Association for Information Systems
AIS Electronic Library (AISeL)

BLED 2016 Proceedings

BLED Proceedings

2016

Seeing the Forest: Applying Latent Semantic Analysis to Smartphone Discourse

Jacob Miller
Drexel University, jlm479@drexel.edu

David Gefen
Drexel University, gefend@drexel.edu

VK Narayanan
Drexel University, vkn22@drexel.edu

Follow this and additional works at: http://aisel.aisnet.org/bled2016

Seeing the Forest:
Applying Latent Semantic Analysis to Smartphone Discourse

Jacob Miller
LeBow College of Business, Drexel University, USA
JLM479@drexel.edu
David Gefen
LeBow College of Business, Drexel University, USA
gefend@drexel.edu
VK Narayanan
LeBow College of Business, Drexel University, USA
vkn22@drexel.edu

Abstract

We apply latent semantic analysis (LSA) to understand how media discourse and cognition about smartphones evolved over time. LSA is a useful method to take advantage of large amounts of available text, discern meaning within the text, and see how meanings change over time, across the media coverage in the sector. We explain the theory of LSA, the process, and apply it to a dataset of over 83,000 media articles to create a semantic model of document and word meanings. We measure how groups of documents differ and then visualize how the discourse changes over time. We find that LSA is useful for measuring how discourse shifts across this broad set of data. In our empirical case, we find that smartphone discourse went through four distinct periods, with different dynamics of transition and stability. These characteristics suggested particular theoretical bases which LSA is also well suited to examine.

Keywords: Latent Semantic Analysis, Smartphones, Text Analysis

1   Introduction

In December 2006, the elites of the business and political worlds were "addicted" to their "Crackberries." Society knew what a smartphone was - a rather bulky mobile phone with a keyboard for email. However, 2007's iPhone launch introduced a radical new design and a redefinition of the collective cognitive frames regarding the smartphone. By 2013, smartphones were for "apps," keyboards were virtual on a capacitive touchscreen, and the formerly leading handset companies, Motorola, Nokia, and Research In Motion, were sold. The emergence of a dominant smartphone design in the early 2000s, and the subsequent transition to a new design were not just changes in technology, but the collective technological frames about the category (Orlikowski & Gash 1994). Changes in technology and markets are accompanied by

changes in understandings of what the technology is, how it is used, and where it is going (Orlikowski & Gash 1994).

Traditionally, collective cognition has been studied either qualitatively, with some complex manual coding (e.g. Gamson & Modigliani 1989), or archivally with word counts and frequencies (e.g. Fiss & Hirsch 2005). However, qualitative methods are limited by the volume of text. Counts presume that words have consistent meanings and ignore synonyms.

We are faced with this question: how can we better understand shifts in collective cognition about technology, quantitatively and at a large scale? Our approach is to apply a series of analyses based on Latent Semantic Analysis (LSA) (Landauer, McNamara, Dennis, & Kintsch 2006) to study discourse. LSA's vector space model of word meaning can be used to compute distances between sets of text, which is theorized to approximate the meanings of the text. We use these distances to visualize and analyze how aggregate media discourse chances over time.

In this paper, we show how LSA can be used to study large volumes of text, preserving more of its meaning, and providing insights by comparing different texts. We first discuss LSA theoretically, and overview how to perform an analysis. We then apply LSA in the case of the development of smartphones as a context in which to demonstrate LSA-based analysis and interpretation. We build a semantic space, and use the distances of texts in a heatmap to visualize how media discourse shifted over the period from 1992-2010.

2   LSA Theory

Latent Semantic Analysis (LSA) attempts to model human cognition through mapping the meaning of language (Landauer 2006). Theoretically, LSA's model of meaning inference via word association has been claimed to correspond to the human language acquisition process (Landauer 2006). Word meanings are gathered primarily from relations to other words, not by looking up terms in a dictionary. As people encounter new concepts, they try to understand them in terms of concepts and language they already know. The language acquisition process is implicitly a communication process. Word associations are created by the writer or speaker, not the reader, thus this process is also one by which meaning is spread through groups.

LSA analyzes word usage patterns and theorizes that co-occurrences between groups of words have implies some sort of common meaning. LSA processes a large set of documents, and based on word co-occurrences, identifies the similarity and differences between texts (terms or documents) in terms of these appearances. Because words with similar meanings are theorized to be used in similar contexts, with other similar words, LSA theory suggests that this approach captures hidden meanings, and thus, is a semantic approach based on latent word meaning, rather than a lexical approach based on specific words or word counts, or dictionary definitions. It may be better capture the real meaning of a statement when compared to a keyword-oriented approach, since texts are typically evaluated at a statement, paragraph, or document level. For example, if an actor uses a rival's term, but does so in a statement that has meanings very different than the term "normally would," LSA's use of the aggregate spatial position of the larger text will better capture the true meaning of the text.

Compared to manual coding, LSA will likely be less precise, and miss certain nuances in communication. However, LSA allows the analysis of far more text, and is a reproducible process that is not subject (at least a priori) to subjective judgments. Both techniques will involve judgment in interpretation.

Documents that are relevant to the topic and representative of the knowledge of a target audience are processed to create a multi-dimensional semantic space. This space is theorized to represent the range of word meanings known to the audience (Landauer 2006). Sentences are composed of sets of words, and the meaning in the sentence arises largely from that combination. Documents and statements are then "projected" into the space for comparison and evaluation.

LSA has the potential to add a great deal to social science because it is a tool to quantitatively measure differences between texts, and at a large scale. With this capability, texts can be clustered based on semantic similarity, not simply word similarity. This may be useful to identify themes in the discourse. In addition, researchers can add metadata like dates and authors, to compare discourse across time or between different parties. Latent Semantic Analysis has been used in Information Systems literature as a means of indexing and information retrieval, but has not seen widespread adoption for text analysis (Evangelopoulos, Zhang, & Prybutok 2012).

In the rest of this section, we overview the LSA process, and discuss some caveats for interpreting the semantic model.

2.1 The LSA Process

To better understand how to apply Latent Semantic Analysis to social science issues, we will describe how to model the semantic space. LSA involves three major stages, followed by interpretation:

Collecting a corpus (database of text) that reflects the span of meanings and ideas under examination.

Generating a high-dimensional semantic vector space based on word associations in the corpus

Projecting additional documents into the space to identify differences between sets of documents

The first stage involves collecting the corpus of text that will be used as the basis of the semantic space. There are several potential issues regarding the content of the corpus (Quesada 2006). The corpus must be large enough to capture sufficient variety and meaning. A small corpus will also be overly sensitive to a small set of interrelated documents. The corpus must also be sufficiently representative of the concepts and topics to be studied, because unrepresentative corpora will not produce spaces that accurately represent the meanings that are the target of the model.

The second stage generates the semantic space. This process creates a document-term matrix (DTM), listing co-occurrences of all words in each document. A document, for the purposes of this matrix, may not be a "document" like an article, but a paragraph or sentence within an article. Since the LSA is a bag-of-words approach, the paragraph represents a "smaller bag" and because paragraphs themselves bound logical groups of meaning, it can be a good level at which to calculate associations (Quesada 2006).

When creating the DTM, it is common to omit numbers as well as very common words like "the" or "and." These "stopwords" are used to structure sentences, rather than contain meaning independently. LSA, like other bag-of-words analysis, focuses on word meaning rather than sentence structure, and so typically omits them (Quesada 2006).

The DTM is typically weighted in a manner that increases the significance of rarer words, and diminishes the significance of common words. Then, the weighted DTM is decomposed using singular value decomposition, producing three matrices: a term-dimension matrix, singular matrix of dimension-to-dimension (with values on the diagonal, and otherwise zero), and a document-dimension matrix. The term-dimension matrix that is produced in this process is the semantic space.

Only a limited number of dimensions are retained, though there are not a priori heuristics to determine how many dimensions to retain (Quesada 2006). Different operations seem to have more satisfactory results with different numbers of dimensions. For large, general datasets, 300 dimensions seem to produce good results (Martin & Berry 2006), but more specialized sets seem to work better with fewer dimensions (Kontostathis 2007).

The third stage of LSA plots the position of the documents of interest, if they are different from the documents used to generate the space. Since the semantic space was created as an n-dimensional space, each term (word) in the corpus has a position in the space, represented as a vector. So, if a semantic space is generated with 30 dimensions, the term "app" would be represented in the space with a vector of length 30. Passages, often called psuedodocuments, can be created by adding all of the vectors of the constituent words together to produce a vector for the passage. In this way, larger passages can be plotted in the semantic space. The positions of text in the semantic space are valuable for research when used to compare between texts - to find similar terms and documents, or to measure distances (differences) in meanings.

2.2 Interpreting the Semantic Model

While LSA can be a powerful technique, there are a few conceptual issues to consider in interpreting the model. The first is: is what is, and is not, signified by LSA's dimensions. When thinking about "dimensions of meaning" in LSA, it is important to understand that these orthogonal dimensions are not directly interpretable (Hu, Cai, Wiemer-Hastings, Graesser, & McNamara 2006). In social sciences, "dimensions" are often are a single concept on a continuum. A dimension in LSA does not represent a single concept, but layers of concepts that are empirically useful to differentiate texts. Singular value decomposition is sometimes used as the method to conduct Principal Component Analysis, and identifies components in the data that explain the most variance. One stream of research has emphasized the identification of factors in the data (e.g.Evangelopoulos et al. 2012, Ruef 2000, Sidorova, Evangelopoulos, Valacich, & Ramakrishnan 2008), and does rotate dimensions as is common in PCA or factor analysis. We suggest that there is great value in focusing on the distances between texts, as has been used as the basis for cluster analysis (e.g.Larsen & Monarchi 2004, Larsen, Monarchi, Hovorka, & Bailey 2008).

In a large dataset, there are many groupings of text, many different meanings within the documents, and a single dimension will have terms at various points. For example,

the classic social science approach might evaluate a "black-white" dimension. In LSA, "black" and "white" often have extremely similar positions since they are used together to describe a range of topics (e.g. color, race, dichotomizing, obviousness, etc.) The use of a single dimension to assess meaning can be useful when trying to determine whether there is some particular change from one text to another, (e.g. "in 2006, discourse flipped from high to low on dimension 15"). However, just as LSA dimensions each reflect a range of meanings, they are also not conceptually distinct individually. Analysis should generally emphasize the text's position in space, which accounts for multiple dimensions simultaneously, and thus distinguishing between differences in meaning.

Since unrotated dimensions are not individually interpretable, the position of a single text in a semantic space is also not directly interpretable. However, knowing the position of a text in a semantic space is quite valuable when comparing to the position of other texts. In a well-built LSA model, texts that are similar in meaning will be close to each other in the semantic space, while very different ones will be far apart. While there are a variety of distance measures that could be used, cosine distance (e.g. Larsen & Monarchi 2004) is frequently used. Identical texts would have a cosine distance of 1, while entirely unlike texts would have a cosine of -1. Texts which were orthogonal would have a cosine of 0. In our empirical analysis, we will use cosine distances between speech in various periods to evaluate how smartphone discourse changes over time.

3 Empirical Analysis

The smartphone has become a significant technology. From the first mentions of "digital convergence" in the early 1990s to today, the "idea" of the smartphone evolved along with the technology. The form of the phone evolved, as a range of technologies were used as interfaces. Nokia's Symbian operating system supported numeric keypads, a stylus-based touchscreen, and a keyboard/pointer (Tee & Iversen 2007), and the capacitive "multitouch" touchscreen is the dominant one today. However, the changes that came to smartphones were not simply within the products themselves, but in the technological frames that surrounded them. What is a smartphone *for* (Orlikowski & Gash 1994)? In 2006, a smartphone had a strong emphasis on email, and especially in a corporate setting. Consumer phones were becoming "smarter" with cameras and music functionality. Then, in January 2007, Steve Jobs took the stage at MacWorld and made a range of bold claims (Kast 2007). Announcing the first iPhone, he said that Apple was going to "reinvent the phone," of competitors, "The most advanced phones are called smart phones. So they say… they're not so smart," and that these devices provided "the 'baby Internet'" and a phone should have access to a full range of websites instead of specially limited ones. Some researchers have since argued that this web access was the first "killer app" for the iPhone design (West & Mace 2010).

Apple has a reputation for being a master of media and publicity. Their announcements are intensely covered by the media, with rumors before an announcement, and reporting afterward. With LSA as a tool, we can examine how the media covered the smartphone industry, and see how coverage changed over time.

LSA theory suggests that semantically similar texts should be near each other in the semantic space, and thus have high cosine similarity. Even beyond intentional attempts to shift collective cognition, discourse (e.g. product reviews) that happens within a common context (e.g. a consensus view of a technological frame like "phone is *for* email") should also have meanings in common and appear closer, relative to discourse from a different context (e.g. frames that hold that "phone is *for* apps"). In periods where a population has reached consensus about a topic, the discourse, on average, should be in the same region of the semantic space over time. However, when there are changes in the discourse - related to changes in how the population is thinking about the topic - we should see discourse move in the space.

For this exploration, we use Lexis/Nexis to generate a set of 83,532 news articles from 1992-2010 that dealt with smartphones or their predecessors. For the years 1992-2007, our search terms are "smartphone, smart phone, digital convergence, cameraphone, camera phone, pda phone, computer phone." For 2008-2010, searches were on the term "smartphone," as the term came into more consistent use. In addition, the Lexis/Nexis database contains metadata about the articles, including major themes and firms. As a result, the "smartphone" category may appear in the metadata even if the word is not present, and would thus be included in the search.

We used these articles to generate a semantic space, as well as to be our subject documents. We stemmed words, dropped standard stopwords (using the default list in R), but retained numbers. We kept all words that appeared in at least 6 different articles in the dataset. We initially created a space with 60 dimensions, but after some examination, we determined that 30 dimensions gave us a great deal of explanatory power. (More detail on this process is available on request.) Based on this semantic space, and the documents' positions within the space, we proceeded to examine how the discourse changed over time.

From the matrix of document vectors (a document/dimension matrix), we standardized each vector to have a magnitude of 1. This step gave each document in the set equal weight, rather than a weight that reflects its length. Then, we grouped the documents by the quarter in which they were released, and found the mean discourse position for all of the news articles released in that period. We then calculated the cosine distance between each period. Using the cosine distance, we then plotted heatmaps to examine how the discourse changed over the study period.

3.1 Heatmap

We then plotted the cosine distances between media discourse by quarter as a heatmap, in Figure 1. Each cell in the graphic indicates the cosine distance between the mean of articles in the quarter on the X axis and the quarter on Y. The color code ranges from dark red to yellow to white, as an increasingly hot fire. Darker colors are more distant, while lighter colors indicate more similar positions in the semantic space, based on relative similarity of this period to all others. The X axis marks all quarters (1992Q1-2010Q4) from left to right, while Y has them bottom to top. The diagonal indicates when a period is compared to itself. The heatmap shows four separate areas, each of which suggests that the discourse in the quarters in that region are much more similar to other quarters within that area compared to those outside the area.

The first period extends from 1992-1999Q3. Here, there is broad similarity between media coverage of this emerging market. This period is orange on the map, indicating that discourse in this period is generally similar, across a large number of quarters. Brighter, yellow spots on the diagonal indicate that discourse in these particular quarters was more distinct from others, because the coding scale is relative. All diagonal cells have a value of 1, so periods with less distinct discourse have comparisons to many other similar periods. Discourse seems to start shifting a bit in the late 1990s, The last quarter of 1999 and first of 2000 seem to be a transition point, closely related to each other, before the start of the second period.

The second major period is from 2000Q2-2002Q2. This period indicates some similarity to period 1, though it is distinct, and its quarters are clearly more related to each other than before or after, leading to a much brighter yellow within the period. In this period, there is much more consistency between media discourse in these quarters than in the first period.

A third period emerges in 2002Q3-2006, with an apparent transition from the second. The first five quarters also seem to be transitional, as these quarters relate more strongly to closely neighboring quarters, as indicated by the yellow band on the diagonal. If they were related, but not in transition, this would appear to be more squared-off, as we from 2003Q4-2006Q4.

The final period starts abruptly in 2007Q1 through the rest of the data, 2010Q4. This period's discourse is quite different from other periods. While this period is clearly distinct, it is not a squared off shape on the map, indicating that there are changes occurring in the discourse, even while the new discourse is a marked change from prior discourse. By using LSA to measure the distances between media statements in different periods of time, we are able to visualize changes of media discourse in text.
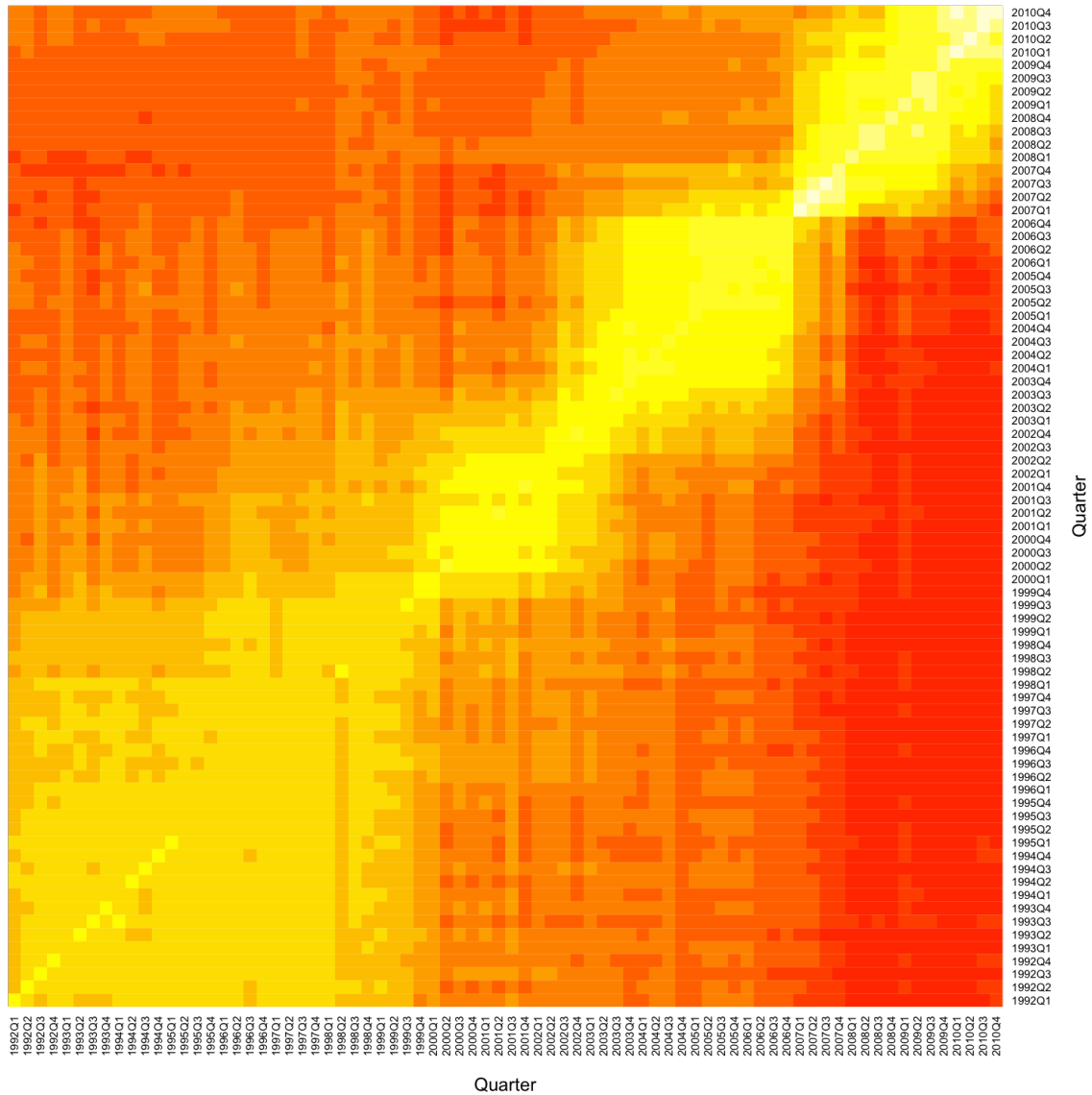
Cosine Distances Between Mean Quarterly Media

Figure 1: Heatmap of Quarterly Media Discourse Distances, 1992-2010

4   Discussion and Interpretation

From 1992-2010, our analysis shows that media discourse about smartphones and their predecessors went through four separate periods. Showing the LSA-derived distances in a heatmap lets us see these comparisons between a large number of datapoints, and see trends emerge in these comparisons.

In the first period, pundits were postulating the coming of "digital convergence." Discourse was broadly similar in these quarters, as this was before a true market emerged. This suggests that we may be identifying category emergence (Navis & Glynn 2010), wherein there is discussion about what the technology could or should or will be.

While the first "smartphone," the Simon from IBM was marketed in 1994, the first real market for smartphones emerged around 2000, when we see the second period arise. We see a shift in the collective discourse, which remains consistent for about two years, suggesting that consensus emerged on the technology (Drazin, Glynn, & Kazanjian 1999). This is consistent with theory that holds that prototypes and products change how technology develops by affecting how people think and speak about it (Leonardi 2011, Suarez 2004).

In the third period, discourse shifts over a year, and then reaches a new, multi-year "stable" position. In the market, traditional handset companies took control of the market in this time (Canalys 2007) with media-centric consumer offerings with music and cameras, and email-centric business smartphones like the Blackberry (Gillette, Brady, & Winter 2013). Our study groups media by time period, and does not separately compare business media and consumer media. Therefore, it is likely that our mean position for media discourse conflates distinct media that might emphasize different aspects of different product lines. In addition, since consumer-focused phone publications are likely to be covered in a wide range of general purpose publications, while business products are likely to be more narrowly evaluated, our results likely skew toward the consumer product lines. An aggregation scheme that distinguishes groups between types of media outlet might produce somewhat different results.

The fourth period begins abruptly in 2007Q1, with discourse strongly shifting away from prior meanings. It seems likely that this is the result of the January 2007 announcement of the original iPhone, since the quantity of articles in the dataset rose from 1253 in 2006Q4 to 2362 in 2007Q1, and the stemmed term 'iphon' appears in 962 of these. However, while the media intensively covered Apple, it did not automatically adopt Apple's technology frames. The non-squared shape of the period on the heatmap suggest that the discourse evolved over time, and that it initiated a renewed debate about smartphones. Android's appearance in 2008 (Tseng 2008) did not spark a new period of discourse, but may have shaped the evolution of the debate. It seems likely that "Android" became important to the evolving ideas about smartphones, but it did not have a key "moment" like the iPhone seems to have, since there we observe no sudden changes in the overall discourse, either at announcement, at product availability, or as it gained significant market share.

By using LSA, we are able to quantify relationships across large quantities of text. We are "seeing the forest" and "not just the trees" in this way. In the applied example of technology cognition, we are therefore able to identify four separate periods in our timeframe, and that the final period is different from the others in important ways. In this case, we are examining discourse at an aggregate level, which allows us to draw inferences about the overall movement of the market. So, the shape of discourse suggests support for a cognitive aspect to the technology lifecycle (Anderson & Tushman 1990, Suarez 2004, Suarez, Grodal, & Gotsopoulos 2015). The data also suggests that there may be market-wide framing contests built into these processes (Kaplan 2008), with the technological discontinuity representing a frame break for participants, driving new debate (Goffman 1974).

We use careful language in describing our results, because we are evaluating the semantic positions of collections of documents, which lets us visualize changes in

discourse that then suggest underlying theoretical mechanisms. Although there is certainly strong circumstantial evidence based on timing for the impact of the iPhone announcement on discourse, at this aggregate level of analysis, we cannot claim specific mechanisms that drive the discourse. However, LSA is used to generate positions for individual words, and so can be used to evaluate positions in the semantic space at different theoretical levels. For example, researchers could compare how the meaning attached to a product category changes over time, or how company discourse shifts in meaning even with few changes in word usage. Semantic similarity can be used to categorize documents, or their identify meanings (Larsen & Monarchi 2004, Larsen et al. 2008). This can then be used to identify other theoretical constructs in the data.

LSA has the potential to be a useful tool in understanding meanings of text, however, it requires large amounts of text and appropriately representative text both to create the semantic space, and as the subject of analysis. A space built from text that does not represent an audience's inbound information will be distorted and produce incorrect distances. In this case, we were considering the overall, market-wide discourse, and used all available media throughout the period. By contrast, a study of meanings understood by IT managers might be better evaluated primarily through publications within vertically-targeted media, with a small sample of general media publications added because they do not work in a vacuum. The corpus required to produce a good semantic model will depend on the research question, and what is already understood about likely meaning in the data. In our data, the meaning of city names (Espoo, Waterloo, Cupertino) are nearly synonymous with the companies based there (Nokia, Research In Motion, Apple), which would be misleading for non-IT research contexts. An LSA research project on internal company documents should ideally use a space built using other internal documents so that firm-specific jargon would be reflected in the space.

LSA is not a perfect tool, as it can never capture the full range of potential nuance in a text, and indeed, explicitly ignores meaning embedded in language structure and syntax. It does, however seem to provide a useful lens into overall similarities and differences between texts, which we can apply to answer different kinds of questions.

5   Conclusion

In this paper, we used demonstrated the use of Latent Semantic Analysis for study of discourse and collective cognition in the market for an emerging technology. Through a multi-stage process, we examined how the media presented the evolving smartphone industry. We collected a large media coverage corpus, and built a semantic space from these documents. We then grouped media chronologically to expose trends in the discourse. We used a heatmap of semantic distances as a graphical exploratory tool to understand groupings of chronologically-related positions in the semantic space. Our results show distinct periods in the media coverage of smartphones, with distinct shifts in discourse, and with periods that demonstrate different dynamics of transition and stability.

We show how LSA can be used to gauge the direction of discourse automatically and, importantly, numerically. This *numeric* aspect allows both nuanced and sophisticated

analysis of what is actually happening, across large sets of text. As has been attributed to Peter Drucker, "if you cannot measure it, you cannot manage it." LSA allows us to measure meanings in text, across a very broad range of publications and types of text. This exploratory work should be seen as preliminary in terms of the potential application of this method to this class of problem. By quantifying semantic distance, many of our existing quantitative methods can be applied to sets of text, allowing new kinds of questions on new sets of data. LSA can be applied to model the meaning of individual terms, or aggregated to study industry-wide trends as we do here, to better see "the forest of ideas" and not just a few highly-visible "trees."

References

Anderson, P. and M. L. Tushman. (1990) Technological Discontinuities and Dominant Designs: A Cyclical Model of Technological Change. Administrative science quarterly. pp. 604-633. 10.2307/2392832.

Canalys (2007) 64 Million Smart Phones Shipped Worldwide in 2006, in Over 20 million converged devices ship in final quarter of year, Reading, UK. Reading, UK: Canalys Research.

Drazin, R., M. A. Glynn, and R. K. Kazanjian. (1999) Multilevel Theorizing About Creativity in Organizations: A Sensemaking Perspective. Academy of Management Review. 24 (2), pp. 286-307. 10.2307/259083

Evangelopoulos, N., X. Zhang, and V. R. Prybutok. (2012) Latent Semantic Analysis: Five Methodological Recommendations. European Journal of Information Systems. 21 (1), pp. 70-86. 10.1057/ejis.2010.61.

Fiss, P. C. and P. M. Hirsch. (2005) The Discourse of Globalization: Framing and Sensemaking of an Emerging Concept. American Sociological Review. 70 (1), pp. 29-52.

Gamson, W. A. and A. Modigliani. (1989) Media Discourse and Public-Opinion on Nuclear-Power - a Constructionist Approach. American Journal of Sociology. 95 (1), pp. 1-37. 10.1086/229213

Gillette, F., D. Brady, and C. Winter (2013) The Rise and Fall of Blackberry: An Oral History [Electronic version]. Business Week.

Goffman, E. (1974) Frame Analysis: An Essay on the Organization of Experience: Harvard University Press.

Hu, X., Z. Cai, P. Wiemer-Hastings, A. C. Graesser, and D. S. McNamara (2006) Strengths, Limitations, and Extensions of Lsa, in T. K. Landauer, D. S. McNamara, S. Dennis, and W. Kintsch (Eds.) Handbook of Latent Semantic Analysis, Mahwah, NJ: Lawrence Erlbaum Associates.Mahwah, NJ: Lawrence Erlbaum Associates

Kaplan, S. (2008) Framing Contests: Strategy Making under Uncertainty. Organization Science. 19 (5), pp. 729-752. 10.1287/orsc.1070.0340.

Kast, B. (2008) Transcript – Iphone Keynote 2007. Retrieved Nov 22, 2014 from http://www.european-rhetoric.com/analyses/ikeynote-analysis-iphone/transcript-2007/

Kontostathis, A. (2007) Essential Dimensions of Latent Semantic Indexing (LSI) in 40th Annual Hawaii International Conference on System Sciences, 2007. Jan 3-6, 2007 (73-73). Waikoloa, HI: IEEE

Landauer, T. K. (2006) Lsa as a Theory of Meaning, in T. K. Landauer, D. S. McNamara, S. Dennis, and W. Kintsch (Eds.) Handbook of Latent Semantic Analysis, Mahwah, NJ: Lawrence Erlbaum Associates.Mahwah, NJ: Lawrence Erlbaum Associates

Landauer, T. K., D. S. McNamara, S. Dennis, and W. Kintsch (2006) Handbook of Latent Semantic Analysis, Mahwah, NJ: Lawrence Erlbaum Associates.

Larsen, K. R. and D. E. Monarchi. (2004) A Mathematical Approach to Categorization and Labeling of Qualitative Data: The Latent Categorization Method. Sociological Methodology. 34 (1), pp. 349-392.

Larsen, K. R., D. E. Monarchi, D. S. Hovorka, and C. N. Bailey. (2008) Analyzing Unstructured Text Data: Using Latent Categorization to Identify Intellectual Communities in Information Systems. Decision Support Systems. 45 (4), pp. 884-896. 10.1016/j.dss.2008.02.009.

Leonardi, P. M. (2011) Innovation Blindness: Culture, Frames, and Cross-Boundary Problem Construction in the Development of New Technology Concepts. Organization Science. 22 (2), pp. 347-369. 10.1287/orsc.1100.0529.

Martin, D. I. and M. W. Berry (2006) Mathematical Foundations Behind Latent Semantic Analysis, in T. K. Landauer, D. S. McNamara, S. Dennis, and W. Kintsch (Eds.) Handbook of Latent Semantic Analysis, Mahwah, NJ: Lawrence Erlbaum Associates.Mahwah, NJ: Lawrence Erlbaum Associates

Navis, C. and M. A. Glynn. (2010) How New Market Categories Emerge: Temporal Dynamics of Legitimacy, Identity, and Entrepreneurship in Satellite Radio, 1990-2005. Administrative Science Quarterly. 55 (3), pp. 439-471. 10.2189/asqu.2010.55.3.439.

Orlikowski, W. J. and D. C. Gash. (1994) Technological Frames: Making Sense of Information Technology in Organizations. ACM Transactions on Information Systems. 12 (2), pp. 174-207. 10.1145/196734.196745

Quesada, J. (2006) Creating Your Own LSA Space, in T. K. Landauer, D. S. McNamara, S. Dennis, and W. Kintsch (Eds.) Handbook of Latent Semantic Analysis, Mahwah, NJ: Lawrence Erlbaum Associates.Mahwah, NJ: Lawrence Erlbaum Associates

Ruef, M. (2000) The Emergence of Organizational Forms: A Community Ecology Approach. American Journal of Sociology. 106 (3), pp. 658-714. 10.1086/318963

Sidorova, A., N. Evangelopoulos, J. S. Valacich, and T. Ramakrishnan. (2008) Uncovering the Intellectual Core of the Information Systems Discipline. Mis Quarterly. 32 (3), pp. 467-482.

Suarez, F. F. (2004) Battles for Technological Dominance: An Integrative Framework. Research Policy. 33 (2), pp. 271-286. 10.1016/j.respol.2003.07.001.

Suarez, F. F., S. Grodal, and A. Gotsopoulos. (2015) Perfect Timing? Dominant Category, Dominant Design, and the Window of Opportunity for Firm Entry. Strategic Management Journal. 36 (3) pp. 437-448. 10.1002/smj.2225.

Tee, R. and E. Iversen (2007) Competing for Centrality–a Nested Hierarchy Approach for the Establishment of Core Components in the Smartphone Market, in DIME Conference on Demand, Product Characteristics and Innovation. Jena, Germany.

Tseng, E. (2008) The First Android-Powered Phone, in Google Officlal Blog, vol. 2016: Google.

West, J. and M. Mace. (2010) Browsing as the Killer App: Explaining the Rapid Success of Apple's iPhone. Telecommunications Policy. 34 (5), pp. 270-286. 10.1016/j.telpol.2009.12.002.