1. **Trend analysis model: trend consists of temporal words, topics, and timestamps**

**Temporal words:** The words tied to specific times, e.g., “election” during voting season.

**Non-Temporal words:** General words like “analysis”

* Topic evolution, how topics change over time.

**Time-Stamped Data:** Documents with associated timestamps (e.g., tweets, news articles, research papers).

**Latent Variables for trend detection**:

**Trend class variable** (per document):

* A distribution over the topics (theme)
* A distribution over temporal words
* A continuous time distribution (when the trend appears)

**Switch variable** (per word/token):

* A temporal word distribution or
* A topic distribution

**Project documents into a latent scope** (simplified representation)

* Similar content + similar timestamp = Same trend class
* Tracks topic co-occurrence patterns over time

**Generative Model**

* TAM generates new lines while respecting the time-based trends
* Predicts how words/topics evolve in future documents

**TM-LDA:** Tracks topic transitions in **user-level sequence** (e.g., one person’s tweet over time).

**TAM:** Focuses on global trends across many documents, separating time-specific words from general ones.

1. **TM-LDA: efficient online modeling of latent topic transitions in social media**

(Temporal-Latent Dirichlet Allocation)

* Statice Corpora
* Efficient online learning. Traditional LDA (basically the static LDA) processes all the data at once, but the TM-LDA updates topic transition parameters incrementally as new posts arrive.

TM-LDA is an upgraded LDA designed for real-time, short-msg analysis, making it ideal for social media and other stemming text data.

**LDA**

LDA (Unsupervised ML technique) helps by automatically discovering the hidden topics based on word patterns.

* Uses Bayesian Inferences
* Each doc is a mixture of topics
* Each topic is a distribution over words
* LDA uncovers both: what the topics are, and how much each topic is present in each document

Generate topics based on word frequency from a set of documents.

Data cleaning:

* Tokenizing: converting a document to its atomic elements.
* Stopping: removing meaningless words.
* Stemming: merging words that are equivalent in meaning.

Assigns a random topic to each word of the provided corpus of documents.

**How much doc likes topic X How much topic likes word**

How prevalent the topic is in the document, and how prevalent is the word across the topic.

**Unseen, Untold, Until now!**

1. **Topic evolution based on the probabilistic topic model: a review**

* Probabilistic Topic Model: Statistical frameworks (e.g., LDA) that infer topics from word patterns.
* Structured Evolution Analysis: How models capture changes in
* topics/user interest over time.

1. **Identifying interesting Twitter contents using topical analysis**

* Trend Sensitive-Latent Dirichlet Allocation (TS-LDA)
* Efficiently extract latent topics from contents by modeling temporal trends on Twitter over time.

1. **Survey on trends of cross-media topic evolution map**
2. **Trend analysis of news topics on Twitter**

* Novel method based on MACD (Moving Average Convergence-Divergence)
* New concept trend momentum and use it to predict the trend of news topics

1. **Personalized recommendation based on knowledge graph**

* Semantic recommendation method
* KG to calculate interest similarity between users

<https://link.springer.com/article/10.1007/s12652-017-0491-7>

1. **Time based collective factorization for topic discovery and monitoring news**

* Collective Factorization: Document-term matrix (rows= documents, columns= words)
* A topic-term matrix
* A document-topic matrix

**Unifying text, time, and other data into a single model**

1. **Generation of Topic Evolution graph from short text streams**

* Encoder-only Transformer [Language Model](https://www.sciencedirect.com/topics/social-sciences/language-modeling) (ETLM) to quantify the relationship between words.
* weighted [Conditional random field](https://www.sciencedirect.com/topics/computer-science/conditional-random-field) regularized Correlated Topic Model (CCTM), which leverages semantic correlations to discover meaningful topics and topic correlations.

1. **Spatio-Temporal Topic modeling in mobile social media for location recommendation**

* STT (Spatio-Temporal Topic), to capture the spatio-temporal aspects of user check-ins in a single probabilistic model for location recommendation.

1. **Leveraging Social context for Modeling Topic evolution**

* Non-negative matrix Factorization

1. **Predicting Socio-Economic Indicators using News Events**

* Event class notion, manifested in news articles in the form of event triggers
* Like food prices and predict the price of 12 different crops based on real-world events that potentially influence food price volatility, such as transport strikes, festivals etc.
* RMSE (Root mean square error)
* ARIMA

1. **An Online Semantic-Enhanced Graphical Model for Evolving Short Text Stream Clustering**
2. **Dynamic Non-Parametric Joint Sentiment Topic Mixture Model**

* Based on non-parametric Hierarchical Dirichlet Process (HDP) topic model, (dynamic NJST, dNJST).

1. **TUT: A Statistical model for trend estimation, user interests in social media**

* Trend (short for trending story) corresponds to a series of continuing events or a storyline

1. **An Evolutionary Context-aware Sequential Model for Topic evolution of Text Stream**

* Evolutionary Context-aware Sequential model (ECSM).
* Tracking the evolution of an event and predicting its subsequent trends.

1. **Drop Message Hypergraph Attention Network**

* Construct a hypergraph based on cascade sequence.

1. **Hierarchical Evolving Dirichlet Processes for Modeling non-Linear Evolutionary Traces in Temporal Data**

* A hierarchy is a system where entities are arranged in a nested levels, with higher level governing the behavior of lower levels

1. **Supervised N-gram Topic Model**

* Bayesian nonparametric topic model that rep- resents relationships between given labels and the corresponding words/phrases, from supervised articles
* <https://dl.acm.org/doi/abs/10.1145/2556195.2559895?casa_token=YRAFEq2-sn0AAAAA:zdmjS7HX_KKN9qj_c-J_i_q5Pf8Xp-MTsIDPYJmOZ04Q1UCAURrFb2GRob_5Z8OiPaO9xyj9yP8UOA>

1. **Sparse Joint Dynamic Topic Model with Flexible Lead-Lag Order**