

Chapter 10

Flickering Emotions: Feeling-Based Associations from Related Tags Networks on Flickr

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ABSTRACT

Using the emotion words of Robert Plutchik's "Wheel of Emotions" (based on his multidimensional emotion model) as seeding terms to extract related tags networks (and related thumbnail imagery) from Flickr (at 1 deg., 1.5 deg., and 2 deg.), it is possible to formulate (1) insights about emotions and their interrelationships (through the lens of collective folksonomic tagging), (2) understandings about what the related tags in the networks may suggest about the image item holdings on Flickr, and (3) awareness of the collective mental models of the Flickr users regarding particular emotions, and (4) fresh methods of research to folk tagging through the extraction and analysis of related tags networks and related thumbnail imagery. This chapter introduces this case of analyzing related tags networks to more deeply understand public conceptualizations of emotions through data labels.

INTRODUCTION

A by-the-numbers summary of Flickr shows a social media platform with 112 million users from 63 countries. Since its founding in February 2004, Flickr has amassed some 10 billion shared images and averages about a million photos shared daily. As a social media platform, Flickr hosts some two million groups. A hundred institutions participate in the Flickr Commons digital collection (with a total of 4 million images shared through the Flickr Commons). Flickr users have shared some 53 million tags and nearly a quarter million comments (Smith, Aug. 10, 2015).

Informal tagging by the users who share their digital contents online tends to be egocentric and localized. Such users are generally thinking in a localized and personalized way, and their applied labels (described as "lightweight descriptions") may reflect that mindset. The tagging structures that are extracted from such informal amateur-labeled digital contents are known as folksonomies—or "folk" "taxonomies," as termed by Thomas Vander Wal in 2005. Folksonomies are also known as "social classifications" or

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“ethnoclassification” or what one author himself calls “communal categorization” (Sturtz, 2004, p. 1). Social tagging has long been seen as a “collaboration tool” (Begelman, Keller, & Smadja, 2006, p. 1) that enables interactive browsing of shared contents.

Broadly speaking, folksonomies consist of users, digital resources, and tags (freeform keywords). These classification hierarchies reflect the organic, bottom-up, and evolving nature of such metadata labels. A “broad folksonomy” is one which has “many people tagging the same object and every person can tag the object with their own tags in their own vocabulary,” according to Vander Wal (Feb. 21, 2005). With so many people tagging in a collective way, the tags may be seen to fall into a power law curve (with highly popular terms and many lesser used ones which fall into a long tail), observes Vander Wal. A “narrow folksonomy,” by contrast, is one in which objects are tagged by the individual who uploaded the contents and (potentially) others within his or her friend network. This self-indexing was seen as a way to help re-find contents placed on the Web and Internet. Colloquially, this is referred to as “self-tagging” vs. “free-for-all” tagging. The goal of a narrow folksonomy is to help the individual user re-find the object on the Web or Internet and may be more elusive to analyze because of idiosyncratic usage (Vander Wal, Feb. 21, 2005). Auray (2007) sees narrow folksonomies as being “less casual” than broad folksonomies in the labeling of an object, but these features may prove to be its strength, enabling “more open, more random, exploration of content” in the wild (Auray, 2007, p. 74).

‘Narrow’ folksonomy, however, because it is less casual as regards the attachment of a key word to a piece of content, reveals its strength in finding precise content from a key word search. It is particularly useful when it comes to building databases on content, which cannot be easily found by text-based searches using the standard tools. An indirect advantage is that it allows for the grouping of content on a basis of the co-occurrence of key words within the groups by ascending classification methods 3. A high level of importance is attributed to grouping by Flickr, for example, allowing photographs with a similar content to be tracked down by ascending classification. (Auray, 2007, p. 73)

The folk tags tend to be more “novel” and dynamically “volatile” (Auray, 2007, p. 68). Other researchers highlight the subjectivity of tags as a form of self-expression (Gupta, Li, Yin, & Han, 2011, p. 452). Such collectively-created folk tags also tend to be “noisy,” without the professional discipline of a pre-made disambiguated label and data structure. Those created user-generated contents are writing in the vernacular, in the “comfort vocabulary of everyday usage” (Vander Wal, Feb. 21, 2005). With the advent and popularization of social sharing on social media platforms, initially, there were no taxonomies that fully captured the dynamism and lingo of the Web and Internet, with the #hashtagged words, run-together terms, abbreviations, non-words, and other aspects.

Taxonomies (with controlled vs. free-text vocabularies), while authoritative for the respective fields within which they are used, tend to be expensive to create both in terms of human hours and time. Such structured data labels did not actually exist for the freeform data when content sharing sites were popularized. Folksonomies have been compared with selected structured taxonomies of pre-labeled data to understand the differences. Folksonomies have been studied for a variety of applications—such as improving online social media services by understanding users’ better by analyzing their tagging streams. There have been automated suggestions for creating candidate tags (keywords) and tag sets for particular digital images. In recent years, computer scientists and programmers have been developing ways to deploy artificial intelligence (AI) to auto-tag multimedia contents, to “recognize” objects in the image frame, and to identify specific people in an image.

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