Singapore Management University
Institutional Knowledge at Singapore Management University

Research Collection School Of Information Systems

School of Information Systems

7-2016

Word clouds with latent variable analysis for visual comparison of documents

Tuan M. V. LE
Singapore Management University, vmtle.2012@phdis.smu.edu.sg

Hady W. LAUW
Singapore Management University, hadywlauw@smu.edu.sg

Citation

LE, Tuan M. V. and LAUW, Hady W.. Word clouds with latent variable analysis for visual comparison of documents. (2016). *Proceedings of the 25th International Joint Conference on Artificial Intelligence IJCAI 2016: New York, July 9-15*. 2536-2543. Research Collection School Of Information Systems.
Available at: https://ink.library.smu.edu.sg/sis_research/3357

Word Clouds with Latent Variable Analysis for Visual Comparison of Documents

Tuan M. V. Le
School of Information Systems
Singapore Management University
vmtle.2012@phdis.smu.edu.sg

Hady W. Lauw
School of Information Systems
Singapore Management University
hadywlauw@smu.edu.sg

Abstract

Word cloud is a visualization form for text that is recognized for its aesthetic, social, and analytical values. Here, we are concerned with deepening its analytical value for visual comparison of documents. To aid comparative analysis of two or more documents, users need to be able to perceive similarities and differences among documents through their word clouds. However, as we are dealing with text, approaches that treat words independently may impede accurate discernment of similarities among word clouds containing different words of related meanings. We therefore motivate the principle of displaying related words in a coherent manner, and propose to realize it through modeling the latent aspects of words. Our WORD FLOCK solution brings together latent variable analysis for embedding and aspect modeling, and calibrated layout algorithm within a synchronized word cloud generation framework. We present the quantitative and qualitative results on real-life text corpora, showcasing how the word clouds are useful in preserving the information content of documents so as to allow more accurate visual comparison of documents.

1 Introduction

The abundance of text motivates the development of text analysis tools. One such need is to aid users in comparing several documents. For instance, a user may go through Web search results to determine how they differ from one another. A researcher needs to get an overview of various papers within a proceeding or a journal issue. Similar needs are faced by librarians or analysts. In such scenarios, users need to quickly gain a sense of whether several documents are similar.

Visualization may help in document comparison, by providing visual representations that allow users to perceive similarities and differences tangibly. There are various visualization forms. One is a scatterplot, showing documents as coordinates in a 2 or 3-dimensional space [Kruskal, 1964]. While it allows easy determination of whether two documents are similar (based on their distance in the scatterplot), it is not effective in conveying contents, which are important in providing meaning or justification to similarities.

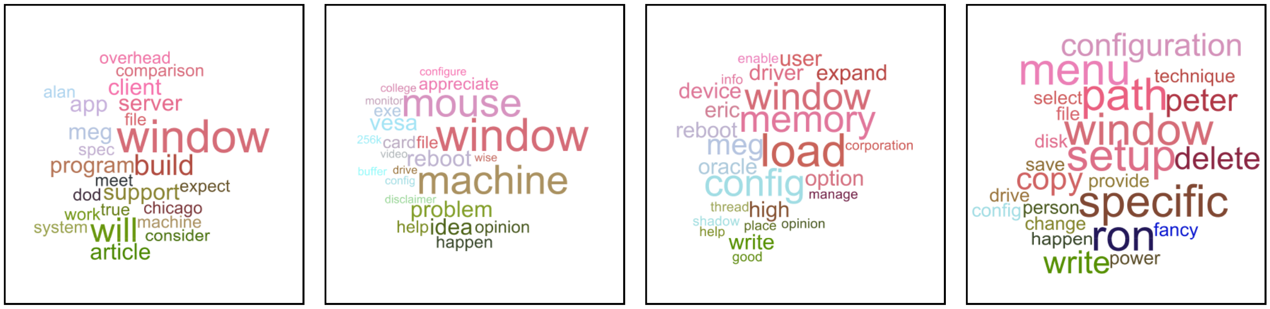
Therefore, we focus on another visual representation, i.e., a *word cloud* displaying a subset of words within a document, by assigning greater visual prominence to more important words. Because a word cloud still displays the actual words, it is better at conveying the content of the corresponding document than a scatterplot. In addition, word cloud as a visualization form is extremely popular [Viegas *et al.*, 2009]. For instance, Wordle[1] has generated more than 1.4 million publicly posted word clouds [Steele and Iliinsky, 2010].

Problem. We seek effective visual comparison of documents via word clouds. Ideally, documents with similar contents have word clouds of similar appearances. Traditional approaches fall short of this ideal, as word clouds of different documents are generated independently using a layout algorithm [Viegas *et al.*, 2009; Seifert *et al.*, 2008]. Two documents may feature similar words that are placed in different colors and positions within their respective word clouds, placing a burden on the viewer in corroborating their similarities.

The state-of-the-art approach, *Word Storms* [Castella and Sutton, 2014], employs a synchronized generation of the word clouds of all documents within a corpus. A word is expected to have the same color and position across word clouds. This aims to reduce the cognitive effort needed for comparing word clouds. However, it has two shortcomings. First, it only seeks to synchronize the appearance of each distinct word. This is problematic, as text frequently uses different words to refer to the same concept. Second, its synchronization of all word clouds imposes sizeable runtime requirement that prevents real-time generation of word clouds.

These issues arise because word clouds are still high-dimensional representations, with dimensionality the size of the vocabulary. Our insight is that a word cloud can encode information at *several dimensionalities* simultaneously. In addition to the actual words, the *position* of a word in the two-dimensional canvas space can reflect some two-dimensional word representation that captures relatedness among words, such as embedding that assigns nearby coordinates to "related" words, e.g., [Kruskal, 1964]. We can also have the word *color* reflect some k-dimensional word representation that captures k latent "aspects" of words. Each aspect may capture words of similar meaning or words often used together to describe a certain concept.

[1] `http://www.wordle.net/`



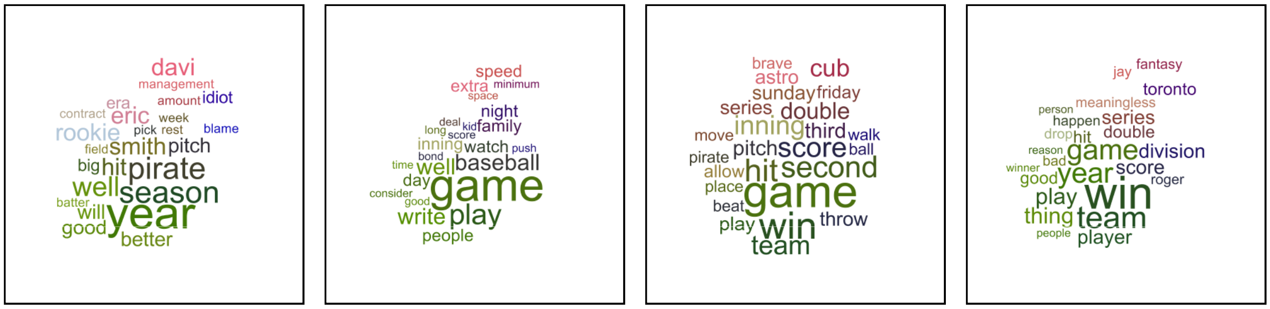
a. Doc101 by Word Flock

b. Doc111 by Word Flock

c. Doc132 by Word Flock

d. Doc136 by Word Flock

Figure 1: Word clouds by Word Flock for 4 documents from *comp.os.ms-windows.misc* of $20News$ (best seen in color)



a. Doc472 by Word Flock

b. Doc473 by Word Flock

c. Doc495 by Word Flock

d. Doc499 by Word Flock

Figure 2: Word clouds by Word Flock for 4 documents from *rec.sport.baseball* of $20News$ (best seen in color)

Approach. To realize the vision of multiple dimensionalities within a word cloud, we propose a technique called Word Flock. The name is inspired by the idiom "birds of a feather flock together". In our case, *words* of a "feather" (similar aspects/colors) flock together (similar positions).

To illustrate how word clouds could provide effective visual comparison of documents, Figure 1 and Figure 2 show example word clouds generated by Word Flock for documents in the $20News$ dataset[2]. The four word clouds in Figure 1 are for documents from the *comp.os.ms-windows.misc* category, pertaining to Windows computing. Words such as "window", "file", and "memory" have similar colors (reddish hue) and positions (top right) across the four word clouds. The four word clouds in Figure 2 are for documents from the *rec.sport.baseball* category, with words such as "hit", "play", "game", and "team" sharing similar greenish hues and bottom left positions. Quick perusal of them is sufficient to convey which documents are similar (same category). Note that category labels had not been used in generating word clouds.

Word Flock is underpinned by a novel approach of employing latent variable analysis for word cloud generation. Given a vocabulary of words, we seek to learn their latent representations in two forms. The first is coordinate representation in a two-dimensional space, which is derived from a latent embedding model. The second is a probability distribution over k latent aspects. This representation learning phase can be done offline once for a given vocabulary. Thereafter, we generate a word cloud for a document online, incorporating these representations in a calibrated layout algorithm.

Contributions. We make the following contributions:

- Word Flock is the first to integrate *two levels* of "synchronization" principles for word clouds: *similar documents* share similar word clouds, and *related words* of the same latent aspects are displayed similarly.
- Word Flock is novel in employing latent variable analysis through *joint* usage of *embedding* (synchronized positioning) and *latent aspect modeling* (coloring) among words of similar concepts.
- Comprehensive experiments on real-life document corpora showcase the effectiveness of Word Flock via an empirical comparison to the baseline *Word Storms* [Castella and Sutton, 2014], on objective quantitative metrics, as well as a user study.
- The *two-phase* approach attains the synchronization of word representations *offline*, so as to obviate the need to generate all word clouds together. This allows an *online* generation of individual word clouds at near-instant speed, which eludes the baseline *Word Storms*.

2 Related Work

Word clouds are popular for aesthetic, social, and analytical purposes [Viegas *et al.*, 2009]. Here, we focus on the use of word clouds for visual comparison of documents. This application is advanced by Word Storms [Castella and Sutton,

[2] http://web.ist.utl.pt/acardoso/datasets/

2014], which introduced synchronization at corpus level. We go one step further and model the coherence of words within and across word clouds. In Section 6, we compare to Word Storms as our baseline.

Our work models latent aspects of words and increases the coherence of word clouds by displaying related words with similar colors and positions. Word similarity was previously considered only in the context of an individual word cloud [Hassan-Montero and Herrero-Solana, 2006; Knautz *et al.*, 2010; Bernstein *et al.*, 2010], and based on similarity measures such as cosine [Barth *et al.*, 2014; Cui *et al.*, 2010; Wu *et al.*, 2011]. In contrast, we model the coherence of *synchronized* (rather than individual) word clouds for comparison of documents. Moreover, we employ latent variable analysis to learn the probability distribution over k latent aspects (rather than similarity). We are also the first to employ joint modeling of embedding and latent aspects for word clouds.

Other approaches for document comparison deviated from the traditional word cloud format, e.g., graph visualization [Chen *et al.*, 2009], or topographic map [Fujimura *et al.*, 2008]. Some showed comparisons in a modified format, e.g., intersecting or common words [Coppersmith and Kelly, 2014; Lohmann *et al.*, 2015], different topics [Oelke *et al.*, 2014] or corpora [Rodrigues, 2013; Paulovich *et al.*, 2012].

There are formats for document visualization other than word clouds. One is embedding to a low-dimensional space [Kruskal, 1964]. However, a scatterplot does not offer a way to indicate the contents of documents. Towards modeling the semantic contents of documents, recent approaches marry embedding and topic modelling of documents, such as PLSV [Iwata *et al.*, 2008] and Semafore [Le and Lauw, 2014]. We leverage on such techniques to learn both the two-dimensional and k-dimensional latent representations of words, with a key distinction being our objective of modeling the latent aspects of words, rather than the latent topics of documents.

Some works build a visual system with rich user interactions [Wei *et al.*, 2010; Shi *et al.*, 2010] to help users explore text corpora. These use topic modeling for documents in text visualization, which is different from our work in that we use aspect modeling for words in word cloud visualization.

There are also methods designed to visualize the latent topics of documents [Chuang *et al.*, 2012; Dou *et al.*, 2013]. They are fundamentally different, being oriented towards analysing the topic model itself, rather than developing a word cloud representation of a document.

3 Overview of WORD FLOCK

Problem Statement. We assume that the scope is defined by a vocabulary $\mathcal{W}$, the set of words that could appear in any word cloud in a corpus. As input, we are given a corpus of documents $\mathcal{D} = \{d_1, d_2, \ldots, d_N\}$. Every document d_n consists of words drawn from the vocabulary $\mathcal{W}$. The objective is to generate a set of word clouds $\{C_1, C_2, \ldots, C_N\}$, one for each document in $\mathcal{D}$, so as to aid visual comparison of documents through their respective word clouds.

We display each word in a cloud according to a number of visual attributes. There are various visual variables within a word cloud, and in general different visual features may be good for different types of information [Bateman *et al.*, 2008]. Here, we make use of three visual attributes: font size, color, and position. Each word w in C_n for d_n is associated with a tuple $\langle s_w, p_w, l_w \rangle$, where s_w is the font size, p_w is the word position in terms of 2D coordinates, and l_w is the color. Fixing the orientation to horizontal prevents the cognitive overload of reading randomly oriented words.

Solution Framework. We now discuss the principles for the design of our word cloud algorithm WORD FLOCK.

Principle #1: Display related words similarly. Words in a document are not independent. Some words may capture a particular concept or aspect. It is far easier to understand a word cloud in terms of a small number of coherent concepts, rather than in terms of a large number of independent words. Among the visual attributes, we rely on *position* (p_w) and *color* (l_w). Through a dimensionality reduction task known as *embedding*, we seek to derive coordinates for each word in a latent two-dimensional space, such that two related words are nearby in this space. The continuous spectrum of color is also appropriate to convey the underlying aspects or concepts of words. We discover these aspects automatically through *latent aspect modeling*. We pursue these tasks jointly, computing them offline once for the corpus to support the synchronization of positions and colors across all word clouds.

Principle #2: Similar documents have similar word clouds. Aimed squarely at aiding visual comparison of documents, this principle motivates the coherent appearances of word clouds of similar documents. This is achieved by infusing and calibrating the layout algorithm with the coordinated positions and colors determined by the embedding and latent aspect. Consequently, the online layout of each new word cloud requires only a small marginal computational cost.

In the next two sections, we describe the two phases of the WORD FLOCK algorithm. Due to the limitation of canvas space, conventionally only the more important words are included [Seifert *et al.*, 2008]. Word prominence is indicated by the *font size* (s_w). There are various notions of "importance" of a word. Without loss of generality, here we use the well-accepted term frequency (*tf*), after removing stop words.

4 Embedding and Latent Aspect Modeling

The objective is to derive coordinates in a 2D space, as well as a k latent aspects of words. To do so, we need to associate words with informative feature space representation. By feature space representation, we refer to a feature vector $\mathbf{w}$ for each word w, capturing information on how words are associated with one another. To express $\mathbf{w}$, each word w is considered a "pseudo-document" containing all words that w co-occurs with. Each $\mathbf{w}$ is expressed in terms of word counts where each element of $\mathbf{w}$ corresponds to how frequently another word v co-occurs with w in some reference corpus. This corpus may be a large independent corpus (e.g., Wikipedia), or the specific corpus of interest. The co-occurence of two words can be determined by their appearance within a document or a window. This way of modeling is consistent with [Zuo *et al.*, 2015]. Intuitively, two different words with similar co-occurrence counts are likely to share a similar meaning.

The task is to reduce the high-dimensional $\{\mathbf{w}\}_{w\in\mathcal{W}}$ to lower-dimensional representations. In obtaining 2D coordinates $\{x_w\}_{w\in\mathcal{W}}$ for each word, the aim is similar to embedding, whereas in obtaining latent aspects of words, it is feasible to learn it from word cooccurrences [Zuo *et al.*, 2015]. While embedding and latent aspect modeling could be done independently, recent works [Iwata *et al.*, 2008; Le and Lauw, 2014] show that it is beneficial to join the two tasks into a single joint model to ensure consistency in objectives. We therefore adapt the state-of-the-art model Semafore [Le and Lauw, 2014], originally designed for topics in documents, now to model latent word aspects, with the following generative process:

1. For each latent aspect $z = 1, \ldots, k$:
   (a) Draw z's distribution of words: $\theta_z \sim \mathrm{Dirichlet}(\alpha)$
   (b) Draw z's coordinate: $\phi_z \sim \mathrm{Normal}(0, \beta^{-1}I)$
2. For each word $w \in \mathcal{W}$:
   (a) Draw w's coordinate: $x_w \sim \mathrm{Normal}(0, \gamma^{-1}I)$
   (b) For each occurrence of a co-occurring word $v \in \mathbf{w}$:
      i. Draw a latent aspect: $z \sim \mathrm{Multi}(\{\mathrm{P}(z|x_w, \Phi)\}_{z=1}^{k})$
      ii. Draw a co-occurring word: $v \sim \mathrm{Multi}(\theta_z)$

α is a Dirichlet prior, I is an identity matrix, β and γ control the variance of the Normal distributions. $\mathrm{P}(z|x_w, \Phi)$ defines how the coordinate of each word x_w transforms into the probability of each latent aspect z, according to Equation 1. The closer is x_w to the aspect coordinate ϕ_z, the higher is the probability. Φ is the collection of aspect coordinates.

$$\mathrm{P}(z|x_w, \Phi) = \frac{\exp(-\frac{1}{2}||x_w - \phi_z||^2)}{\sum_{z'=1}^{k}\exp(-\frac{1}{2}||x_w - \phi_{z'}||^2)} \tag{1}$$

The log likelihood function is shown in Equation 2.

$$\mathcal{L} = \sum_{w\in\mathcal{W}}\sum_{v\in\mathbf{w}}\log\sum_{z=1}^{Z}\mathrm{P}(z|x_w, \Phi)\mathrm{P}(v|\theta_z) \tag{2}$$

To ensure the local consistency of words in the manifold, the method employs neighborhood regularization as in Equation 3. λ is the regularization parameter. y_{ij} encodes the manifold graph, with $y_{ij} = 1$ signifying that w_i and w_j are neighbors in the manifold graph built from feature space representation, and $y_{ij} = 0$ otherwise. The regularized $\mathbf{L}$ reflects the idea that similar (neighboring) words should have closer coordinates, while different (non-neighboring) words should have further coordinates.

$$\mathbf{L} = \mathcal{L} - \frac{\lambda}{2}\left[\sum_{\substack{i,j=1\\ i\neq j}} y_{ij}||x_i - x_j||^2 + \sum_{\substack{i,j=1\\ i\neq j}}\frac{1 - y_{ij}}{||x_i - x_j||^2 + 1}\right] \tag{3}$$

The parameters are learned from $\{\mathbf{w}\}_{w\in\mathcal{W}}$ based on maximum a posteriori estimation through EM [Dempster *et al.*, 1977]. The outputs are the coordinates x_w, as well as probability distribution over k latent aspects $\{\mathrm{P}(z|x_w, \Phi)\}_{z=1}^{k}$, for every word w in the vocabulary $\mathcal{W}$. These outputs underpin the online generation of word clouds described next.

5 Word Cloud Layout with Scale Calibration

We include only top M words in a document by weight (e.g., term frequency). The font size s_w is controlled by this weight.

The color of each word l_w is determined based on its aspect probabilities $\{\mathrm{P}(z|x_w, \Phi)\}_{z=1}^{k}$ from the first phase. l_w is expressed in terms of a color representation, such as RGB. There are different schemes for transforming the aspect probabilities into word colors. For instance, we could assign each aspect a color, and for each word we take the weighted average of its aspects' colors, or that of the strongest aspect. However, these approaches would require associating a color to each topic, which itself is not a straightforward task.

A better approach to assign colors to words automatically, which we adopt here, is to have a color map based on the aspect probabilities. Since RGB colors lie in a three-dimensional (3D) space (i.e., R, G, and B axes), we employ PE [Iwata *et al.*, 2007] to find the embedding of the k aspect probabilities of all words into a 3D space. We then map these 3D coordinates to the RGB space using min-max normalization to find the word colors. This way, words with similar aspect probabilities would share similar colors.

The word position p_w should be similar, if not identical, to the word coordinate x_w from the first phase. There are two issues. First, the canvas space over which p_w is defined has a different scale from the embeding space of x_w. We therefore introduce a scaling factor Γ, i.e., $p_w = \Gamma \times x_w$.

Second, even if the former could be calibrated, some words may have similar x_w's, causing overcrowding. This is not unique to us. Classically, word clouds have had to deal with how to position words in a compact and non-overlapping way [Seifert *et al.*, 2008]. Similarly to *Word Storms* [Castella and Sutton, 2014], we build on Wordle's algorithm. Our layout algorithm is shown in Algorithm 1. It works in a greedy and incremental manner. As indicated previously, our requirement is different in having to deal with the scale calibration issue.

The scaling factor Γ is calibrated so as to optimize an objective function that captures the aesthetic quality. First, it is desired that a word cloud is compact, expressed in terms of smaller distances of the final word positions $p_w{}'$ from the origin. Second, it is desired that similar words are placed close to one another. Suppose that η_w is the set of m closest neighboring words of w in C_n (based on their embedding coordinates x_w's). We would like w to have a final position $p_w{}'$ that is as close as possible to its neighbors in η_w. To achieve this, we propose the objective function in Equation 4.

$$\sum_{n=1}^{|\mathcal{D}|}\sum_{w\in C_n}\left[||p_w{}'||^2 + \frac{1}{|\eta_w|}\sum_{v\in\eta_w}||p_w{}' - p_v{}'||^2\right] \tag{4}$$

During the calibration process, we investigate various scaling factors Γ to minimize Equation 4. We further advocate an offline calibration to arrive at a single Γ for any new document. There is usually a single scaling factor that works for most documents. This also saves time in the online generation of word cloud that only needs to run the layout algorithm.

6 Evaluation

Evaluating word clouds is challenging because of the various purposes that they could be aimed at, e.g., gisting, word re-

Algorithm 1 Spiral Algorithm with Calibration of Scaling

```
Require: $M_n$ words for each document $d_n$, 2D coordinates
    $\{x_w\}_{w \in \mathcal{W}}$ obtained from embedding in offline phase,
    and a set of scaling factors $\Gamma$.
Ensure: Final scaling factor $\gamma$ and for each document $d_n$,
    positions $\mathbf{p}_n$ of $M_n$ words in the word cloud of $d_n$.
for each scaling factor $\gamma \in \Gamma$ do
    for all document $d_n$, $n \in \{1, \ldots, N\}$ do
        for all words $w \in \{w_1, \ldots, w_{M_n}\}$ do
            Initialize $p_w = \gamma \times x_w$
            while $p_w$ intersects any previous words do
                Move $p_w$ one step along a spiral path
            end while
        end for
    end for
    Compute the objective function value in Equation 4.
    Store the $\gamma$ and all $\mathbf{p}_n$ with the best objective function
        value so far.
end for
```

call [Rivadeneira *et al.*, 2007]. We focus on the task of visual comparison of documents. This involves a multi-prong approach, including qualitative examples, quantitative metrics involving objective ground truth, as well as a user study.

6.1 Experimental Setup

First, we describe the experimental setup.

Datasets. We rely on two publicly available datasets of text documents, where each document has a known category label. These labels are not required for training. Rather, they are used in evaluation as an objective proxy for defining what constitute "similar" documents (i.e., same category). The two datasets[3] are: $20News$ containing newsgroup documents partitioned into 20 classes, and $Reuters$ containing newswire articles from 8 classes. To create a balanced dataset, we sample 50 documents from each class, resulting in 1000 and 400 documents respectively. After removing stopwords and infrequent words (< 5 occurrences), the vocabulary consists of 3744 words for $20News$, and 1933 words for $Reuters$.

Methods. Word Flock incorporates synchronization principles for both documents and words for visual comparison of documents. The most appropriate baseline for this task is *Word Storm* [Castella and Sutton, 2014], which applies synchronization of word clouds across documents, but does not address relatedness among words. We use the authors' implementation in GitHub[4].

As longer documents may result in word clouds that are too "busy", we show up to twenty five words based on weight. The same words are visualized by the comparative methods.

For Word Flock, we also need to specify the number of latent aspects of words k. We experiment with k in the range [5, 25]. For each k, we tune the scaling factor Γ to minimize the Equation 4. Γ is tuned with $|\eta_w| = 3$. The optimal Γ ranges from 20 to 25. Through experimentation, we discover that $k = 20$ works best for both $20News$ and $Reuters$. Note that the number of colors in a word cloud generated by Word Flock is not directly determined by k. We map the aspect distribution of words across the full RGB spectrum (see Section 5). If all words in a document were distinctly different, they would show up with different colors. However, words appearing within a document tend to be related. Usually only a small number of colors are seen in a word cloud by Word Flock due to the relative coherence of words in a document.

6.2 Qualitative Analysis

We begin with an exploration of example word clouds from $20News$. Figure 3 shows *Word Storm*'s word clouds for four documents from the *soc.religion.christian* category. Figure 4 shows the corresponding word clouds by Word Flock. There are several words that capture the semantic meaning of the documents, such as "god", "christ", "jesus", "faith" and "christian". *Word Storm* disperses these words across each word cloud, because it does not address their relatedness and relies on having the exact same words for comparison, which fails when documents use different words. In Figure 3(a) and Figure 3(d), *Word Storm* uses the same location and color for "body", but other words are different across the two clouds. In contrast, Word Flock groups related words in similar positions and colors, yielding four strikingly coherent word clouds. This is also evident from the previous examples of Word Flock's word clouds for *comp.os.ms-windows.misc* category in Figure 1 and for *rec.sport.baseball* in Figure 2.

Examples from $Reuters$ also reveal the contrast between *Word Storm* and Word Flock. Figures 5 and 6 shows the respective word clouds by *Word Storm* and Word Flock for four documents from the *ship* category of $Reuters$. While related words such as "ship", "vessel", "canal", "port", "seaman", and "shipping" are grouped together by Word Flock, these words are dispersed and have different colors in *Word Storm*'s word clouds.

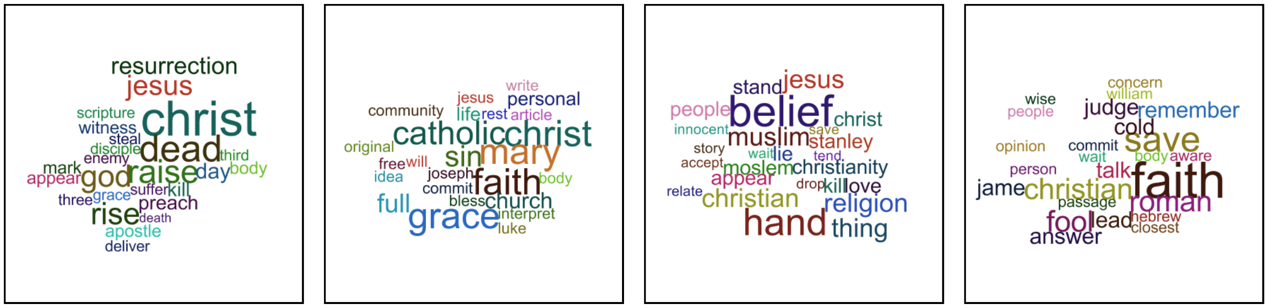
6.3 Classification

We seek further evidence through an automatic evaluation that offers a repeatable and objective validation. Each word cloud is represented as a vector of image pixels, where each pixel is represented by its RGB value. We validate how well the pixel representation of the word cloud images may be used as features in classification, with the simple nearest neighbors classifier. For every document, we hide its class label. We then identify its t-nearest neighbors based on cosine similarity over the pixel representations, and assign the document the majority class among its neighbors. $ClassificationAccuracy(t)$ is the fraction of documents for which the classification derives the correct labels. We average the accuracies across ten runs. This is merely for evaluation, and is not meant as a technique for document classification.

Figure 7(a) shows that Word Flock has significantly higher accuracies than *Word Storm* on $20News$. A random classifier would have an accuracy of 0.05. *Word Storm* performs at around 0.08. Word Flock attains more than 100% increase in accuracy over *Word Storm*. For $Reuters$ in Figure 7(b), Word Flock is also better. The improvements over *Word Storm* are statistically significant at 0.01 level. The

[3] `http://web.ist.utl.pt/acardoso/datasets/`

[4] `https://github.com/quimcastella/WordStorm`


resurrection jesus scripture witness christ steal disciple enemy dead third mark appear god raise day body three grace suffer kill preach rise death apostle deliver
write jesus personal community life rest article original catholic christ free will sin mary idea joseph commit faith body full bless church grace interpret luke
stand jesus people belief christ innocent muslim save stanley story wait lie tend accept moslem christianity relate appear drop kill love christian religion hand thing
concern wise william people judge remember cold opinion commit save wait body aware person talk jame christian faith passage roman fool lead hebrew answer closest

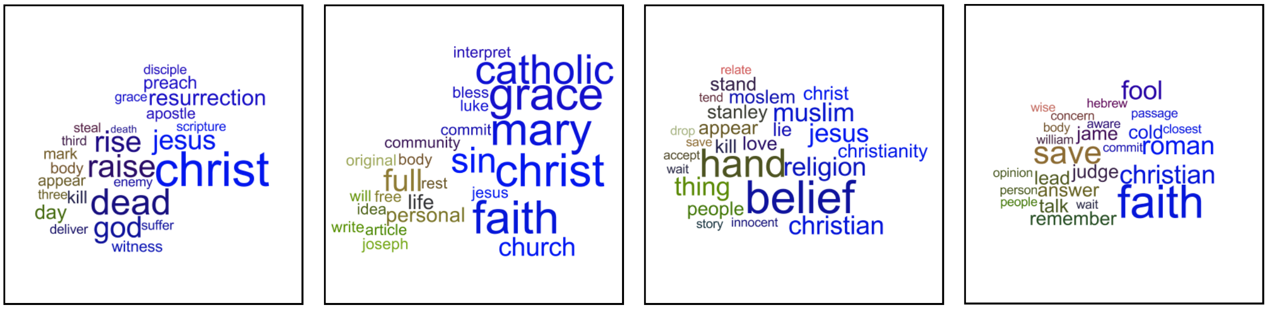
a. Doc762 by Word Storm

b. Doc770 by Word Storm

c. Doc788 by Word Storm

d. Doc790 by Word Storm

Figure 3: Word clouds by *Word Storm* for 4 documents from *soc.religion.christian* of $20News$ (best seen in color)


disciple preach grace resurrection apostle steal death scripture third rise jesus mark body raise christ appear enemy three kill dead day deliver god suffer witness
interpret catholic bless grace luke commit mary community original body sin christ full rest jesus will free life idea personal faith write article joseph church
relate stand tend moslem christ stanley muslim drop appear lie jesus save kill love christianity accept hand religion wait thing belief people story innocent christian
fool wise hebrew concern passage body aware jame cold closest william commit roman save opinion lead judge christian person answer people talk wait faith remember

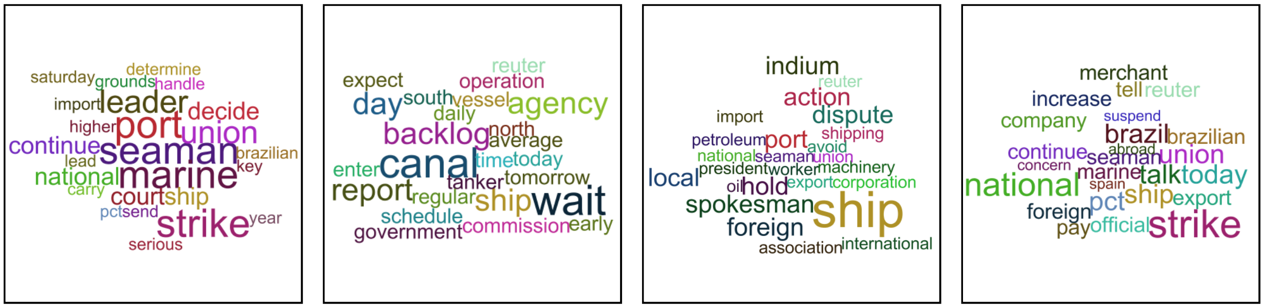
a. Doc762 by Word Flock

b. Doc770 by Word Flock

c. Doc788 by Word Flock

d. Doc790 by Word Flock

Figure 4: Word clouds by Word Flock for 4 documents from *soc.religion.christian* of $20News$ (best seen in color)


determine saturday grounds handle import leader decide higher port union continue seaman brazilian lead key national marine carry court ship pct send strike year serious
reuter expect operation day south vessel agency daily backlog north average enter canal time today tanker tomorrow report regular ship wait schedule government commission early
indium reuter action import dispute shipping petroleum port avoid national seaman union machinery president worker local oil hold export corporation spokesman ship foreign association international
merchant increase tell reuter company suspend brazil brazilian continue abroad seaman union concern marine talk today national spain pct ship export foreign pay official strike

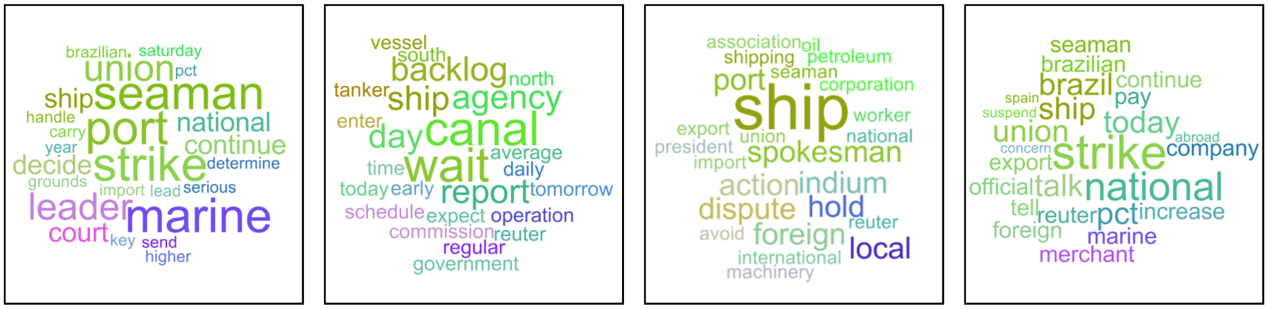
a. Doc165 by Word Storm

b. Doc169 by Word Storm

c. Doc171 by Word Storm

d. Doc199 by Word Storm

Figure 5: Word clouds by *Word Storm* for 4 documents from *ship* of $Reuters$ (best seen in color)


brazilian saturday union pct ship seaman handle carry port national year continue decide strike determine grounds import lead serious leader marine court key send higher
vessel south backlog north tanker ship agency enter day canal average time wait daily today early report tomorrow schedule expect operation commission reuter regular government
association oil shipping petroleum port seaman corporation ship worker export union national president spokesman import action indium dispute hold reuter avoid foreign local international machinery
seaman brazilian brazil continue spain pay suspend ship today union abroad concern strike company export official talk national tell reuter pct increase foreign marine merchant

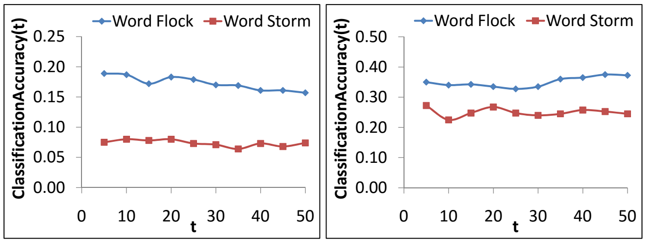
a. Doc165 by Word Flock

b. Doc169 by Word Flock

c. Doc171 by Word Flock

d. Doc199 by Word Flock

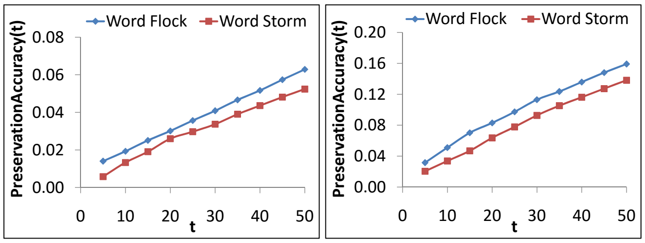
Figure 6: Word clouds by Word Flock for 4 documents from *ship* of $Reuters$ (best seen in color)



a. *20News*

b. *Reuters*

Figure 7: $ClassificationAccuracy(t)$ for various t



a. *20News*

b. *Reuters*

Figure 8: $PreservationAccuracy(t)$ for various t

performance is closer because $Reuters$ is an "easier" dataset (a random classifier would attain 0.125 accuracy).

6.4 Neighborhood Preservation

Ideally, a word cloud should be a faithful representation of its original document. In the next evaluation task, given a query document, we seek to retrieve the t most similar documents. We consider the ground truth to be the most similar documents over the original text representation of documents (i.e., cosine similarity over the 25-word term frequency vectors). $PreservationAccuracy(t)$ is defined as the fraction of t ground-truth documents that are "preserved" or identified among the t retrieved images (based on cosine similarity over the pixel representation). Figure 8(a) for $20News$ and Figure 8(b) for $Reuters$ show that Word Flock has higher preservation accuracies than *Word Storm* over various t's. This indicates that the resulting word clouds by Word Flock better preserve the similarities among the original documents. The difference between the two methods is statistically significant at 0.01 level in all cases.

6.5 User Study

We conduct a pilot user study on $20News$ to confirm our results in the quantitative analyses. The study involves two types of questions/tasks related to visual comparison of documents, which were similar to the study conducted in [Castella and Sutton, 2014]. For the first type, each user views six clouds, and is asked to identify the most different one. Among the six, five come from the same category, and one (the ground truth) comes from a different category. For the second type, each user views one query cloud and six answer clouds, and is asked to identify which answer cloud is most similar to the query cloud. Among the six, only one (the ground truth) comes from the same category as the query.

Question	Accuracy (%)		Time (s)	
	Word Storm	Word Flock	*Word Storm*	Word Flock
Type 1: Select the most different cloud	71.1	**78.9**	15.7	**14.6**
Type 2: Select the cloud most similar to a given cloud	63.6	**70.0**	16.6	**16.1**

Table 1: Results of the user study (bold is better)

For each type, a user has to complete 30 multiple-choice questions, with a time limit of 30 seconds per question. The clouds for each question are generated either by *Word Storm* or by Word Flock and each user is randomly presented with one of the two versions. There are 6 users involved in the study. Therefore, each question is answered 3 times using *Word Storm* and 3 times using Word Flock . The 6 clouds are sorted randomly and the users do not know how many methods there are, or which method is used for each question. We track accuracy and average time to answer each question.

Table 1 summarizes the results of the user study. For Type 1 questions, Word Flock helps users to attain a higher accuracy, 78.9% as compared to 71.1% for *Word Storm*, and with less time too (the time spent to answer was reduced by about a second). For Type 2, Word Flock also has a higher accuracy of 70.0% vs. 63.6% for *Word Storm*, again with slightly improved timing. The results are quite consistent among users, with 5 out of 6 users achieving higher accuracy with Word Flock than with *Word Storm* for both types.

6.6 Brief Comment on Efficiency

We comment briefly on one efficiency advantage of Word Flock over *Word Storm*, in our ability to generate individual word clouds in an online fashion. *Word Storm* must process all word clouds together. For the 1000 documents in $20News$, it requires 15 minutes on Intel Core i7 2.4Ghz machine with 8GB memory. Adding a new document requires looping over all the previously generated word clouds again to ensure consistency. In contrast, Word Flock achieves synchronization offline, so as to enable online generation of each word cloud independently, which requires only between 100 to 200 millisecond for every new word cloud.

7 Conclusion

We are interested in producing effective word clouds for visual comparison of documents within a corpus. The key idea is to construct word clouds to show related words with similar appearances, to enhance cognition of aspects across multiple word clouds. Word Flock achieves this via latent variable analysis, including offline embedding and latent aspect modeling, followed by online generation of word clouds. Through multi-faceted evaluation on two public datasets, we show evident outperformance by Word Flock over the baseline.

There are several potential directions for future work. One direction is to further enrich the word clouds by encoding some useful information in other visual attributes such as word orientation. Another direction is to further investigate the use of word clouds in specific application scenarios such as document retrieval or document summarization.

References

[Barth *et al.*, 2014] Lukas Barth, Stephen G Kobourov, and Sergey Pupyrev. Experimental comparison of semantic word clouds. In *Experimental Algorithms*, pages 247–258. Springer, 2014.

[Bateman *et al.*, 2008] Scott Bateman, Carl Gutwin, and Miguel Nacenta. Seeing things in the clouds: The effect of visual features on tag cloud selections. In *HT*, 2008.

[Bernstein *et al.*, 2010] Michael S. Bernstein, Bongwon Suh, Lichan Hong, Jilin Chen, Sanjay Kairam, and Ed H. Chi. Eddi: Interactive topic-based browsing of social status streams. In *UIST*, pages 303–312. ACM, 2010.

[Castella and Sutton, 2014] Quim Castella and Charles Sutton. Word storms: Multiples of word clouds for visual comparison of documents. In *WWW*, 2014.

[Chen *et al.*, 2009] Ya-Xi Chen, Rodrigo Santamaría, Andreas Butz, and Roberto Therón. Tagclusters: Semantic aggregation of collaborative tags beyond tagclouds. In *Smart Graphics*, pages 56–67. Springer, 2009.

[Chuang *et al.*, 2012] Jason Chuang, Christopher D Manning, and Jeffrey Heer. Termite: Visualization techniques for assessing textual topic models. In *AVI*, 2012.

[Coppersmith and Kelly, 2014] Glen Coppersmith and Erin Kelly. Dynamic wordclouds and vennclouds for exploratory data analysis. *Sponsor: Idibon*, page 22, 2014.

[Cui *et al.*, 2010] Weiwei Cui, Yingcai Wu, Shixia Liu, Furu Wei, Michelle X Zhou, and Huamin Qu. Context preserving dynamic word cloud visualization. In *PacificVis*, 2010.

[Dempster *et al.*, 1977] A. P. Dempster, N. M. Laird, and D. B. Rubin. Maximum likelihood from incomplete data via the EM algorithm. *JRSS*, 39(1):1–38, 1977.

[Dou *et al.*, 2013] Wenwen Dou, Li Yu, Xiaoyu Wang, Zhiqiang Ma, and William Ribarsky. Hierarchicaltopics: Visually exploring large text collections using topic hierarchies. *TVCG*, 19(12):2002–2011, 2013.

[Fujimura *et al.*, 2008] Ko Fujimura, Shigeru Fujimura, Tatsushi Matsubayashi, Takeshi Yamada, and Hidenori Okuda. Topigraphy: Visualization for large-scale tag clouds. In *WWW*, pages 1087–1088. ACM, 2008.

[Hassan-Montero and Herrero-Solana, 2006] Yusef Hassan-Montero and Victor Herrero-Solana. Improving tag-clouds as visual information retrieval interfaces. In *InSciT*, 2006.

[Iwata *et al.*, 2007] Tomoharu Iwata, Kazumi Saito, Naonori Ueda, Sean Stromsten, Thomas L Griffiths, and Joshua B Tenenbaum. Parametric embedding for class visualization. *Neural Computation*, 19(9):2536–2556, 2007.

[Iwata *et al.*, 2008] Tomoharu Iwata, Takeshi Yamada, and Naonori Ueda. Probabilistic latent semantic visualization: topic model for visualizing documents. In *KDD*, 2008.

[Knautz *et al.*, 2010] Kathrin Knautz, Simone Soubusta, and Wolfgang G Stock. Tag clusters as information retrieval interfaces. In *HICSS*, pages 1–10. IEEE, 2010.

[Kruskal, 1964] Joseph B Kruskal. Multidimensional scaling by optimizing goodness of fit to a nonmetric hypothesis. *Psychometrika*, 29(1):1–27, 1964.

[Le and Lauw, 2014] Tuan M. V. Le and Hady W. Lauw. Manifold learning for jointly modeling topic and visualization. In *AAAI*, 2014.

[Lohmann *et al.*, 2015] Steffen Lohmann, Florian Heimerl, Fabian Bopp, Michael Burch, and Thomas Ertl. Concentri cloud: Word cloud visualization for multiple text documents. In *InfoVis*, pages 114–120. IEEE, 2015.

[Oelke *et al.*, 2014] Daniela Oelke, Hendrik Strobelt, Christian Rohrdantz, Iryna Gurevych, and Oliver Deussen. Comparative exploration of document collections: a visual analytics approach. *Computer Graphics Forum*, 33(3):201–210, 2014.

[Paulovich *et al.*, 2012] Fernando V Paulovich, Franklina Toledo, Guilherme P Telles, Rosane Minghim, and Luis Gustavo Nonato. Semantic wordification of document collections. *Computer Graphics Forum*, 31(3pt3), 2012.

[Rivadeneira *et al.*, 2007] Anna W Rivadeneira, Daniel M Gruen, Michael J Muller, and David R Millen. Getting our head in the clouds: toward evaluation studies of tagclouds. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pages 995–998. ACM, 2007.

[Rodrigues, 2013] Nils Rodrigues. Analyzing textual data by multiple word clouds. Master's thesis, Universität Stuttgart, Holzgartenstr. 16, 70174 Stuttgart, 2013.

[Seifert *et al.*, 2008] Christin Seifert, Barbara Kump, Wolfgang Kienreich, Gisela Granitzer, and Michael Granitzer. On the beauty and usability of tag clouds. In *InfoVis*. IEEE, 2008.

[Shi *et al.*, 2010] Lei Shi, Furu Wei, Shixia Liu, Li Tan, Xiaoxiao Lian, and Michelle X Zhou. Understanding text corpora with multiple facets. In *VAST*, pages 99–106. IEEE, 2010.

[Steele and Iliinsky, 2010] Julie Steele and Noah Iliinsky. *Beautiful visualization: looking at data through the eyes of experts.* " O'Reilly Media, Inc.", 2010.

[Viegas *et al.*, 2009] Fernanda B Viegas, Martin Wattenberg, and Jonathan Feinberg. Participatory visualization with wordle. *TVCG*, 15(6):1137–1144, 2009.

[Wei *et al.*, 2010] Furu Wei, Shixia Liu, Yangqiu Song, Shimei Pan, Michelle X Zhou, Weihong Qian, Lei Shi, Li Tan, and Qiang Zhang. Tiara: a visual exploratory text analytic system. In *KDD*, pages 153–162. ACM, 2010.

[Wu *et al.*, 2011] Yingcai Wu, Thomas Provan, Furu Wei, Shixia Liu, and Kwan-Liu Ma. Semantic-preserving word clouds by seam carving. *Computer Graphics Forum*, 30(3):741–750, 2011.

[Zuo *et al.*, 2015] Yuan Zuo, Jichang Zhao, and Ke Xu. Word network topic model: A simple but general solution for short and imbalanced texts. *Knowledge and Information Systems*, pages 1–20, 2015.