

Misleading Online Content: Recognizing Clickbait as “False News”

Yimin Chen

Language and Information
Technology Research Lab (LIT.RL)
Faculty of Information & Media Studies
University of Western Ontario,
London, Ontario, CANADA
ychen582@uwo.ca

Niall J. Conroy

Language and Information
Technology Research Lab (LIT.RL)
Faculty of Information & Media Studies
University of Western Ontario,
London, Ontario, CANADA
nconroy1@uwo.ca

Victoria L. Rubin

Language and Information
Technology Research Lab (LIT.RL)
Faculty of Information & Media Studies
University of Western Ontario,
London, Ontario, CANADA
vrubin@uwo.ca

ABSTRACT

Tabloid journalism is often criticized for its propensity for exaggeration, sensationalization, scare-mongering, and otherwise producing misleading and low quality news. As the news has moved online, a new form of tabloidization has emerged: ‘clickbaiting.’ ‘Clickbait’ refers to “content whose main purpose is to attract attention and encourage visitors to click on a link to a particular web page” [‘clickbait,’ n.d.] and has been implicated in the rapid spread of rumor and misinformation online. This paper examines potential methods for the automatic detection of clickbait as a form of deception. Methods for recognizing both textual and non-textual clickbaiting cues are surveyed, leading to the suggestion that a hybrid approach may yield best results.

General Terms

Algorithms, Reliability, Experimentation, Human Factors, Standardization, Verification.

Keywords

Clickbait, fake news, news verification, automated deception detection, automation, reader behavior.

1. INTRODUCTION

In recent years, journalism and media scholars have warned about the increasing tabloidization of news [Chittum, 2013; Rowe, 2011]. Tabloid journalism is widely considered ‘yellow’ or ‘bad’ journalism – “it simplifies, it personalises, it thrives on sensation and scandal” [Örnebring & Jönsson, 2004] – in short, the antithesis of traditional journalism’s ideals of objectivity and accountability “driven by the quest for truth” [Fisher, 2014]. Much of this process is driven by economic incentives, as circulation and subscriptions continue to fall and news producers depend more and more on online advertising revenue based on page views [Barthel, 2015]. Thus, the current state of online news is one that heavily incentivizes the speed and spectacle over restraint and verification in the pursuit of ad dollars [Chen, Rubin, & Conroy, 2015].

The primary danger posed by tabloidization is not that ‘hard’ news topics (e.g., politics, science, economics) will be replaced by ‘soft’ ones (e.g., entertainment, sports, gossip) [Reinmann, et al., 2011], but that the focus on attention-grabbing, shareable reporting has led to “the willful blurring of lines between fact and fiction” [O’Neil, 2013]. Instead of the quest for truth, online news is now often driven by the quest for page views and one symptom of this change is a proliferation of clickbait headlines. Clickbait refers to “content whose main purpose is to attract attention and encourage visitors to click on a link to a particular web page” [‘clickbait,’ n.d.]. Often misleading and unverified, and seldom corrected, these types of headlines are a major contributor to the spread of fake news on the internet [Silverman, 2015].

Irresponsible reporting can have real consequences, both socially and economically. For example, a 2008 hoax claiming that Apple CEO Steve Jobs had suffered a serious heart attack led to the company’s stock price falling by 10% [Sandoval, 2008]. Furthermore, scholars have argued that the current trend towards a merging of commercial and editorial interests is detrimental to democratic values [Couldry & Turow, 2014]. This paper offers a preliminary discussion of clickbait as an example of false or misleading news, reviews its identifying characteristics, and potential methods for the detection of this type of deception.

2. LITERATURE REVIEW

The term ‘tabloidization’ has been used in the communications and journalism literature since at least the 1980s [Bird, 2008]. While the prevailing theme has been that tabloidization is detrimental to professional journalism [Esser, 1999; Nice, 2007; Silverman, 2015], there has been some resistance to the blanket claim that tabloids are all ‘bad’. These dissenting arguments often point to the role of tabloid media as representing and promoting the interests of audiences outside of the political, economic, and cultural elites in the public sphere [Gripsrud, 2000; Örnebring & Jönsson, 2004]. Furthermore, it is important to distinguish between what are considered tabloid topics (‘soft news’) and tabloidization as a presentational strategy that exaggerates the importance of news items by presenting them as “more interesting, extraordinary and relevant than might be the case” [Molek-Kozakowska, 2013; see also Skovsgaard, 2014]. This difference is illustrated in Figure 1: Headline (a) introduces an article about the publication of a new biography on Michelle Obama. Headline (b) frames the same, otherwise-simple story but in sensationalistic, scandalous terms.

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee.

ACM WMDD '15, November 9, 2015, Seattle, Washington, USA.

Copyright 2015 ACM 1-58113-000-0/00/0010 ...\$15.00.

Headline (b) is an example of clickbaiting.



Figure 1. Two headlines reporting on Michelle Obama’s new biography showing (a) traditional and (b) clickbaiting presentation styles.

Whereas there is a compelling argument for the democratizing role of ‘soft news’ reporting in mainstream media, the deceptive tactics of clickbaiting are much more problematic. Reporting unverified rumors as truth and willfully manipulating facts to entice more readers to click and share links is harmful to both the notion of journalistic integrity and the public good, especially in the online environment. Nowadays, “people read by social media stream rather than by publication” [Adler, 2014], which means that content is often divorced from context. On social media sites like Facebook, an article from *the New York Times*, looks just like an article from *the Onion* and either may come with the endorsement of the friend who shared it. Given how quickly misinformation can spread on the internet, clickbaiting can have costly consequences and “should not be ignored or considered collateral damage in the war for readers if considered ethically and not financially” [Blom & Hansen, 2015].

Some of the factors that make clickbaiting content so compelling to readers can be understood through the concept of sensemaking. Theoretical formulations of information seeking in Library and Information Science (LIS) use sensemaking metaphors to describe the process through which information needs are recurrently generated and satisfied during the information search process [Dervin, 1992]. Gaps in knowledge emerge, which are then satisfied through the construction of linkages, or bridges, between discrete information. Such metaphors are useful in understanding the origin of curiosity which arise as the result of linguistic cues of clickbait headlines. The characteristics of curiosity: its intensity, transience, association with impulsivity, and tendency to disappoint [Loewenstein, 1994] lead to cognitively induced deprivation - a knowledge gap - which motivates exploring activity from the reader. Since clickbait headlines create and exploit these knowledge gaps to entice readers to click through to see the full article, it stands to reason that these curiosity-piquing factors could serve as cues for an automated system to detect and flag this type of low-quality news. While there have been attempts to automate news verification in the past [Rubin, Conroy, & Chen, 2015], these methods have not yet been applied to clickbait.

3. METHODS

Methods to detect clickbait can be directed at various levels, from the presence of individual words (lexical choices) used in the headlines, to more complex language and grammatical structures, to the genre or subject matter itself. When taken together, a hybrid approach based on an amalgamation of measures can be a basis for for automating clickbait detection (see Rubin, Chen, & Conroy, 2015 for more in-depth discussion of ‘fake news’ data sources).

3.1. Content Cues

The ‘choice gap’ [Bockzowski & Peer, 2011] is the distance between what news producers tend to promote, and what news readers are actually choosing to read. This idea is explored in the examination of 1260 stories from both within and across different news websites. Results show a sizeable contrast in journalists’ and consumers’ choices of what stories are selected—aligning with other studies that show a reduced interest in public affairs, and that journalists’ penchant for public affairs do not conform to those of users [Bockzowski & Peer, 2011].

Attempts to unravel which content cues trigger induced cognitive deprivation were made by Hoyer and Nosser [2015] by examining a large, legacy newspaper in Norway across a period of time. They found that in addition to an increase in the length of news content, soft techniques designed to entice readers, such as the highlighting of conditions and trends, creates context for the lead story. Unity of place, time and action is not fixed, and journalists are not mentioned in newer samples. This represents a de-coupling from traditional practice, since objectives such as currency and inclusivity of authorship have been seen as principal strengths of online sources.

Interactivity and encouragement of user participation in news production is a hallmark of the concepts of fluidity and liquidity in digital news as unpredictable and continuous processes. Some news sources incorporate technology, for example Active Twitter on ABC News, IReport on CNN.com, and user submissions on slashdot.org and BBC [Hasan & Hashim, 2009], which encourage users to contribute with on-the-spot footage and eyewitness accounts. However, there is a lack of clarity and coherence in explaining the concept of liquidity. In attempting to define a methodology through an assessment of news examples, Karlsson [2012] found that multiple versions of the same stories, which may substantially differ in content, could be a distinguishing characteristic. As well, these news forms tend to encourage interactivity of users in contributing, either in text, video, image, hyperlinks and audio modalities. As a result, variation and expansion of existing news content is enhanced.

3.1.1. Lexical and Semantic Levels of Analysis

It is important to attend to the lexics (as a cue to clickbait) since the choice of the vocabulary can have a dependent effect on the subjective response of readers. Using automated methods, Lex et al., [2010] identified a list of stylometric features of text (i.e., parts of speech, word length and subjective terms) that can be used to discriminate between two journalistic formats (‘yellow’ vs. ‘high quality’) of test articles. This distinction was found to be existent regardless of topic, with a predictive accuracy of 77%.

Although clickbait is still a recent phenomenon of study, preliminary examinations of popular headlines have introduced cue patterns which may be assistive in the identification of clickbait. These cues include such diverse examples as the use of numbers, activity words to inspire action, and celebrity names [Clark, 2015]. Blom and Hansen [2015] postulated examples of clickbait of this sort are most prominent in commercial sites and found its manifestations in ‘yellow journalism’ or ‘soft news’ content [Lex et al., 2010], in the form of demonstrative pronouns, adverbs, interrogatives, and imperatives.

Two methods, *Support Vector Machines (SVM)*, and *Naive Bayes* classifiers, rely on counting key words and gathering training examples, and can be useful approaches to automatically detect misinformation [Lary et al., 2010]. In a nutshell, a high probability is assigned to words in a prototypical clickbait headline, not those

in an atypical clickbait headline. Conversely, low probability is assigned to words which are not found in clickbait, and vice versa. The individual probabilities are then combined through Bayes' formula or vector distances which can then form a probability filter. Other methods may be used to generate word frequencies in defined semantic categories (i.e., affective words or action words) from compiled dictionaries (e.g., LIWC). Previous studies have shown this to be instrumental in determining degree of misinformation and deception [Rubin & Conroy, 2012].

3.1.2. Syntactic and Pragmatic Levels of Analysis

A pragmatic function of headlines invokes forward-referencing [Jenkins, 1990] by making reference to forthcoming parts in the discourse, or through the use of unresolved pronouns. Thus, headlines semantically depend on the article's content and serve to essentially bait the reader. Empty slots cannot be filled with confidence until the ensuing text has been read. For instance, the headline "*He loves Beatles, menthol cigs..and longs for muscles like Van Damme [sic]*" is cataphoric in the sense that "He" refers to a name which is located within the text [Blom & Hansen, 2015]. *UpWorthy*, an online news site prominently featured in many Facebook feeds, accounts for far more sharing activity compared to sites who produce substantially more news content. Co-founder, Peter Koechly, has said that in order to attract a large audience, headlines should pique the reader's curiosity and get them engaged emotionally [Clark, 2015]. The examples below are real *UpWorthy* headlines: the first demonstrates forward referencing, with extensive use of numerals. The second combines disparate topics and provocative use of adjectives.

Example 1. *Here's What Happens When You Put A Few Little Kids In A Room With 2 Dolls In 2 Different Colors.*

Example 2. *This Is The Most Inspiring Yet Depressing Yet Hilarious Yet Horrifying Yet Heartwarming Grad Speech* [Clark, 2015]

Other methods can take into account more complex language patterns including the use of reverse narrative. Students' affective reactions to manipulated news texts, designed to foster a sense of suspenseful appeal, have been measured for their effect on curiosity. Here, the linguistic features of narrative (linear, reversal and inverted) were used to substantiate effects on three subjective emotional measures (suspense, curiosity and reading enjoyment). It was found that reversal significantly affects curiosity level. Further experimentation shows that the linear type evokes more suspense than the reversal and the inverted type, and reading enjoyment is at a maximum when narration is prepared in the linear form [Knobloch et al., 2004].

Quantifying the effect of headlines may be an elusive goal, however apparent and pronounced they may be to human observers. To approximate grammatical structure, Probability Context Free Grammars (PCFG) [Feng et al., 2012] have been applied to generate constituent syntactic structures of texts, with successful outcomes in deception detection studies. Applying this method to detecting the presence of narrative structure and forward referencing at the outset, together with word-level cues may be a promising hybrid approach for determining the presence of clickbait (see Conroy, Chen, & Rubin, 2015 for further discussion of hybrid methods in deception detection for news).

3.2. Non-Text Cues

Information gleaned from news sites, apart from textual content, can also be valuable in automatically assessing the presence of

clickbait. A key variable in clickbait is emotion ["An emerging science," 2015]. The use of the configurations of emotional valence (positive, negative) and arousal (strong, weak) are knowingly used by publishers to misdirect readers. Guerini and Staiano [2015] say that posts generate more comments when they are associated with high arousal than emotions of less control such as fear and sadness. By contrast, posts generate more social votes when associated with emotions of control, such as inspiration.

3.2.1. Image Analysis

One known method to efficiently manipulate emotion in observers is the strategic use of images, as well as directing perceptions through the proximity of the images to the headline. Ecker et al. [2014] hypothesized that like headlines, images can serve to attract attention and are usually processed before the full article is read. It is found that clickbait often integrates the use of images as a way to interest users through misinformation. Readers spontaneously integrated information from a headline with a photo in the associated article. The congruence of headline and photo therefore affected subsequent valence ratings: headlines that were incongruent with the photo led people to make judgments that were more in line with the headline. Techniques to locate not only the existence of certain images as part of the headline should, therefore, be part of an automatic assessment process. Emotional ratings compiled through user feedback and sentiment analysis tools for text [Pang & Lee, 2008] can be instrumental in flagging incongruence between textual content and images, and thus point to potential misinformation.

3.2.2. User Behavior Analysis

Other content-independent methods are useful since they assess how news readers engage with news once it is clicked. Leading generators of internet news content are drawing in on close to 50 million unique visitors a month ["An emerging science," 2015]. Their strategy is founded upon pumping traffic through their site while pushing it towards sponsored stories. They, however, acknowledge that while they try to write headlines to motivate sharing, they do not want to fool users to the extent that they stop reading and regret visiting their site. The hypothesis follows the intuition that what users actually do with the content, rather than the content itself, signifies the presence of misleading headlines. Two indicators of user interest: time spent reading the article, and sharing and commenting behavior, taken from the quantitative analysis of web traffic, may be used as a clickbait diagnostic, since interest reflects a low choice gap and a low probability for clickbait [Boczkowski & Peer, 2011].

4. Limitations & Future Work

Some limitations with this study may be apparent. First, the broad range of methods explored entails that we have addressed only surface descriptions of each technique for clickbait detection. Further examination of the linguistic patterns and cues mentioned (see Table 1) can provide a basis for a clickbait corpus and the development of automation tools. Second, our review does not depict a concrete implementation which merges methods to a prototype application.

Our future work is to address these limitations in order. The current survey is the basis for the construction of a more refined description of clickbait in the form of a word corpus and a primary list of linguistic features.

A proof of concept application will focus around clustering techniques described here, provided a representation that models

clickbait headlines along feature dimensions. Such an application must be considered in three separate use case-scenarios: 1) news production (e.g., in newsroom automation case-scenario, to support the work of journalists); 2) news aggregation and distribution (e.g., to support online content management systems, on-demand online news delivery with discriminative dispatching), and 3) news consumption (e.g., to filter out undesired misleading online content for lay news readers or professional news analysts).

Furthermore, the identified, functional use of images in the semantic assessment of clickbait means that image analysis forms a component of data collection. We consider the distance between the pre-iconographical level or “ofness” of a picture [Shatford, 1986] (the depicted objects and events), and congruence to headlines and story content. In this way, we build a set of requirements for an automation tool with regards to image assessment, and an additional level of depth in the automation design.

5. Conclusion

‘Soft’ news and tabloid journalism is prone to exaggeration, sensationalization, and other forms of misinformation. Our findings

show that tabloidization of news and the shift towards digital content incentivizes the use of clickbait to generate interest in news readers. Clickbaiting can be identified through a consideration of the existence of certain linguistic patterns, such as the use of suspenseful language, unresolved pronouns, a reversal narrative style, forward referencing, image placement, reader’s behavior and other important cues (see Table 1). All are potential variables useful for identifying the probability of clickbait. This work responds to a recent call to “expand formal studies of deception cues to data derived from mass media communications”, as noted in a recent methods survey [Fitzpatrick, Bachenko, & Fornaciari, 2015, p. 51]. The ultimate goal of this research is the creation of an automated assistive tool with the ability to flag potential instances of clickbait and other types of online misinformation for users. This tool is intended for several types of users (lay news consumers, professional news analysts, online content managers, and news aggregators) to quickly and efficiently filter out low-quality information. The conceptual clickbait patterns discussed here could also be used in schools and libraries to support information literacy programs.

Table 1. Clickbait Cues and Methods.

A variety of linguistic and image patterns combined with news reader behaviors are proposed here as cues (predictive variables) for the identification of potential clickbait as misleading online content.

Clickbait Cue Types	Cue Mechanisms	Identification Methods
<i>Lexics/Semantics</i> Unresolved pronouns Affective language & action words Suspenseful language Overuse of numerals	Curiosity piquing Emotional engagement Motivation for action Suspenseful appeal	Support Vector Machines (SVM) Naive Bayes Frequency analysis
<i>Syntax/Pragmatics</i> Forward Reference Reverse Narrative	Resolving ambiguities Reading enjoyment	Probability Context Free Grammars (PCFG) Neural network analysis
<i>Images</i> Placement Emotional content	Directed perceptions Emotional incongruence	Image detection Image caption analysis
<i>News Reader Behavior</i> Reading time Sharing behavior Commenting behavior	Manifestation of interest User participation Interactivity	Web traffic analysis Web metadata analysis

6. ACKNOWLEDGMENTS

This research has been funded by the Government of Canada Social Sciences and Humanities Research Council (SSHRC) Insight Grant (#435-2015-0065) awarded to Dr. Rubin for the project entitled *Digital Deception Detection: Identifying Deliberate Misinformation in Online News*.

7. REFERENCES

- Adler, B. (2014, Mar 11). Tabloids in the age of social media. *Columbia Journalism Review*. http://www.cjr.org/news_literacy/national_enquirer_hoffman_hoax.php
- Allen, M. (2015). How click bait articles work <http://www.thepinchandzoom.com/blog/2015/5/2/click-bait#sthash.MGkHil5p.dpuf>
- An emerging science of clickbait. (2015, Mar 25). *MIT Review*. <http://www.technologyreview.com/view/536161/an-emerging-science-of-clickbait>
- Barthel, M. (2015). Newspapers: Fact Sheet. <http://www.journalism.org/2015/04/29/newspapers-fact-sheet>
- Bird, S. E. (2008). Tabloidization. In Donsbach, W. (Ed.), *The international encyclopedia of communication*. Malden : Blackwell.
- Blom, J. N., & Hansen, K. R. (2015). Click bait: Forward-reference as lure in online news headlines. *Journal of Pragmatics*, 76, 87-100.
- Boczkowski, P. & Peer, L. (2011). The Choice Gap: The Divergent Online News Preferences of Journalists and Consumers. *Journal of Communication*.

8. Chen, Y., Rubin, V. L., & Conroy, N. J. (2015). News in an Online World: The Need for an "Automatic Crap Detector". In *Information Science with Impact: Research in and for the Community (ASIST2015)*, November 6-10, St. Louis
9. Chittum, R. (2013, Dec 6). Audit Notes: BS as business model, Larry Kudlow, Third Way revealed. *Columbia Review of Journalism*.
http://www.cjr.org/the_audit/audit_notes_bs_as_business_model.php
10. Clark, R. (2014). Top 8 Secrets of How to Write an Upworthy Headline. *Poynter*. Retrieved from <http://www.poynter.org/news/media-innovation/255886/top-8-secrets-of-how-to-write-an-upworthy-headline/>
11. 'Clickbait.' (n.d.) In *Oxford Dictionaries*.
<http://www.oxforddictionaries.com/definition/english/clickbait>
12. Conroy, N. J., Chen, Y., & Rubin, V. L. (2015). Automatic Deception Detection: Methods for Finding Fake News. In *Information Science with Impact: Research in and for the Community (ASIST2015)*, November 6-10, St. Louis
13. Couldry, N. & Turow, J. (2014). Advertising, Big Data, and the Clearance of the Public Realm: Marketers' New Approaches to the Content Subsidy. *International Journal of Communication*, 8, 1710-1726.
14. Dervin, B. (1992). From the mind's eye of the user: the sense-making qualitative and quantitative methodology. In J. D. Glazier, & R. R. Powell, *Qualitative research in information management* (pp. 61-84). Englewood, CO: Libraries Unlimited.
15. Ecker, U. Lewandowsky, S. Chang, E. & Pillai, R. (In Press. 2014). The Effects of Subtle Misinformation in News Headlines.
16. Esser, F. (1999). Tabloidization of News: A Comparative Analysis of Anglo-American and German Press Journalism. *European journal of communication*, 14(3), 291-324.
17. Fitzpatrick, E., Bachenko, J. & Fornaciari, T. (2015). Automated Detection of Verbal Deception. In Synthesis Lectures on Human Language Technologies (#29). Morgan & Claypool.
18. Gripsrud, J. (2000). Tabloidization, popular journalism and democracy. In Sparks, C. & Tulloch, J. (Eds) *Tabloid tales: Global debates over media standards*, 285-300. Lanham : Rowman & Littlefield.
19. Guerini, M. & Staiano, J. (2015). Deep Feelings: A Massive Cross-Lingual Study on the Relation between Emotions and Virality. <http://arxiv.org/abs/1503.04723v1>
20. Hasan, H. & Hashim, L. (2009). What's new in online news. In: *Pacific Asia Conference on Information Systems*.
21. Hoyer, S. & Nosser, H. (2015). Revisions of the news paradigm: Changes in stylistic features between 1950 and 2008 in the journalism of Norway's largest newspaper.
22. Karlsson, M. (2012). Charting the liquidity of online news: Moving towards a method for content analysis of online news. *International Communication Gazette*.
23. Knobloch, S., Patzig, G., Mende, A. M., & Hastall, M. (2004). Affective news effects of discourse structure in narratives on suspense, curiosity, and enjoyment while reading news and novels. *Communication Research*, 31(3), 259-287.
24. Lary, D., Nikitkov, & Stone, D. (2010). Which Machine-Learning Models Best Predict Online Auction Seller Deception Risk?
25. Lex, E., Juffinger, A., & Granitzer, M. (2010, June). Objectivity classification in online media. In *Proceedings of the 21st ACM conference on Hypertext and hypermedia* (pp. 293-294).
26. Loewenstein, G. (1994). The psychology of curiosity: A review and reinterpretation. *Psychological Bulletin*, Vol 116(1), Jul 1994, 75-98.
27. Molek-Kozakowska, K. (2013). Towards a pragma-linguistic framework for the study of sensationalism in news headlines. *Discourse & Communication*, 7(2), 173-197.
28. Nice, L. (2007). Tabloidization and the Teen Marker: Are teenage magazines dumberer than ever? *Journalism Studies*, 8(1), 117-136.
29. O'Neil, L. (2013, Dec 23). The Year We Broke the Internet. *Esquire*. <http://www.esquire.com/news-politics/news/a23711/we-broke-the-internet>
30. Örnebring, H., & Jönsson, A. M. (2004). Tabloid journalism and the public sphere: A historical perspective on tabloid journalism. *Journalism Studies*, 5(3), 283-295.
31. Pang, B., & Lee, L. (2008). Opinion mining and sentiment analysis. *Foundations and trends in information retrieval*, 2(1-2), 1-135.
32. Reinemann, C., Stanyer, J., Scherr, S., & Legnante, G. (2012). Hard and soft news: A review of concepts, operationalizations and key findings. *Journalism*, 6(2), 221-239.
33. Rowe, D. (2011). Obituary for the newspaper? Tracking the tabloid. *Journalism*, 12(4), 449-466.
34. Rubin, V. L., Conroy, N., & Chen, Y. (2015). Towards News Verification: Deception Detection Methods for News Discourse. *The Rapid Screening Technologies, Deception Detection and Credibility Assessment Symposium*, Hawaii International Conference on System Sciences (HICSS48), January 2015.
35. Rubin, V. L., Chen, Y., and Conroy, N. (2015). Deception Detection for News: Three Types of Fakes, In *Information Science with Impact: Research in and for the Community (ASIST2015)*, November 6-10, St. Louis.
36. Rubin, V. L. & Conroy, N. J. (2012). Discerning truth from deception: Human judgements and automation efforts. *First Monday*, 17(3-5).
<http://firstmonday.org/ojs/index.php/fm/article/view/3933>.
37. Sandoval, G. (2008, Oct 7). Who's to blame for spreading phony Jobs story? Cnet. <http://www.cnet.com/news/whos-to-blame-for-spreading-phony-jobs-story>.
38. Shatford, S. (1986): Analyzing the subject of a picture: A theoretical approach, *Cataloging & Classification Quarterly*, 6(3), 39-62
39. Silverman, C. (2015). Lies, Damn Lies, and Viral Content: How News Websites Spread (and Debunk) Online Rumors, Unverified Claims and Misinformation.
<http://towcenter.org/research/lies-damn-lies-and-viral-content>.