ICA Handbook of Computational Communication Research

Chapter15. Time-dynamic Analysis

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Abstract

In communication research, scholars often analyze news articles, speech transcripts or social media posts to reveal how important public issues are discussed. They employ computational tools to examine how media content changes over an extended time period, but this remains challenging because the relationship between words and concepts shifts across different time periods. Therefore, understanding historical media discourses requires methods that account for temporal changes in word meanings and usages. To achieve this, scholars should employ time-dynamic analysis, in which machine learning models are applied to media content from specific time windows. This chapter explains how to design research using longitudinal media data and how to apply computational tools to perform dynamic analysis. It argues that cross-sectional time-varying analysis is particularly well-suited to computational communication research and demonstrates how dynamic analysis can be implemented using a range of unsupervised or semi-supervised machine learning models for document scaling and classification.

Introduction

In communication research, scholars often analyze news articles, speech transcripts and social media posts. News provides insight into current elite opinions on social, political and economic issues (Trubowitz & Watanabe, 2021) and plays a key role in shaping public attitudes towards these issues (Young & Soroka, 2012).[1] Social media offers a timely and frequent source of information on both elite and non-elite opinions (Heidenreich et al., 2022; Michael J. Jensen, 2017). Political speeches, while less frequent, provide direct insight into the views and ideologies of political leaders (Baturo et al., 2017; Curini & Vignoli, 2021). By drawing on these types of media data, scholars can study how media coverage is influenced by their organizational characteristics such as political affiliation, ownership, location, editorial policy, marketing strategy or target audience.

The development of computational tools has enabled scholars to analyze media content over extended time periods. For instance, Dehler-Holland et al. (2021) examined renewable energy topics in German newspapers from 2000 to 2017. Watanabe et al. (2022) compared the emphasis on nuclear threats in Japanese and Israeli newspapers from 2009 to 2018. Yamao (2024) analyzed sectarianism in Iraqi newspapers from 2007 to 2021. Longitudinal analysis has also been applied to speech and social media data. Mahrenbach and Pfeffer (2021) examined Indian people's attitudes toward the nationwide biometric database using microblog posts from 2009 to 2019. Ito et al. (2025) analyzed political speeches to track changes in Chinese leader's economic policy orientations from 2012 to 2013.

[1] In communication research, the mass media is usually seen as either a mirror that reflects the opinions of political leaders (Bennett, 1990; Wang et al., 2016) or the agent of agenda setting (Cook et al., 1983; McCombs & Shaw, 1972; Soroka, 2003) or issue framing (Entman, 1993; Jasperson et al., 1998; Kiousis, 2001).

Among these media types, newspapers are particularly well suited for longitudinal analysis because they consistently report on a wide range of topics following established journalistic routines (Donsbach, 2004; Gans, 1979; Shoemaker & Cohen, 2006). For example, if scholars find that conservative outlets express more skepticism about human causes of climate change than liberal outlets, they can argue that political ideology influences how environmental issues are reported (e.g. Boykoff & Boykoff, 2004). Although factors such as technological innovations, market demands, ownership changes and industrial disputes affect news production (Klinenberg, 2005; McManus, 1994; Schlesinger, 1978), major outlets maintain extensive digital archives, allowing scholars to study their coverage over long historical periods.

However, scholars still rely on static dictionaries or models that assume stability of word meanings over time. This false assumption can lead to inaccurate interpretations of past discourses. For example, a historical analysis of *The New York Times* reveals that the meaning of "equality" shifted from racial issues in the 19th century to international relations in the mid-20th century to gender issues in more recent years (Rodman, 2020).

To better capture these changes scholars should use dynamic text analysis methods that account for shifts in word meanings and usages over time. By applying machine learning models to data from specific time periods, scholars can track how relationships between words and concepts evolve. Such dynamic analysis has become increasingly feasible due to the growing availability of large media data and the advances in computational tools.

The following sections explain how to design longitudinal media research and how to implement dynamic analysis using machine learning techniques. This chapter argues that cross-sectional time varying analysis is particularly effective in computational communication research (CCR) because it incorporates both attribute-based and content-based variables while adjusting for changes in word meanings over time. In this design, static analysis of media content can be implemented using conventional tools, whereas dynamic analysis requires advanced unsupervised or semi-supervised models to ensure consistent results throughout the study periods. Although the discussion focuses on the analysis of news media, the same approach can be applied to other types of media, such as social media posts and speech transcripts.

Research Design

In longitudinal communication research, scholars seek to understand how different types of public issues and media attributes influence news reporting. To do so, they analyze media content over extended periods and identify changes that occur alongside relevant events. When such changes are observed, researchers often explain them by the outlets' characteristics. For example, they might argue that a liberal newspaper's sympathetic coverage of incoming migrants reflects its editorial stance. However, this reasoning can be overly simplistic because media coverage is shaped by multiple factors, including both organizational characteristics and the nature of the events.

Scholars should compare the coverage of the same events between outlets with and without a specific attribute to measure its impact precisely. If the outlets are similar in all other respects, researchers can more confidently conclude that differences in coverage are due to the target attribute. For instance, comparing coverage of a refugee crisis across liberal and conservative newspapers can help reveal the influence of editorial policies. Such comparisons help minimize the influence of other variables that may also shape news coverage.

Media outlets report important public issues differently because news production processes— such as gatekeeping—are shaped by their organizational characteristics (Berkowitz, 1990; White, 1950). Therefore, when comparing outlets with and without a particular attribute , scholars should expect to observe changes in news content following key events. In this approach, outlets with the attribute of interest are referred to as 'target' outlets, while and without it are called 'baseline' or 'benchmark' outlets.

This comparative approach draws on the difference-in-differences technique developed in econometrics (Card & Krueger, 1994). It requires careful selection of target and baseline outlets to measure the impact of the attribute. Two key assumptions underlie this approach: (1) the news production process should differ between the target and baseline outlets only with respect to the target attribute and (2) the difference in content should be constant in the absence of key events. While the first assumption can only be met partially in practice, the second can be tested empirically using longitudinal data from periods prior to the key events.

The selection of key events also requires careful consideration because irrelevant events can distort the results of the analysis. To address this, scholars should develop a detailed understanding of the study period using both media and non-media sources, and select events that are clearly defined and temporally distinct. To draw more reliable conclusions, researchers may also incorporate multiple key events by extending the study period.

Data Collection

Longitudinal analysis of media content requires collecting data over an extended period that covers several key events. Data sources should supply documents continuously throughout the study period in a digital format that clearly separates main texts from meta data (e.g., title, author, timestamp, etc.). These sources should also include multiple outlets to support comparative analysis.

Scholars may use public websites or commercial databases as data sources, but they have limitations. Public websites do not always provide complete access to older content, while commercial databases often restrict the automated downloading of large numbers of documents. A more effective approach is to use application programming interfaces (APIs), which allow users to download tens of thousands of documents using computer programs (see chapter 9 in this handbook).

Although news websites and databases often have built-in topic classification functions, scholars should avoid relying on them because their mechanisms typically lack transparency (Barberá et al., 2021). Instead, scholars should download either all available documents or their subset by performing Boolean keyword searches. In the former case, they can apply their own classification methods to select relevant documents for further analysis.

Time-series vs Cross-sectional Analysis

In economics and international relations, time-series analysis is commonly used to identify relationships between variables over time (e.g., unemployment rates, stock prices, geopolitical events). When a time-series analysis is implemented using a multivariate regression model, the coefficients of independent variables indicate their ability to forecast the dependent variable. Since these variables must be measured at regular intervals and be unique to each time point, variables derived from media content (content-based variables) must be aggregated by day, week or month.

In communication research, however, cross-sectional analysis is often more suitable because it does not require such aggregation. The dependent variable should be the most important aspect of the content for the study, while the independent variables should capture the aspects of the content that are associated with the dependent variable. For example, sentiment (dependent variable) is often associated with mentions of issues or people (independent variables) in news articles. Regression analysis of content-based variables reveals the types of documents that are significantly high (or low) with respect to the dependent variable.

When a multivariate regression model is applied to cross-sectional media data, the coefficients of the independent variables indicate changes in the dependent variables associated with them. In a simple model, the dependent variable is created through text analysis, while the independent variables include identifiers for media outlets (g), periods following key events (e), and interactions between them:

$$Y \approx \beta_0 + \delta g + \sum \beta_i e_i + \sum \gamma_i e_i g + \varepsilon.$$

In this model, δ captures differences in Y between outlets in the absence of events (pre-event difference); β_i captures changes common to the outlets following event e_i (post-event change); and γ_i captures changes specific to outlet g. Statistically significant γ_i suggests that the target outlet is more responsive to the events potentially due to the target attribute (Figure 1).

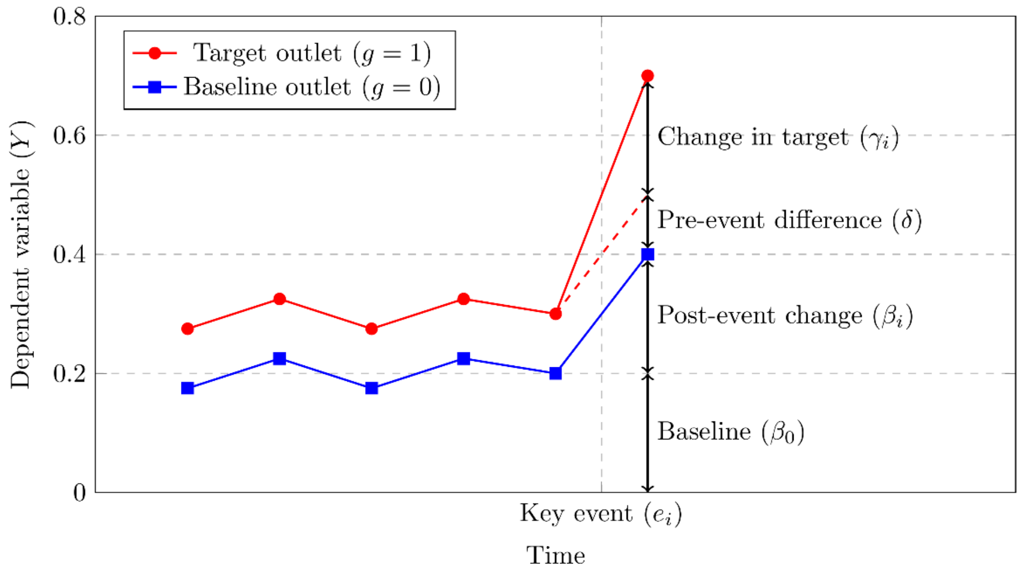


Figure 1: Cross-sectional regression analysis with key events.

It is also possible to include additional variables (x_j) to the regression model to explain variation in Y. These control variables may be drawn from document meta data (e.g., authors, sections, front-page) or generated through text analysis (e.g., keyword analysis, topic classification):

$$Y \approx \beta_0 + \delta g + \sum \beta_i e_i + \sum \gamma_i e_i g + \sum \theta_j x_j + \varepsilon.$$

Including control variables improves the comparability of outlets and helps explain differences between them. If the added control variables are statistically significant, they indicate which documents are causing differences in news coverage between outlets.

The dependent variable in the regression analysis is usually a continuous measurement created through text analysis. Although binary or count variables can also be used, continuous variables are preferred because they provide greater statistical power and allow for the use of simpler ordinary least-squares (OLS) regression models. Hierarchical regression models with a random intercept can also be used to account for fluctuations in the dependent variable (Watanabe, 2017), but they often lead to similar conclusions.

Event dummy variables take a value of one (otherwise zero) for articles published during the period following those events. The duration of the event window may vary from a few days to several weeks, depending on how quickly media outlets respond. If the window is too small or too large, the coefficients may become statistically insignificant (due to a small number of observations) or biased (because of other events that occurred within the period). Ideally, the duration should be determined based on changes in the volume of event-related content.

Control variables are typically binary, count, or categorical measures derived either from the content or meta data of the articles. Binary and count variables capture mentions of entities (e.g., persons, institutions, places) or sources (e.g., news agencies, government officials) in the texts, while categorical variables represent the main topic or country . Combining control variables with outlet identifiers as interaction terms also reveals differences in specific types of articles.

Static vs Dynamic Analysis

Scholars usually train machine learning models on documents collected from the entire study period. This approach seems appealing because models can estimate parameters with greater confidence on larger data, the analytical pipeline remains simple only with a few trained models, and the result of analysis with a single model is highly consistent throughout the study period. However, the longitudinal analysis of media content requires more sophisticated approaches to deal with the changes in the usage of words during the study period. For example, words such as “terrorist,” “nuclear” and “sanctions” are important words for security issues in US newspapers, but their relevance changed significantly from 2000 to 2020 (see below).

Similar changes in the relationship between words and concepts can be observed even in shorter study periods.

Scholars can capture changes in word usage by training models dynamically over segments of the study period or by using structural models that incorporate temporal variables. While the former approach requires multiple models trained on the subsets of data, the latter demands special models that allow interaction between the content and time indicators (Eshima et al., 2023; Roberts et al., 2014). The dynamic approach is preferred when the goal is forecasting future events (e.g., armed conflicts, stock price changes) or the dataset is too large for a single model. Recently developed complex models (e.g., large language models) can distinguish between different usages of words, but they rely on textual contexts rather than temporal contexts because their training data was not collected from specific time windows.

The results of dynamic content analysis must be consistent throughout the study period: scaling and classification of documents should be performed over the same dimensions (or categories) to ensure that results from different time windows can be meaningfully compared. Scholars can easily produce consistent results using supervised machine learning models (see chapter 18 in this handbook) because these models replicate the scaling or classification recorded in the training data. These models are expensive to train, but their results remain comparable as long as training data are annotated consistently across time windows.

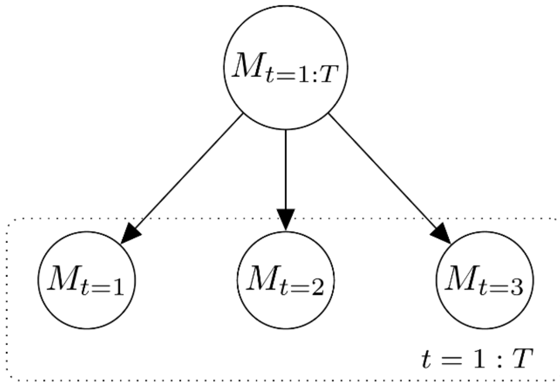
It is more difficult to produce consistent results using unsupervised machine learning models because they automatically identify the most discriminatory dimensions (or categories) in the data (see chapter 19 in this handbook), which tend to shift over time. Even if unsupervised models appear to capture the same dimensions in different time windows, their agreement is often coincidental. One solution is to guide the learning process using a model trained on data from across windows (global model) or the preceding window (local model). In the former case, scholars train a global model on the data from the entire study period ($t = 1, 2 \cdots T$ or $1{:}T$) and use it to guide all local models (Figure 2-a):

$$M_t = \mathrm{P}(X_t, M_{1:T}) \text{ where } M_{1:T} = \mathrm{P}(X_1, X_2, \cdots, X_T).$$

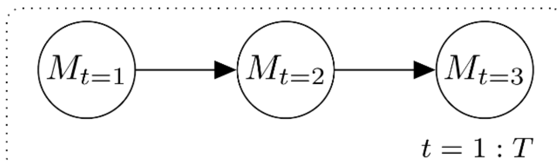
Since the local models M_t are informed about the future by the global model $M_{1:T}$, this approach is not strictly time-specific but can still capture the uniqueness of the content in each time window $(X_1, X_2, \cdots, X_T)$. In the latter case, scholars train local models sequentially and guide each model using the previous model M_{t-1} (Figure 2-b):

$$M_t = \begin{cases} \mathrm{P}(X_t), & t = 1 \\ \mathrm{P}(X_t, M_{t-1}), & t > 1 \end{cases}.$$

Since each model is informed only by current and past information, this approach is strictly time-specific.



(a) Globally aligned unupervised models



(b) Locally aligned unupervised models

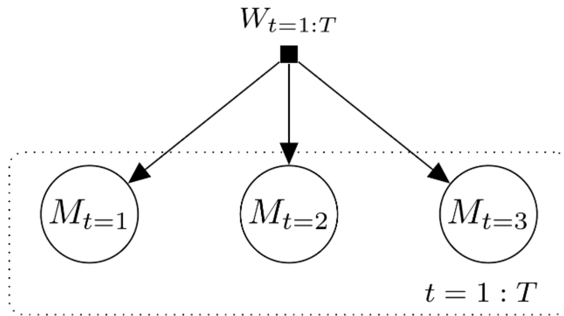
Figure 2: Dynamic analysis using unsupervised models.

Another solution is to use semi-supervised machine learning models that can be guided by seed words W chosen manually or automatically. If seed words are chosen manually, all the models are guided by seed word $W_{1:T}$ provided by the user (Figure 3-a). If seed words are chosen automatically, they are selected by a model trained on the data from across windows (Figure 3-b):

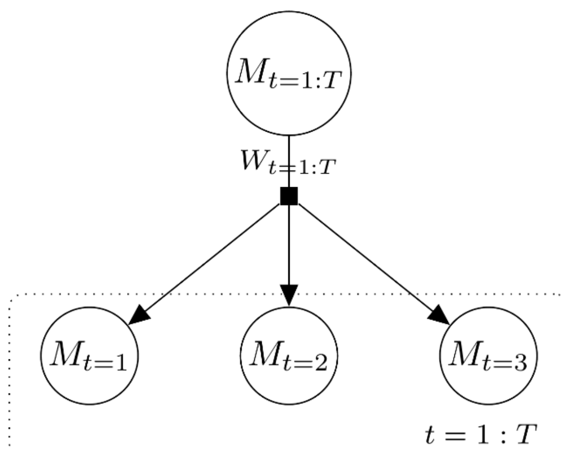
$$M_t = \mathrm{P}(X_t, W_{1:T}).$$

Since these seed words are chosen based on the knowledge of the data from the entire period, neither approach is strictly time specific. To make the analysis time-specific, seed words W_{t-1} should instead be selected automatically by the previous model M_{t-1} to guide the current model M_t (Figure 3-c):

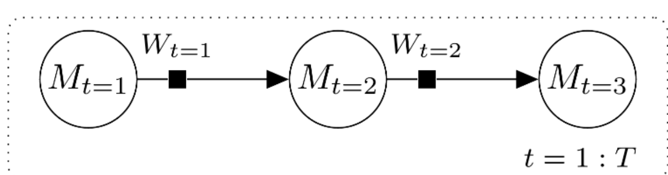
$$M_t = \begin{cases} \mathrm{P}(X_t)\,, & t = 1 \\ \mathrm{P}(X_t, W_{t-1})\,, & t > 1 \end{cases}.$$



(a) Globally aligned semi-supervised models with manual seed words selection



(b) Globally aligned semi-supervised models with automated seed words selection



(c) Locally aligned semi-supervised models with automated seed words selection

Figure 3: Dynamic analysis using semi-unsupervised models.

For example, when semi-supervised LDA models are trained annually on a corpus of US newspapers using the top ten topic terms from the previous year as seed words, they capture the evolution of topics (Table 1). The overarching topic is security, but its focus shifts over time—from terrorist attacks (“attacks,” “terrorist,” “terrorism”) to wars in the Middle East (“troops,” “fighting,” “arab”) to international negotiations (“talks,” “agreement,” “rules”).

The size of time windows can vary from a few weeks to several months depending on the research question and data sizes. When models are trained sequentially, it is common to partially overlap local windows because clear breaks in data makes the results less consistent even if they are guided by models or seed words. . In a monthly analysis of news, for instance, scholars can use a 3-month rolling window, in which two-thirds (first two months) of the content is identical to the previous periods.

Year	Topic Terms
2000	officials, clinton, security, administration, policy, military, foreign, un, nuclear, weapons, defense, trade, international, countries, official, nations, department, relations, congress, agreement, missile, agency, european, intelligence, secretary, efforts, threat, aid, cia, lee
2004	officials, security, administration, international, defense, policy, military, foreign, weapons, nuclear, intelligence, department, agency, official, program, cia, threat, attacks, terrorist, secretary, terrorism, un, bush, homeland, agencies, commission, pentagon, nations, countries, mass
2008	officials, international, security, administration, policy, foreign, military, defense, nuclear, countries, weapons, bush, trade, european, agreement, nations, union, efforts, program, secretary, global, deal, aid, leaders, congress, europe, crisis, un, intelligence, talks
2012	officials, international, security, policy, foreign, military, countries, administration, defense, nuclear, forces, attack, attacks, killed, un, regime, opposition, weapons, nations, al, troops, border, conflict, peace, sanctions, iran’s, fighting, arab, violence, intelligence
2016	officials, policy, security, international, administration, foreign, countries, military, defense, nuclear, forces, islamic, nations, obama, un, fighting, peace, sanctions, official, conflict, regime, talks, troops, including, region, weapons, aid, fight, allies, putin
2020	officials, administration, security, policy, countries, international, trade, foreign, defense, military, european, trump, border, agreement, global, immigration,

	department, sanctions, including, china's, eu, official, nations, efforts, europe, nuclear, rules, policies, relations, union

Table1: The evolution of the security topic in dynamic topic analysis over 20 years.

Text Analysis Methods

To create variables from media content through text analysis (see chapter 12 in this handbook), scholars should choose analytical methods based on three factors: the level of measurement, the direction of bias, and the degree of control. First, scholars should choose analytical methods based on the level of measurement required for regression analysis. In OLS regression analysis, for example, the dependent variable must be continuous and symmetrically distributed, while the independent variables can be continuous, categorical, or binary. Continuous variables are most sensitive to differences in media content, whereas binary variables are least sensitive. In text analysis, the creation of continuous variables is called "scaling," while the creation of categorical or binary variables is called "classification."

Second, scholars should consider the direction of bias that analytical methods may induce to the regression analysis. Statistical analysis can reveal the true relationships between variables even if they contain measurement errors because random noises are cancelled out. However, some errors are systematic due to the nature of the analytical method. The strength of association is overestimated if dependent variables have high false positive rates or if independent variables have high false negative rates. Ideally, variables in regression models should have equal false positive and false negative rates to produce unbiased results.

Third, scholars should consider the amount of manual input required to create variables. Usually, there is a strong correlation between the amount of user input for analysis and the level of user control over the results. For example, it is expensive to create keyword dictionaries or train supervised machine learning models, but these methods allow scholars to measure the target concept precisely. Unsupervised or semi-supervised algorithms are less expensive but often yield unintended results. Using existing dictionaries or pre-trained models is even less expensive, but the options are limited.

Scholars should choose analytical methods considering all three factors because the quality of research depends not only on the accuracy of measurements but also on their relevance to the concepts (Adcock & Collier, 2001) (see chapter 4 in this handbook). In other words, scholars should balance the accuracy and relevance of the measurements using inexpensive methods because regression analysis can reveal the true relationship between variables even if they have random measurement errors.

Scaling

Scaling refers to creating continuous variables from texts that measure their position on a linear dimension. For example, a continuous variable represents the expression of generic sentiment, political ideology, or policy orientation. These continuous variables often serve as a dependent variable in regression analysis and also help visually identify trends when a smoothing technique is applied (e.g., kernel smoother or local regression). There are several analytical methods for scaling, but they have strengths and weaknesses in dynamic analysis.

The simplest method is dictionary analysis, where computer programs scan texts for keywords and record their occurrences in each document. Dictionary analysis is widely used because users can create new measurements by adding or removing keywords. If the dictionary contains many keywords strongly associated with the target dimension, the analysis produces valid results. However, dictionary analysis is often insufficiently sensitive to subtle differences between documents due to the absence of relevant keywords, which leads to high false negative rates. Typically, each category in a dictionary must contain a few hundred to one thousand keywords to discriminate effectively between documents on a continuous scale (e.g., Young & Soroka, 2012).

Dictionary analysis is based on keyword matching, but users can produce continuous scores by computing the ratios of two frequency counts: $y = \frac{(m+\alpha)}{(n+\alpha)}$ where m and n are the frequencies of words for opposite concepts and α is a constant for smoothing (typically $\alpha = 0.5$). For example, if m and n denote the frequencies of positive and negative words in the document, respectively, y becomes its sentiment score. The use of raw frequency count should be avoided in scaling because document lengths strongly affect word frequencies.

Scholars may employ existing dictionaries to save effort, but adopting a dictionary developed for one corpus to another often reduces measurement validity because concepts may be expressed differently in the corpora. This problem becomes more complicated in longitudinal analysis because words change during the study period. Therefore, scholars must inspect how keywords are used in the corpus and remove them from the dictionary if their usage changes significantly during the study period.

Machine learning models are useful for automatically identifying associations between words and concepts. Supervised machine learning models can replicate human analysis when trained on a sample of documents with manually assigned scores (see chapter 18 in this handbook). In static analysis, a single global model can be trained on a sample drawn from across the study period, but multiple local models must be trained separately on samples from each time window in dynamic analysis. Since this demands annotation of data for each time window, dynamic analysis of media content can be prohibitively expensive.

Unsupervised machine learning models require no manual inputs because they automatically identify the most discriminatory dimension within the corpus (see chapter 19 in this handbook). Users can train separate models for each time window with minimal additional effort but scores produced by these models are not necessarily comparable in dynamic analysis. To align local models, users must initiate them with parameters from a global model, but few document scaling algorithms support non-random initial values.[2]

Semi-supervised machine learning models require seed words rather than manually assigned scores for training. Typically, two sets of words with opposite meanings are chosen as seed words to define a linear dimension on which documents are scaled. For example, a set of 10 to 20 sentiment seed words can produce similar results as a dictionary with thousands of words (Watanabe, 2020). Seed words must have stable relationships with the concepts throughout the study period to train local models.

Classification

Classification refers to creating binary or categorical variables from texts that indicate group membership of documents. For example, binary variables record whether a document mentions issues, people or organizations; categorical variables indicate the main topics, themes or countries in the texts. Usually, these variables serve as independent variables in cross-sectional analysis to explain variation in the dependent variable.

Dictionary analysis is commonly used in document classification because users can create dummy variables simply by detecting the occurrences of keywords. The number of keywords required in this task is usually much smaller than in scaling, because the binary

[2] For example, Wordfish (Slapin & Proksch, 2008) is an unsupervised document scaling algorithm used in political research. Its estimation process can be initiated with non-random values, but this functionality is not yet made available in widely used packages.

variables only record their presence or absence in each text. Yet, dictionary analysis can still result in high false negative rates if the number of keywords is too small (i.e., missing relevant words).

Dictionary analysis is useful for creating binary variables but less effective for generating categorical variables, because it is difficult to assign documents to a single category based solely on keyword counts. Classification of documents into one category is better performed using machine learning algorithms, which can determine the most likely category based on the distribution of probability scores.

Supervised machine learning models are very expensive to use in dynamic analysis because users must annotate documents for each time window. To reduce this cost, scholars can assign labels using dictionary analysis methods and then train local models on the documents.[3] For example, main topics or countries can be identified by training a naïve Bayesian classifier with labels assigned using a dictionary (Arzheimer, 2025; Watanabe, 2018).

Unsupervised machine learning models are far less expensive in dynamic analysis. Unsupervised topic models (Blei et al., 2003) can produce consistent results if the topic-word distributions extracted from a global model or the preceding local model are used as initial values (Figure 2). More recent approaches combine clustering and document embedding techniques (see chapters 19 and 20 in this handbook). For example, *k*-means clustering can be applied to document vectors from *doc2vec* (Le & Mikolov, 2014) to identify topics. In dynamic

[3] Training of supervised machine learning algorithms using keyword dictionaries or other rule-based methods is also called "weak supervision".

analysis, both *doc2vec* and *k*-means should be initiated with parameters from an existing model for alignment.[4]

Semi-supervised topic models (Jagarlamudi et al., 2012; Lu et al., 2011) are less common but useful in dynamic analysis because their topics are defined using seed words selected prior to training the models (Figure 3). When seed words are chosen manually, scholars collect relevant words from the corpus or external sources (e.g., thesauri, glossaries, book indices) (Watanabe & Zhou, 2020). When seed words are chosen automatically, the most important topic terms are extracted from an existing model and used as seed words for new models.[5]

Conclusions

The increasing availability of online data sources and computational tools have greatly expanded the scope of longitudinal analysis in communication research. Longitudinal analysis is particularly valuable because it allows scholars to examine how the characteristics of media organizations shape their coverage of important public issues.

To achieve this effectively, researchers can analyze longitudinal media content using cross-sectional regression models that incorporate key events and media content from multiple outlets. When changes in media content appear only in specific outlets, scholars can interpret these patterns by considering the social, political or economic constraints that shape each organization's content-production process.

[4] In dynamic analysis, the input layer for words should be initiated with the parameters from the previous *doc2vec* model. If the document vectors are aligned, the current *k*-means model should inherit initial centroids of clusters from the previous model.

[5] The most important topic terms are determined based on the probability of the words in the topic-word distribution. The number of topic terms extracted as seed words are usually 10 to 20 to allow the new model to learn topic-word association specific to the time window.

Nevertheless, longitudinal data poses new challenges in CCR because the relationship between words and concepts can change over time. To address this, scholars should implement dynamic analysis methods based on unsupervised or semi-supervised machine learning algorithms (see chapters 18 and 19 in this handbook). These approaches can capture the shifts in word across different time periods. When trained using a rolling window guided by existing models or seed words, these models can produce consistent results for cross-sectional regression analysis.

Longitudinal data also create new opportunities in CCR because they offer time-specific insight into public opinion and perception. By applying dynamic analysis in a strictly time-specific manner, scholars can examine media content as it would have been understood by audiences at that time, using only information available back then. Since pre-trained language models are not well suited for this type of analysis, the development of effective dynamic methods remains an important task for computational communication scholars.

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