Beyond Positive Emotion: Deconstructing Happy Moments based on Writing Prompts

Kokil Jaidka[1] **Niyati Chhaya**[2] **Saran Mumick**[3,4]
Matthew Killingsworth[3] **Alon Halevy**[4] **Lyle Ungar**[3]
[1] National University of Singapore, [2] Adobe Research India
[3] University of Pennsylvania, [4] Megagon Labs
jaidka@nus.edu.sg

Abstract

This study reports experiments with the newly-released CL-Aff HappyDB dataset, which looks beyond positive emotion in modeling descriptions of happy moments collected through writing prompts. The widespread adoption of social media has improved researchers' access to unsolicited expressions and behaviors. However, most of the approaches to analyzing these expressions involve a keyword search and focuses on predicting sentiment or emotional content rather than understanding a deeper psychological state, such as happiness. The CL-Aff HappyDB dataset is the first effort to distinguish the personal agency and social interaction in writings about happiness, which do not yet have an exact equivalent concept in existing text-based approaches. We report that state of the art approaches for emotion detection have different topical characteristics, and do not generalize well to detect happiness in the CL-Aff HappyDB dataset. Language models trained on the dataset, on the other hand, generalize to social media writing and are a valid approach for downstream tasks, such as predicting life satisfaction from social media posts.

Introduction

Many works of science, literature, and art have probed into the existence, nature, and attainment of happiness. Happiness is defined as an emotional self-evaluation of well-being. A large body of work in psychology has investigated the causes, correlates, and consequences of happiness (Seligman 2012; Diener and Suh 2003). Recently, computer scientists have joined forces with psychologists in an attempt to analyze social media posts for happiness measurement (Diener, Oishi, and Tay 2018; Golder and Macy 2011; Dodds et al. 2011; Pew 2018). Much of the work in analyzing language uses measures of positive emotion as a proxy for measuring happiness. While the two do have an association, positive emotion may denote mood rather than a stable psychological trait such as happiness (Sun et al. 2019). Furthermore, positive emotion measurements based on popular approaches have yielded inconsistent measurements against self-reported happiness at the individual level (Sun et al. 2019; Lin, Tov, and Qiu 2014) as well as the regional level (Jaidka et al. In press).

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Our main contribution is to model the language of happiness based on its theoretical underpinnings, and to share a labeled resource for the research community to benefit from our efforts[1]. Our approach is based on the vast body of literature in psychology, which has focused on the role of agency and social interaction to study self-evaluation, well-being, and happiness (Paulhus and Trapnell 2008). We illustrate how the dual axes of agency and sociality can be used to understand happiness, further establishing their validity and predictive performance on downstream tasks. A further contribution is our examination of the generalizability and validity of state of the art emotion-based approaches in detecting happiness from the language of happy moments in our dataset, and in predicting self-reported life satisfaction based on the language in social media posts. We corroborate recent work which has postulated that positive emotion expressed on social media may not have an association with self-reported happiness or life satisfaction but also find evidence supporting the contrary.

Research objectives

This paper aims to characterize written accounts of happy moments according to their causes and constituents. It addresses the following research questions:

1. **Insights:** What are the psycholinguistic characteristics of happy moments?
2. **Novelty:** How do agency and sociality compare against existing psycholinguistic dictionaries? How does the CL-Aff HappyDB dataset compare against standard social media datasets?

Based on the Agency-Communion framework (Paulhus and Trapnell 2008) and the importance of social relationships to wellbeing (Helliwell and Putnam 2004), we also propose the following hypothesis (H1):
People are more likely to report feeling happier for longer (more prolonged duration of happiness) when they describe happy moments about social experiences.

[1]The CL-Aff HappyDB dataset[2] and the associated CL-Aff Shared Task @ AAAI-19[3] extend the original HappyDB collection of happy moments (Asai et al. 2018) with a new collection of happy moments, all of which are enriched with a new set of psychological and content labels.

Next, we establish the validity of measurements using text classifiers trained on the CL-Aff HappyDB dataset:

3. **Benchmarking:** How well do emotion classifiers perform on detecting happiness in a dataset of happy moments?
4. **Predictive performance:** How well do classifiers trained on the language of happy moments predict survey-reported happiness?

Research gaps

The study of language to understand psychology was introduced and subsequently validated by Pennebaker and others (Pennebaker 1993; Seligman 2012) who assigned their subjects (typically undergraduate students) with autobiographical writing exercises and some psychological survey questionnaires. In the present day, data collection efforts have become less obtrusive. Social media posts offer a proxy for autobiographical writing, and it is inexpensive to collect unsolicited personal opinions based on the presence or absence of keywords.

Social media contains expressions of positive emotion (Liu et al. 2015): authors express emotions to communicate with their social network and present a positive, high-affect version of themselves (Liu et al. 2015). Computer scientists then use existing taxonomies of human emotions such as joy, sadness, or anger (Plutchik 2001; Ekman 1992), and search for and collect emotion-related language in social media posts. They then build language-based predictive models of these emotions. “Joy” is considered the nearest proxy to a measurement of happiness (Mohammad, Kiritchenko, and Zhu 2013).

Many studies have reported the troubling finding that measurements of positive emotions from social media posts are not a valid measure of ‘real’ happiness (Kramer 2010; Chen et al. 2017; Lin, Tov, and Qiu 2014). Recent studies applying longitudinal analyses (Wang et al. 2014; Sun et al. 2019) or repeated measures (Kross et al. 2018) have suggested that positive emotion dictionaries applied to social media do not predict people’s self-reported emotion moments. On the other hand, human judges who read the same social media posts can gauge their self-reported emotional moments relatively accurately. This raises the question of whether relying on emotion dictionaries alone is helpful to detect or measure self-reported happiness or life satisfaction. These approaches are also trained on social media datasets, which can be expected to indicate high positivity, social desirability, and self-presentation biases (Lin, Tov, and Qiu 2014; Liu et al. 2015).

As an alternative, we collect descriptions of happy moments using writing prompts issued to participants on Amazon Mechanical Turk, an online platform to solicit participation in surveys and annotation tasks. Based on the data we collected, we provide an annotated corpus of happy moments with labels for the psychological concepts of agency and sociality. In contrast, most emotion datasets and dictionaries – for example, the Extended Affective Norms of English Words (ANEW) dictionary (Warriner, Kuperman, and Brysbaert 2013) and the Language Assessment by Mechanical Turk (LabMT) dictionary (Dodds et al. 2011)) – instead quantify the presence and intensity of emotions.[4].

Theoretical framework

The Agency Communion framework structures people’s interactions with the world in terms of agency that captures individual self-enhancement and how people self-evaluate based on their achievements, and Communion that captures the need to belong, when people submerge themselves in their groups and minimize their social deviance. This framework seems appropriate to represent the experience of happiness because a large body of research has reported on the importance of self-efficacy or personal agency (Bandura 2006) and self-determination (Deci and Ryan 2000), and social interaction and relationships (Helliwell and Putnam 2004; Seligman 2012), for a sense of well-being and happiness (Seligman 2012). Prominent theories and studies have linked perceptions of self-control to personal and professional well-being (Lachman and Weaver 1998; Deci and Ryan 2000; Kobasa, Maddi, and Kahn 1982), including across countries (Chirkov et al. 2003; Tay and Diener 2011). Regarding sociality, a body of work has shown that social support and a sense of belonging is vital to develop a healthy sense of personal and community identity, self-worth, and a positive self-appraisal through external reinforcement (Cohen and Wills 1985; VanderZee, Buunk, and Sanderman 1997), and its importance for happiness (Helliwell and Putnam 2004; Cohen and Wills 1985).

The first dimension along which we categorize each happy moment is the author’s sense of *agency*. Agency is generally defined as an individual’s perception of whether they have personal control over the events in their lives or whether others externally control the events in their lives (e.g., other people, fate, God, or chance) (Bandura 2006). An individual’s personal and professional success and well-being appear to depend upon whether they feel like the agent, as having personal control, or as the “patient”, or being controlled by others or their circumstances (Spector et al. 2002; Krause and Stryker 1984). Agency has many facets to it, such as an individual’s locus of control (Rotter 1966), their internal self-efficacy (Sherer et al. 1982), and their control over their surroundings (Paulhus and Christie 1981). However, few studies have explored how written language expresses the psychological concept of agency, and none have done so in the context of happiness. We use a previously validated annotation scheme that identifies how control is manifested in social media language (Rouhizadeh et al. 2018; Jaidka et al. 2018).

The second dimension we are interested in is the author’s *sociality*, or whether or not the author describes a social situation in a happy moment. There is evidence to show that day-to-day moments of social support and con-

[4]The Extended ANEW offers a ‘Dominance’ score per affective word, which seems arguably similar. However, in univariate analysis, we found that the Pearson’s correlation of Dominance with agency was -0.07 ($p < 0.001$)

Table 1: Dataset statistics

Label	Description	Descriptive statistics
Reflection period	When the happy moment actually occurred	'Within 24 hours' (8819); 'Within 3 months' (8396)
Duration	The length of happiness experienced	'All day, I'm still feeling it' (7140); 'Half a day' (3993); 'At least one hour' (4122); 'A few minutes' (1913); 'Not Applicable' (40);
Agency	Whether or not the author was directly responsible	Yes (12,157), No (5,058)
Sociality	Whether or not the happy moment involved other people.	Yes (9799), No (7416)
Theme	What the happy moment is about	Family, Food, Entertainment, Career, Conversation, Romance, Shopping, Vacation, Education, Animals, Party, Exercise, Technology, Weather, Religion

nection are essential for well-being (Sandstrom and Dunn 2014). Social support, comprising the psychological and material resources provided to those with spouses, friends and family members is considered to 'buffer' the harmful effects of stress, providing a source of "positive affect, a sense of predictability and stability in one's life situation, and recognition of self-worth" (Cohen and Wills 1985), while integrating into a social network can help fulfill individuals' innate need to belong (Baumeister and Leary 1995). Differences in the level of social support (e.g., social isolates vs. socially outgoing individuals) and in the kinds of social contact are also found to have differential effects on psychological well-being. (Killingsworth and Gilbert 2010). Based on pilot testing, we use a simple annotation scheme to denote the presence or absence of other people in any happy moment as the basis for measuring sociality. [5]

Method

Data collection

An Amazon Mechanical Turk (AMT) task was launched to collect three happy moments from each participant based on randomly assigned prompts that asked for happy moments that happened either within the last twenty-four hours or within the past three months. Participants were also asked about the duration (i.e., the length) of happiness they experienced. These directions were adapted from those used to obtain HappyDB corpus (Asai et al. 2018) with additional questions to annotate the duration of the happy moment and are provided in the supplementary materials. After filtering out spam and irrelevant entries, we obtained $17,215$ happy moments.

Annotation

After data collection, a separate task was launched on AMT to annotate each moment according to their agency and sociality, which can be understood according to Table 1. An example of a happy moment with agency is "I made a nice birthday cake today." An example of a happy moment with sociality is "I had a good lunch with my mom." An example of a happy moment with both personal agency and sociality: "I made dinner which my family liked a lot."

[5]Details of the annotation task are provided in the supplementary materials at https://tinyurl.com/claff-icwsm2020.

Classification

The authors of the original HappyDB dataset (Asai et al. 2018) provided us with a list of the fifteen major themes of happy moments that they identified through following an unsupervised clustering approach on their data. Annotates labeled the happy moments by choosing one or more of these themes. The labels are listed in Table 1, and further details about the labeling are provided in the supplementary materials. We used these themes to understand how the CL-Aff HappyDB dataset is different from social media datasets.

Analysis

We divided our analysis into subsections to address each of the four research questions and one hypothesis. To illustrate linguistics insights for (1), we reported the words strongly correlated with agency and sociality in happy moments. To validate H1, we reported an ordinary least squares regression of the language of happy moments against their duration labels. To establish novelty for (2), we performed an ordinary least squares regression of agency and sociality against other psycholinguistic concepts found in the Linguistic Inquiry and Word Count (LIWC) 2015 (Pennebaker et al., 2015) and the Positive Emotion, Engagement, Relationship, Mindfulness and Accomplishment (PERMA) (Seligman 2012) well-being dictionary to look for similar concepts. We also compared the topical characteristics of happy moments against a standard emotion and a random sample social media dataset. For benchmarking in (3), we reported the outcome of using state-of-the-art emotion classifiers on the CL-Aff HappyDB dataset. Finally, to establish predictive validity in (4), we trained and validated classifiers on the CL-Aff HappyDB dataset, which we use on the Facebook MyPersonality dataset (Kosinski, Stillwell, and Graepel 2013) to validate whether a happiness language model is useful for predicting self-reported happiness.

Linguistic insights: The happy moments were tokenized, and the feature set of over 1.2 million words was limited to the 175 words which occurred in at least 1% (or 170) of the moments excluding stopwords related to the writing prompt.[6]. We report an ordinary least squares regression of the distribution of this vocabulary of words against agency and sociality labels. In order to understand the kinds of happiness that can endure for longer or shorter time periods, we reported a Benjamini Hochberg-corrected pairwise correlation between each of these words and the duration of the happy moment.

Novelty: If agency and sociality are novel psycholinguistic concepts, they would be expected to have a low association with the existing concepts in the Linguistic Inquiry and Word Count 2015 (Pennebaker et al. 2015) and the PERMA (Seligman 2012) dictionaries. Accordingly, we tested the novelty of our work by comparing the presence of agency and sociality against the percentage proportion of the LIWC social processes, self-references, drives, and PERMA concepts in each happy moment in a univariate analysis after Benjamini Hochberg p-correction.

A comparison of content characteristics would validate whether a dataset collected using writing prompts is semantically different from one collected from social media using hashtags. Accordingly, we compared the relative distributions of topics in the CL-Aff HappyDB dataset against (a) a sample of posts labeled *#joy* from the NRC Hashtag dataset and (b) a random sample of Twitter posts collected using the Twitter API. The observations in the latter two datasets were labeled by applying fifteen topic classifiers trained by and provided by the authors of the original HappyDB dataset (Asai et al. 2018).

Benchmarking experiments: A classifier trained on social media data would generalize well if it could detect happiness with a high value, low variance, and a large skew on the CL-Aff HappyDB dataset, as compared to the predictions on a random dataset of posts. Accordingly, we explored whether state of the art approaches – specifically, the WWBP Affect model (Preoţiuc-Pietro et al. 2016), the LabMT positive emotion lexicon (Dodds et al. 2011)[7], the extended ANEW lexicon (Warriner, Kuperman, and Brysbaert 2013), the NRC Hashtag Emotion dataset (Mohammad, Kiritchenko, and Zhu 2013), the Joy lexicon from Senticnet (Cambria et al. 2010) and the LIWC 2015 positive emotion lexicon (Pennebaker et al. 2015) – can successfully distinguish the happiness in the CL-Aff HappyDB dataset. We plotted the distribution of predictions from the dataset of happy moments against those from the emotion expressed in a random sample of social media posts.

Predictive validity: A language model of happiness can be assessed based on its utility in downstream tasks. Accordingly, we evaluated whether supervised models trained on happiness labels outperform emotion-based dictionaries for predicting survey-reported happiness. First, we trained the classifiers on the linguistic of happy moments labeled with agency and sociality. The dimensionality of data was reduced by selecting features based on their univariate regression with agency or sociality and performing a randomized principal component analysis. Next, a variety of classifiers were trained separately on a variety of linguistic features to predict agency and sociality labels in a ten-fold cross-validation setting. Predictive performance was measured as the Area Under the Curve (AUC). Finally, we applied these classifiers to our validation dataset and reported Pearson's correlation over a ten-fold cross-validation setting.

The different linguistic features used in our classifiers were:

- **1-grams (175 words):** We use a bag-of-words representation to reduce each happy moment to a normalized frequency distribution, retaining only the top 1% words of the vocabulary.
- **GloVe Word embeddings:** We represent each word as the multi-dimensional neural embeddings obtained from the pre-trained word embeddings trained on the GloVe Twitter corpus of 27 billion tweets.
- **LIWC features:** We represent each happy moment as a frequency distribution of the categories from the Linguistic Inquiry and Word Count (LIWC), which comprises lists of words denoting psychological concepts, parts-of-speech, and emotions.

Predicting self-reported Life Satisfaction: To establish predictive validity, ideally, we would want to compare happiness predicted from the writing to prompts, against emotions measured from unsolicited social media posts at predicting the survey-reported happiness of the same individual. In the absence of such a dataset, we measured predicted happiness against social media posts labeled with survey-reported life satisfaction, shared by the authors of the social media posts. We obtained self-reported life satisfaction and the associated social media posts from the myPersonality Facebook dataset (Kosinski, Stillwell, and Graepel 2013) for 258 participants who took the Satisfaction With Life Scale (life satisfaction) and made posts to Facebook in the six months preceding the quiz. Applying our classifiers to their Facebook language, we obtained agency and sociality scores for each participant, as well as their scores on the state of the art emotion measures such as LabMT (Dodds et al. 2011), LIWC 2015 (Pennebaker et al. 2015), and the NRC Hashtag emotion model (Mohammad, Kiritchenko, and Zhu 2013). Predictive performance was reported as the Pearson's correlation of the predicted measurements against the self-reported satisfaction with life.

Results

Intercoder agreement

The inter-annotator agreement for agency was 88.2%, and for sociality was 91.1%. We found that there is a moderate negative correlation (r = -0.24, p < 0.01) between agency

[6] e.g., 'happy', 'moment', 'month', 'day', 'week' and 'hour'

[7] A positive emotion scale was derived by using those words in the LabMT dictionary which had affect ratings that were higher than one standard deviation above the mean.

Table 2: An error analysis shows that sometimes the interpretation of agency and sociality in a happy moment is not straightforward. Examples along the diagonal are correctly labeled. Other examples are mislabeled.

Description	Agency + Sociality	Agency + ~(Sociality)	~(Agency) + Sociality	~(Agency) + ~(Sociality)
Agency + Sociality	*I was playing basketball and I dunked on someone!*			
Agency + ~(Sociality)	*I watched a funny youtube video*	*I put in a good workout at the gym after procrastinating.*		
~(Agency) + Sociality	*My girlfriend bought me a present.*	*My daughter called me*	*A co-worker gave me a compliment*	
~(Agency) + ~(Sociality)	*I was hungry, and was surprised with breakfast.*	*I received a hefty paycheck*	*I found out my sister is having a baby.*	*A dog gave me a hug.*

and sociality (i.e., happy moments which are labeled with agency are not likely to describe social situations). Annotators were sometimes uncertain of the author's agentic role in a social happy moment. Table 2 provides exemplary moments where the annotators either had complete agreement (along the diagonal) or disagreed (anywhere except the diagonal).

The final agency/sociality labels were assigned to each happy moment via a simple majority vote. 69.9% of the happy moments were annotated as manifesting agency. 54.9% moments were annotated as manifesting sociality. A small proportion (8%) of the happy moments were denoted as having agency = 0 AND sociality = 0.

Linguistic insights

Figure 1a identifies the words most strongly positively correlated with agency (.02 < r_{agency} <= .34) and sociality (.02 < $r_{sociality}$ <= .32) after Benjamini Hochberg p-correction (p < .05). The size of the word reflects a higher Pearson correlation with the duration of happiness. A darker shade reflects a higher frequency in the dataset. Happy moments labeled with agency are most likely to mention the word 'i' (r = .34) as well as 'able,' 'went,' 'with' and 'to' which are words that syntactically relate an individual to their social and physical contexts. While agency in happy moments does involve friends, there are no other significantly associated mentions of people or family members here. On the other hand, Figure 1b denotes the words positively correlated with sociality in happy moments. These moments are most likely to reflect a sense of belonging (Baumeister and Leary 1995) through the semantically similar but conceptually different word – 'my' (r = .32). Social happy moments are more likely to mention family and friends, significant others, and social occasions such as dinners, trips, and birthdays. Figure 2 identifies the words in a happy moment that are significantly negatively (red) and positively (blue) correlated with the duration of the author's happiness. This was done based on a Benjamini Hochberg-corrected pairwise Pearson correlation between the relative frequency of each word in the happy moment and its duration of happiness. The size and shading of the word follow the same scheme as above. We observed that authors who chose moments about social relationships ('family,' 'son,' 'daughter,' 'friends') were more likely to report feeling happier for a longer time, as compared to authors who chose to mention movies, games, videos or meals. This supports H1 that moments involving a social relationship are relatively more enduring happy moments.

Table 3: Ordinary least squares regression (Pearson's r) of agency and sociality against other psycholinguistic concepts and parts of speech (verbs and pronouns). "Social processes" in LIWC and "Relationship" in PERMA can moderately approximate sociality. Nothing appears to measure agency (*: p < .05; ***: p < .001).

Concept	Agency	Concept	Socality
LIWC 2015 (Pennebaker et al. 2015)			
Leisure	$.13^{***}$	Social processes	$.60^{***}$
Money	$.05^{***}$	Drives	$.25^{***}$
Religion	$.04^{***}$	Personal pronouns	$.19^{***}$
Verb	$.03^{***}$	Home	$.07^{***}$
I	$.03^{***}$	Power	$.05^{***}$
Work	$-.06^{***}$	Religion	$-.06^{***}$
Drives	$-.07^{***}$	Cognitive processing	$-.08^{***}$
Power	$-.08^{***}$	Verb	$-.10^{***}$
Family	$-.19^{***}$	Work	$-.10^{***}$
Social	$-.24^{***}$	Money	$-.17^{***}$
PERMA (Seligman 2012)			
Positive emotion	$.02^{*}$	Positive emotion	.00
Engagement	-.01	Engagement	.00
Relationship	$-.02^{***}$	Relationship	$.29^{***}$
Mindfulness	$.02^{***}$	Mindfulness	$-.02^{***}$
Accomplishment	.01	Accomplishment	$-.1^{***}$

Novelty

In Table 3 we show that neither LIWC 2015 nor PERMA have a dictionary conceptually equivalent to agency. Unexpectedly, "Drives" (r = -0.07, p < .001) and "Power" (r = -.08, p < .001) had a negative correlation with agency although conceptually we would expect them to be aligned. For sociality, the LIWC concepts for "Social" (r = .60, p < .0001) and PERMA's "Relationship" (r = .29, p < .001) were associated with sociality.

Topical characteristics: Table 4 shows that the proportion of tweets mentioning careers, conversations, and romance are many orders of magnitude larger in the CL-Aff HappyDB dataset as compared to #Joy tweets and a random sample of tweets. 66.3% of #Joy tweets and 76.3% of the random sample could not be assigned any of the fifteen topic labels. This establishes the novelty of the CL-Aff HappyDB dataset as a gold standard of the language of happiness. It suggests that emotion classifiers trained on

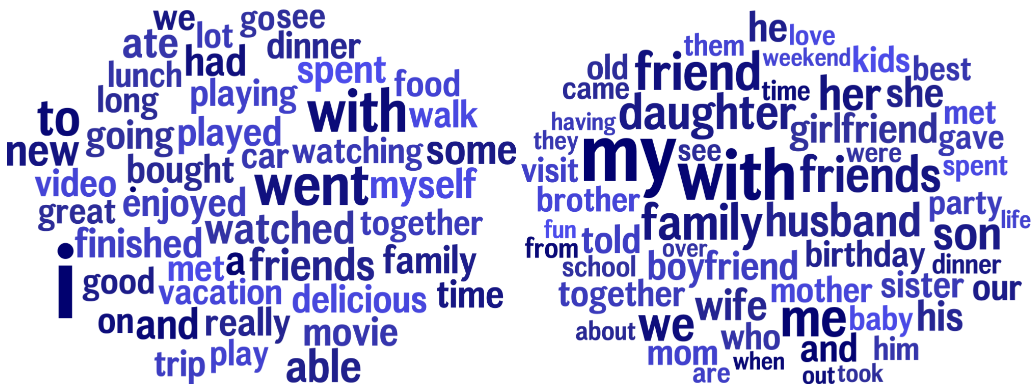

Figure 1: The words most strongly positively correlated with (a) agency (.02<r<.34, p < .05) and (b) sociality (.02<r<.33, p <.05)in happy moments. The size of the word reflects a higher Pearson correlation with the duration of happiness. A darker shade reflects a higher frequency in the dataset.

Figure 2: Words in happy moments negatively and (b) positively correlated with the duration of happy moments (.04 <= r <= .09, p < 10^{-28}).

Table 4: The distribution of topics in the final dataset as a percentage of the total number of observations. We offer a comparison against the relative distribution of the tags in (a) a sample of labeled posts from the NRC Hashtag dataset, and (b) a random sample of Twitter posts.

Topic	**CL-Aff HappyDB**	**'#Joy' tweets (NRC)**	**Random Twitter**
Family	29.9	8.2	2.7
Food	13.9	3.4	3.0
Entertainment	13.2	5.0	6.9
Career	12.7	4.2	2.6
Conversation	7.8	.76	.9
Romance	7.7	1.1	.7
Shopping	7.5	2.1	.9
Vacation	6.2	.91	.5
Education	5.7	5.7	1.7
Animals	5.1	.66	.9
Party	4.9	1.6	.4
Exercise	4.9	1.0	0.7
Technology	2.8	.4	.5
Weather	1.4	1.1	.84
Religion	0.6	.5	0.2
No labels	11.7	66.3	76.3

the NRC Hashtag Emotion (#Joy) dataset could be skewed towards other topics and digress from detecting actual happy experiences.

Benchmarking experiments

The density plots in Figure 3 illustrate the probability distributions of measurements by different emotion language models and lexica on the CL-Aff HappyDB dataset as well as a random sample of tweets. The x-axis has a rescaled value between 0 and 1, and the y-axis has the probability that a generated score has that value. We observe that the WWBP Affect language model (Mean$_{happy}$ = 5.3, SD$_{happy}$ = 0.41) and the LabMT lexicon are more likely to detect higher happiness (higher x-values) more consistently (lower variance) on the CL-Aff HappyDB dataset (Mean$_{happy}$ = 1.49, SD$_{happy}$ = 0.79) than a random Twitter dataset (For Affect, Mean$_{random}$ = 3.93, SD$_{random}$ = 1.43; For LabMT, Mean$_{random}$ = 0.46, SD$_{random}$ = 0.23). There is a substantial difference in the pairs of measurements; thus, these models appear to be better able to generalize to detecting happy moments compared to the other approaches. The other plots, e.g., the LIWC 2015 positive emotion (Mean = 9.6, SD = 5.4) and the NRC Joy language model (Mean = 5.1, SD = 0.58) are as likely to report positive emotion measurements on the CL-Aff HappyDB dataset, as on a random sample of tweets (For LIWC 2015 positive emotion, Mean = 9.9, SD = 7.5; for NRC Joy, Mean = 6.3, SD = 7.1). This finding suggests that domain differences do creep into happiness detection from language. Even though both social media and writing prompts can ostensibly be considered autobiographical writing, not all classifiers trained on the latter can generalize well to the former type of corpus.

Predictive performance of Happiness classifiers

In Table 5, predictive performance for agency and sociality is reported as the Area Under the Curve (AUC) on held out data in 10-fold cross-validation on 1-grams, LIWC features, and their combination. We tried several parametric and non-parametric classifiers and adjusted the different learning rates to achieve the maximum possible performance. We found that the model with the best performance was trained on both 1-grams and LIWC using gradient-boosted classification (GBC) provided by

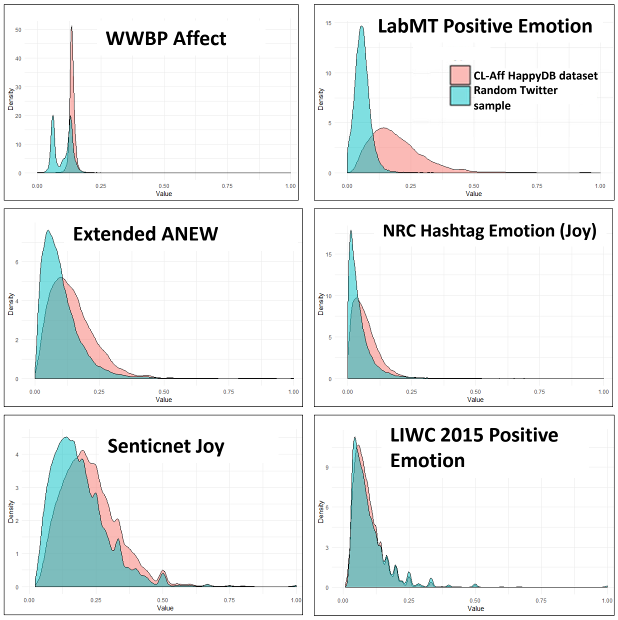

Figure 3: The distribution of positive emotion measurements provided by the state of the art approaches on the CL-Aff HappyDB dataset. As a baseline, we also provide the measurements on a random sample of Twitter posts.

Table 5: Predictive performance for agency and sociality labels trained on (a) different linguistic feature sets and (b) different neural models.

Area Under the Curve (AUC)			
Agency			
Feature Set	**Linear-SVC**	**RFC**	**GBC**
1-grams	.82	.82	.82
LIWC	.74	.77	.76
1-grams + LIWC	.84	.84	.85
Sociality			
Feature Set	**Linear-SVC**	**RFC**	**GBC**
1-grams	.89	.90	.90
LIWC	.87	.93	.94
1-grams + LIWC	.94	.94	.94

	Agency		**Sociality**	
Model	**Accuracy**	**F1**	**Accuracy**	**F1**
cnn-100	0.84	0.82	**0.88**	**0.89**
cnn-glove200	0.86	0.84	0.88	0.87
lstm-glove200	**0.87**	**0.85**	0.85	0.84
fasttext	0.83	0.84	0.83	0.84

Python's scikitlearn package, using 500 estimators with a learning rate of 0.1, a subsample value of 0.4 and a maximum depth of 5. In Table 5, we provide the results using embeddings trained on this data (cnn-100) as well as GloVe embeddings as the input to traditional deep learning pipelines such as Convolutional Neural Networks (cnn-glove200), RNN (lstm-glove200) and the Fasttext framework (fasttext). Linear classifiers performed better than the neural methods, but we would expect to do better with more data and parameter tuning.

Predictions on the MyPersonality dataset

In evaluating our approach to predict self-reported satisfaction, we found that the results were inconclusive and lacked statistical power. The detailed findings are reported in the supplementary materials. Agency, rather than sociality, had a positive albeit non-significant relationship with life satisfaction (r = .09, p >.05). The WWBP Affect model reports a weak association in the correct direction (r = .11, p >.05), and outperformed other language-based approaches. LIWC positive emotion had a negative albeit non-significant association with life satisfaction (r = -.07) which corroborates other recent studies.

Conclusion and Future Work

Autobiographical writing collected on the basis of directed prompts offers a more lucid and rich resource for understanding happy experiences as compared to social media posts. The expressions of happiness in writing also do not stem from the use of positive emotions alone. Our findings suggest that the affordances of agency and social interaction are two critical ingredients in the language of happy moments, and perhaps in the experience of happiness. The dataset and the psycholinguistic dimensions we provide are novel, credible, generalize for use on social media, and are useful for downstream tasks such as life satisfaction prediction. These findings contribute to a growing body of work that has established that social media posts bear signals of mental health and psychological well-being, similar to those that are captured through self-reported surveys (Guntuku et al. 2019; Jaidka et al. 2018). Language-based technologies such as chatbot systems could use the insights from this work to phrase their responses and follow-up questions to elicit higher agency and sociality. Based on a Shared Task conducted as a part of the 2^{nd} AAAI Affective Content Analysis workshop (Jaidka et al. 2019), we reported on other approaches to happiness modeling. For best results, we recommend incorporating syntactic knowledge for inferring Agency and Sociality (Wu et al. 2019), and following a semi-supervised approach enriched with unlabeled data from the same or a different domain (Torres and Vaca 2019; Cheong, Song, and Bae 2019).

Our findings do suggest that agency manifested in social media posts offers a weak association with life satisfaction, while the findings are more mixed for emotion- or sentiment-based approaches. While correlation does not imply causality or replaceability, we argue that the presence of an association with self-reported life satisfaction merits further investigation and replication in more extensive studies. We controlled for many preprocessing factors in making this comparison; however, the results could be further improved through the exclusion of a few erroneous words and posts (Jaidka et al. In press).

A deeper understanding of what makes people happy would have tremendous applications in mental health and governance. As researchers around the world focus on human-centered Artificial Intelligence research, human-computer interfaces, and augmented reality technology, we recommend that evaluating user experiences in terms of agency and sociality could be useful as metrics for effectiveness.

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