from surveys. In this paper, an approach to make training and test sentences that describe an ABMO event. Then we used BERT as an embedding and fine-tuned it
Table 4: Correlation analysis for identities. (a) Correlation between estimated values (EE, EP, and EA) and the affective dictionary value (E, P, and A). We can also compare the correlation of the words in the three dimensions shown in (b) and correlation of the estimated values of the three dimension shown in (c) to find how close the off-diagonal entries are in the estimation comparing to dictionary values.

|       | EE   | P   | A   |       | EE   | P   | A   |       |
|-------|------|-----|-----|-------|------|-----|-----|-------|
| EE    | 0.89 | 0.56| -0.08| EP    | 0.59 | 0.81| 0.29| EA    | 0.02 |
| EP    |      |     |     | EP    | 0.55 | 1.00| 0.25| EP    | 0.62 |
| EA    | 0.05 | 0.25| 1.00|       | 0.05 | 0.25| 1.00|       | 0.04 |

Table 5: Correlation analysis for behaviors. (a) Correlation between estimated values (EA, EP, and EA) and the affective dictionary value (E, P, and A). We can also compare the correlation of the words in the three dimensions shown in (b) and correlation of the estimated values of the three dimension shown in (c) to find how close the off-diagonal entries are in the estimation comparing to dictionary values.

|       | EE   | P   | A   |       | EE   | P   | A   |       |
|-------|------|-----|-----|-------|------|-----|-----|-------|
| EE    | 0.87 | 0.38| -0.37| EP    | 0.36 | 0.80| 0.15| EA    | -0.33|
| EP    |      |     |     | EP    | 0.59 | 1.00| 0.12| EP    | 0.47 |
| EA    | -0.21| 0.12| 1.00|       | -0.42| 0.12| 1.00|       |       |

using a neural network and regression model. Our approach, BERTNN, resulted in state of the art in estimating affective meaning.

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