Automated Tracking of Components of Job Satisfaction via Text Mining of Twitter Data

Louis Hickman[1], Koustuv Saha[2], Munmun De Choudhury[2], & Louis Tay[1]
[1]Purdue University
[2]Georgia Institute of Technology

Among organizational researchers, job satisfaction has long been recognized as both a core motivational construct (Herzberg, Mausner, & Snyderman, 1959) and a key index of worker well-being (Judge & Klinger, 2007) that has implications for organizational and governmental policy (De Neve, Diener, Tay, & Xuereb, 2013; Diener et al., 2017). Today's governmental and intergovernmental organizations seek to supplement traditional economic indicators with social indicators of well-being, but traditional survey methods for assessing well-being are expensive, intrusive, time-consuming, and incur low response rates (Pew Research Center, 2012). Therefore, organizational researchers need new methods for tracking job satisfaction at scale which can also tie into labor-market conditions for policy use (Tay & Harter, 2013).

Among the different well-being indices, job satisfaction as an index of worker well-being is most conceptually related to the suite of core economic indicators used to evaluate the economy. These include labor market economic (e.g., unemployment rates, labor force participation rates, and employment to population ratio) and income-related indicators. For example, the experience of unemployment is conceptually related to worker well-being (McKee-Ryan, Song, Wanberg, & Kinicki, 2005) and labor market indicators such as unemployment rates are linked to national job satisfaction over time (Tay & Harter, 2013). Similarly, income is related to different components of job satisfaction at the national level of analysis (Gazioglu & Tansel, 2006). In fact, it has been argued that job satisfaction is a useful subjective variable in labor market analysis beyond standard economic variables (Freeman, 1978).

Our research seeks to develop a social indicator of job satisfaction by using text mining and machine learning approaches on publicly available Twitter data to automatically track components of job satisfaction (e.g., supervision, pay) using automated, expert-appraised retrieval and scoring algorithms. Social media data collection is inexpensive, unobtrusive, and provides large, diverse samples of real-time data. Data scraped from Twitter can track regional affect, well-being, and life satisfaction, which can predict health outcomes (Lamb et al. 2013; Won et al. 2013; De Choudhury et al., 2013a; De Choudhury et al., 2013b; Eichstaedt et al., 2015; Schwartz et al., 2013; De Choudhury et al., 2016; Saha et al., 2017); stock market trends (Bollen, Mao, & Zheng, 2011); and quantify workplace affect (De Choudhury & Counts, 2013). Applying similar approaches to measure job satisfaction will provide both within-individual (state job satisfaction) and between-individual (trait) data for multilevel evaluation (Judge & Kammeyer-Mueller, 2012) to increase our understanding of how workplace, economic, and legislative changes affect employee well-being.

Therefore, we apply text mining and machine learning approaches to different factors of job satisfaction, specifically to pay and supervisor satisfaction, two facets of the Job Descriptive Index (Smith, Kendall, & Hulin, 1969). Automatically assessing trends in job satisfaction via publicly available data advances our ability to track organizational, regional, and national well-being in real time and provides information about its relation to changing macroeconomic conditions. Politically, it also enables organizational psychologists to bring our research and expertise to bear on governmental policies which has typically been limited to economists.

Methods and Results

The research team developed search terms using existing job satisfaction scales (Balzer, 1990; Russell et al., 2004; Smith et al., 1969) to automatically retrieve pay and supervision satisfaction tweets using Twitter API. Terms were retained for data scraping if they returned a high rate of relevant tweets. Our initial scrape gathered over 100,000 potentially relevant tweets. Two independent coders rated 18,000 of those tweets (10,000 potentially relevant for pay and 8,000 for supervision) for their relevance to the expected facet of job satisfaction and, if relevant, whether they indicate (dis)satisfaction. Consensus was obtained via discussion.

After labeling the dataset, we built machine learning classifiers to automatically label job satisfaction of the remaining posts. We built separate classifiers for pay and supervision to predict relevance and valence. For each post, we extracted multiple *n*-grams ($n = 1, 2, 3$), psycholinguistic attributes using the Linguistic Inquiry and Word Count dictionary (LIWC; Pennebaker, Booth, Boyd, & Francis, 2015), and sentiment using the Stanford CoreNLP library (Manning et al., 2014). We trained the relevance classifiers using n-grams and psycholinguistic attributes, and we trained the valence classifiers using n-grams and sentiment. The classifiers utilized Support Vector Machine models with linear kernels, and we conducted k-fold ($k = 5$) cross-validation for parameter tuning. For pay component, mean cross-validation accuracy was 76% for labeling relevance and 78% for valence. Figure 1 displays n-grams that reliably discriminated pay (dis)satisfaction. For supervision component, mean cross-validation accuracy was 72% for labeling relevance and 74% for valence. Table 1 details the relative contribution of n-grams, LIWC, and sentiment to cross-validation accuracy. We machine labeled the unseen data with these classifiers finding a) 15,980 (out of 50,290) posts relevant to pay satisfaction distributed in proportion of 0.48:0.52 in positive and negative valence, and b) 14,541 (out of 47,874) posts relevant to supervision distributed in proportion of 0.45:0.55 in positive and negative valence. Figure 2 plots the valence of pay and supervision tweets from 2012 through the first quarter of 2018.

Discussion

The relatively high accuracy of these initial classifiers demonstrates the feasibility of tracking job satisfaction on Twitter. This can aid our understanding of how regional, national, and global trends affect workers' lived experiences. Additionally, there are several promising directions for future research.

Existing research has assessed personality traits from social media usage (Park et al., 2015; Youyou, Kosinski, & Stillwell, 2015). Extraversion and neuroticism are associated with both life and job satisfaction (Judge, Heller, & Mount, 2002; Schimmack, Radhakrishnan, Oishi, Dzokoto, & Ahadi, 2002). Confirming relationships between personality traits and job satisfaction would provide construct validity evidence for social media-based assessments of job satisfaction facets.

Changing macroeconomic conditions affect job satisfaction. Specifically, unemployment levels are related to job satisfaction at the national level (Tay & Harter, 2013). Future research should examine the extent to which job satisfaction expressed on Twitter covaries with changing macroeconomic conditions over time. Future research can also determine the extent facet level job satisfaction scores at the national level have convergent or discriminant validity with self-reported job satisfaction.

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Table 1

Mean Cross-Validation Accuracy of Each Feature

		N-grams	**LIWC**	**N-grams + LIWC**
Relevance	Pay	.70	.72	.76
	Supervision	.70	.64	.72
		N-grams	**Sentiment**	**N-grams + Sentiment**
Valence	Pay	.77	.64	.78
	Supervision	.72	.62	.74

Figure 1

Words that reliably discriminate between pay satisfaction (top) and dissatisfaction (bottom)

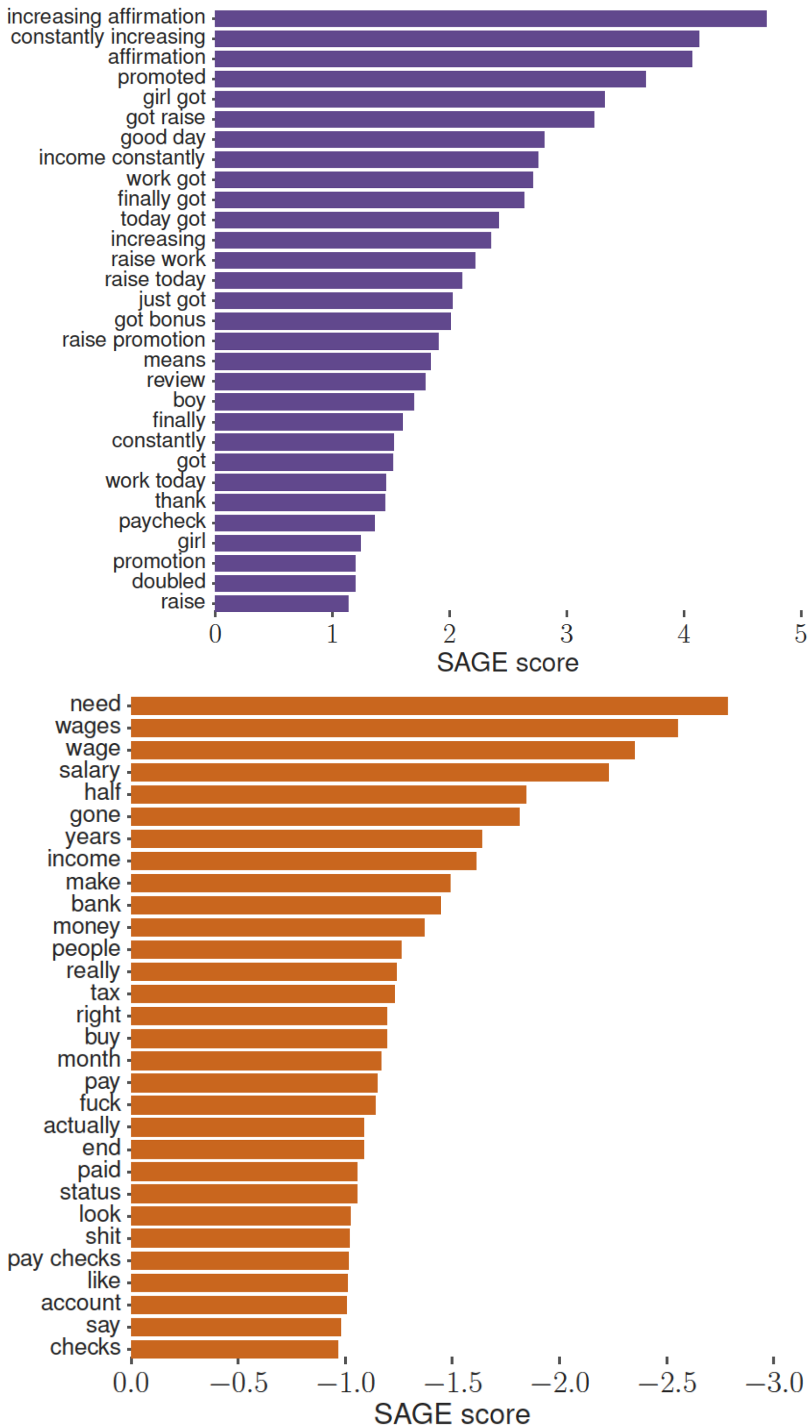
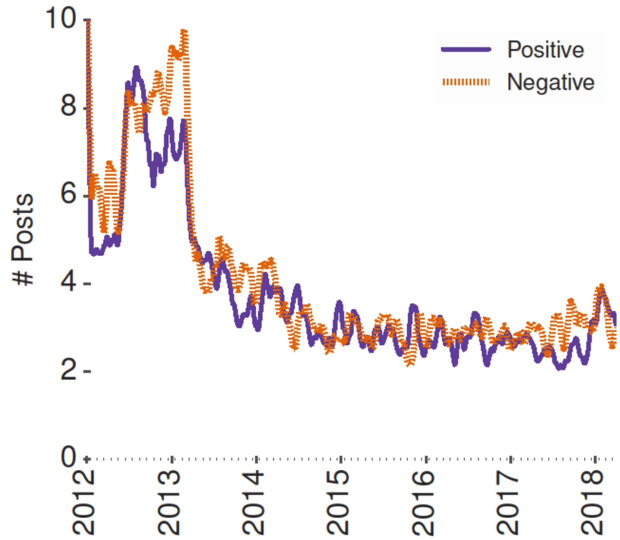


Figure 2

Pay (left) and supervision (right) satisfaction expressed on Twitter over time



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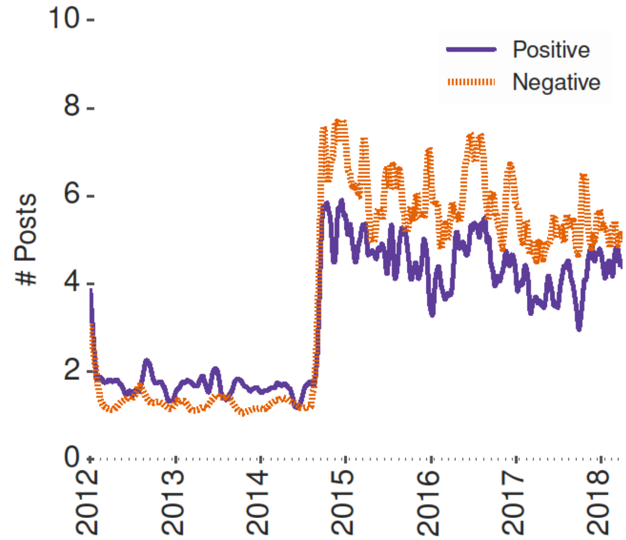

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