

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

Louis Hickman¹, Koustuv Saha², Munmun De Choudhury², & Louis Tay¹

¹Purdue University

²Georgia 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 (Gaziloglu & 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.

References

- Balzer, W. K., Smith, P. C., & Kravitz, D. A. (1990). *User's manual for the Job Descriptive Index (JDI) and the Job in General (JIG) scales*. Department of Psychology, Bowling Green State University.
- Bollen, J., Mao, H., & Zeng, X. (2011). Twitter mood predicts the stock market. *Journal of Computational Science*, 2, 1-8.
- De Choudhury, M., Gamon, M., Counts, S., & Horvitz, E. (2013a). Predicting depression via social media. *ICWSM*, 13, 1-10.
- De Choudhury, M., Counts, S., & Horvitz, E. (2013b). Social media as a measurement tool of depression in populations. In *Proceedings of the 5th Annual ACM Web Science Conference* (pp. 47-56). ACM.
- De Choudhury, M., & Counts, S. (2013). Understanding affect in the workplace via social media. In *Proceedings of the 2013 conference on Computer supported cooperative work* (pp. 303-316). ACM.
- De Choudhury, M., Kiciman, E., Dredze, M., Coppersmith, G., & Kumar, M. (2016, May). Discovering shifts to suicidal ideation from mental health content in social media. In *Proceedings of the 2016 CHI conference on human factors in computing systems* (pp. 2098-2110). ACM.
- De Neve, J. E., Diener, E., Tay, L., & Xuereb, C. (2013). The objective benefits of subjective well-being. In J. Helliwell, R. Layard, & J. Sachs (Eds.), *World Happiness Report 2013* (pp. 54-79). New York: UN Sustainable Development Solutions Network.

- Diener, E., Heintzelman, S. J., Kuslev, K., Tay, L., Wirtz, D., Lutes, L. D., & Oishi, S. (2017). Findings all psychologists should know from the new science on subjective well-being. *Canadian Psychology/Psychologie Canadienne*, 58, 87-104.
- Eichstaedt, J. C., Schwartz, H. A., Kern, M. L., Park, G., Labarthe, D. R., Merchant, R. M., Jha, S., Agrawal, M., Driurzynski, L. A., Sap, M., Weeg, C., Larson, E. E., Ungar, L. H., & Seligman, M. E. P. (2015). Psychological language on Twitter predicts county-level heart disease mortality. *Psychological Science*, 26(2), 159-169.
- Freeman, R. B. (1978). Job satisfaction as an economic variable. *American Economic Review*, 68, 135-141.
- Gazioglu, S., & Tansel, A. (2006). Job satisfaction in Britain: individual and job related factors. *Applied Economics*, 38(10), 1163-1171. doi:10.1080/00036840500392987
- Herzberg, F., Mausner, B., & Snyderman, B. (1959). *The motivation to work*: John Wiley and Sons, Inc.
- Judge, T. A., Heller, D., & Mount, M. K. (2002). Five-factor model of personality and job satisfaction: A meta-analysis. *Journal of Applied Psychology*, 87(3), 530-541.
- Judge, T. A. & Kammeyer-Mueller, J. D. (2012). Job attitudes. *Annual Review of Psychology*, 63, 341-367.
- Judge, T. A., & Klinger, R. (2007). Job satisfaction: Subjective well-being at work. In M. Eid & R. Larsen (Eds.), *The science of subjective well-being* (pp. 393-413). New York: Guilford Publications.
- Lamb, A., Paul, M. J., & Dredze, M. (2013). Separating fact from fear: Tracking flu infections on twitter. In *Proceedings of the 2013 Conference of the North American Chapter of the*

- Association for Computational Linguistics: Human Language Technologies* (pp. 789-795).
- Manning, C., Surdeanu, M., Bauer, J., Finkel, J., Bethard, S., & McClosky, D. (2014). The Stanford CoreNLP natural language processing toolkit. In *Proceedings of 52nd annual Meeting of the Association for Computational Linguistics* (pp. 55-60).
- McKee-Ryan, F., Song, Z., Wanberg, C. R., & Kinicki, A. J. (2005). Psychological and physical well-being during unemployment: a meta-analytic study. *Journal of Applied Psychology*, 90(1), 53-76. doi:10.1037/0021-9010.90.1.53
- Park, G., Schwartz, H. A., Eichstaedt, J. C., Kern, M. L., Kosinski, M., Stillwell, D. J., Ungar, L. H., & Seligman, M. E. (2015). Automatic personality assessment through social media language. *Journal of Personality and Social Psychology*, 108(6), 934-952.
- Pennebaker, J.W., Booth, R.J., Boyd, R.L., & Francis, M.E. (2015). *Linguistic Inquiry and Word Count: LIWC2015*. Austin, TX: Pennebaker Conglomerates (www.LIWC.net).
- Pew Research Center. (2012). Assessing the representativeness of Public Opinion Surveys. Retrieved from <http://www.people-press.org/2012/05/15/assessing-the-representativeness-of-public-opinion-surveys/>
- Russell, S. S., Spitzmüller, C., Lin, L. F., Stanton, J. M., Smith, P. C., & Ironson, G. H. (2004). Shorter can also be better: The abridged job in general scale. *Educational and Psychological Measurement*, 64(5), 878-893. <https://doi.org/10.1177/0013164404264841>
- Saha, K., Chan, L., De Barbaro, K., Abowd, G. D., & De Choudhury, M. (2017). Inferring mood instability on social media by leveraging ecological momentary assessments. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, 1(3), 95.

- Schwartz, H. A., Eichstaedt, J. C., Kern, M. L., Dziurzynski, L., Lucas, R. E., Agrawal, M., . . . Ungar, L. H. (2013). Characterizing geographic variation in well-being using tweets. In *Proceedings of the 7th International AAAI Conference on Weblogs and Social Media*. Association for the Advancement of Artificial Intelligence. Retrieved from <http://www.aaai.org/ocs/index.php/ICWSM/ICWSM13/paper/view/6138/6398>
- Schimmack, U., Radhakrishnan, P., Oishi, S., Dzokoto, V., & Ahadi, S. (2002). Culture, personality, and subjective well-being: Integrating process models of life satisfaction. *Journal of Personality and Social Psychology*, 82, 582–593. <http://dx.doi.org/10.1037/0022-3514.82.4.582>
- Smith, P. C., Kendall, L. M., & Hulin, C. L. (1969). *Measurement of satisfaction in work and retirement*. Chicago: Rand-McNally.
- Tay, L., & Harter, J. K. (2013). Economic and labor market forces matter for worker well-being. *Applied Psychology: Health and Well-Being*, 5, 193–208. <http://dx.doi.org/10.1111/aphw.12004>
- Won, H. H., Myung, W., Song, G. Y., Lee, W. H., Kim, J. W., Carroll, B. J., & Kim, D. K. (2013). Predicting national suicide numbers with social media data. *PloS one*, 8(4), e61809.
- Youyou, W., Kosinski, M., & Stillwell, D. (2015). Computer-based personality judgments are more accurate than those made by humans. *Proceedings of the National Academy of Sciences*, 112(4), 1036-1040.

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)

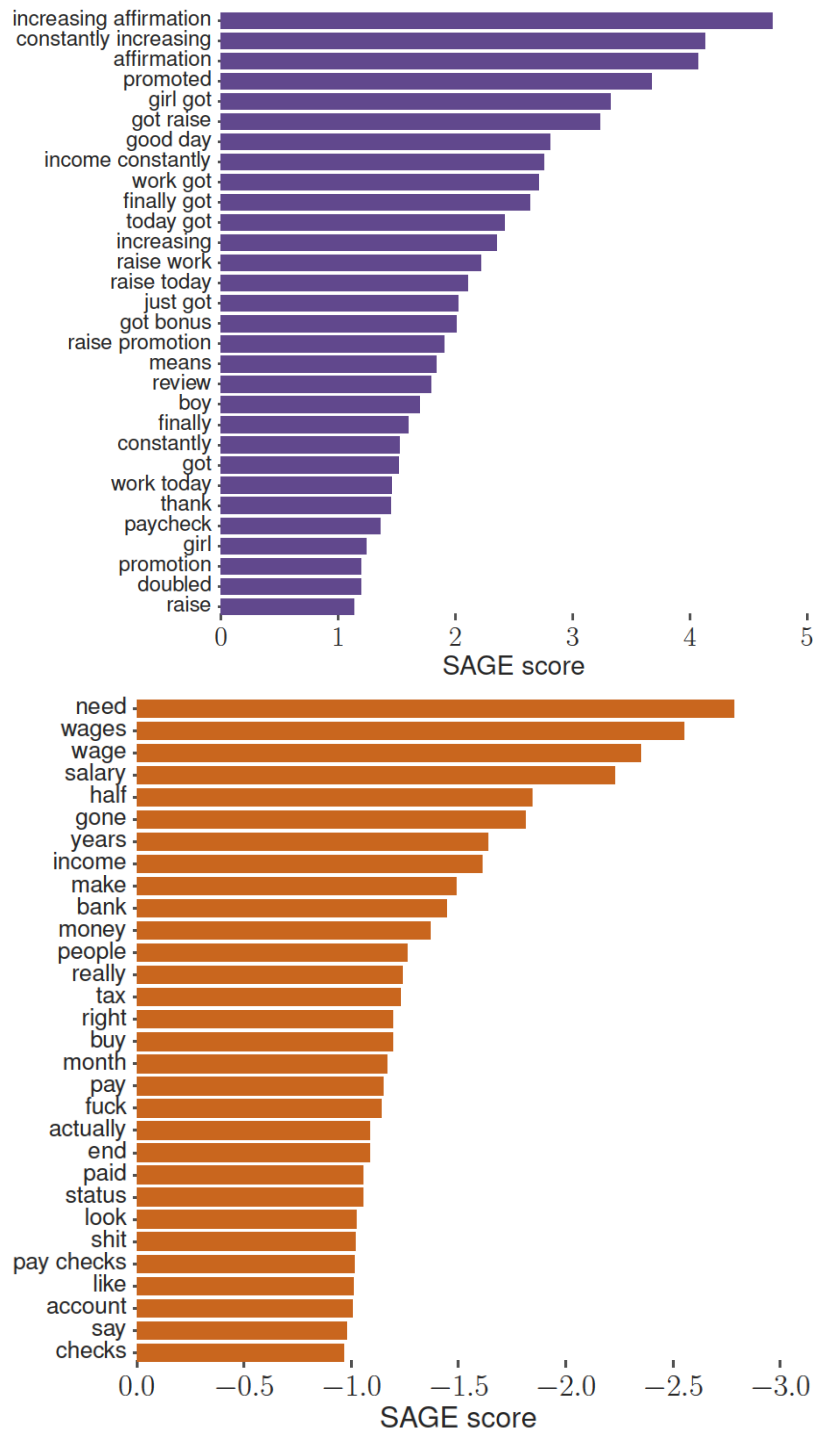


Figure 2

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

