THE UNIVERSITY of EDINBURGH
Centre for Data, Culture & Society

DATA CULTURE SOCIETY

Text Classification in Practice: From Topic Models to Transformers

Zongxiao Wu & Joy Lan

Zongxiao.Wu@ed.ac.uk & plan@ed.ac.uk

20 November 2025

What is Text Classification?

Definition

- Text classification is the task of assigning natural language text to one or more predefined categories.
- It transforms unstructured text into structured data, enabling machines to “understand” content at scale.
- Can operate at **document level** (entire articles), **sentence level** (single sentence), or even **sub-sentence level** (phrases, entities).

What is Text Classification?

History Timeline

- 1950s: Naïve Bayes, rule-based systems.
- 1990s: Statistical NLP models (LDA, TF-IDF)
- 2010s: Neural NLP models (RNNs, CNNs).
- 2018+: Transformers and pre-trained LMs (BERT, GPT, RoBERTa).
- 2022+: Large language models (ChatGPT, Gemini, Llama)

What is Text Classification?

Examples

- **Sentiment Analysis**:

  Classify tweets or product reviews as *positive, negative, or neutral*.

  Example: “The camera quality is amazing!” → *Positive*.

- **News Categorization**:

  Assign news headlines to categories: *Politics, Sports, Technology, Entertainment*.

  Example: “Apple launches new AI chip” → *Technology*.

- **Spam Detection**:

  Classify emails or SMS as *Spam* vs. *Not Spam*.

  Example: “Win a free iPhone!” → *Spam*.

What is Text Classification?

Examples

- **Healthcare Applications**:

  Classify clinical notes into disease categories.

  Example: “Patient reports shortness of breath, prescribed inhaler.” → *Asthma*.

- **Legal and Policy**:

  Categorize case law or government reports for easier retrieval.

Why Text Classification?

Motivation & Value

- **Information Overload:** Every day, billions of documents, posts, and messages are created. Manual reading and labeling is infeasible.
- **Automation:** Text classification automates the categorization process, making unstructured data manageable.
- **Foundation for Natural Language Processing (NLP)**: Many advanced tasks—question answering, summarization, recommendation—rely on classification as a subtask.

Why Text Classification?

Advantages

- **Efficiency**: Handle massive text collections faster than human experts.
- **Scalability**: Adaptable across domains—finance, healthcare, e-commerce, social media.
- **Consistency**: Avoid subjective human bias, ensuring stable decision criteria.
- **Predictive Power**: Extract knowledge patterns that help forecast trends (e.g., market sentiment).

Business Impact:

- Customer support: route tickets to correct department; marketing: segment customers by feedback sentiment, etc.

How Text Classification?

Step 1. Data Collection & Preprocessing

- Gather domain-specific text (e.g., reviews, medical notes, legal documents).
- Clean the data:
  a) Remove noise (HTML tags, emojis, special symbols).
  b) Normalize case (lowercasing, except acronyms).
  c) Handle spelling errors, abbreviations, slang.
  d) Tokenization: split text into words/subwords.
  e) Remove stopwords (e.g., “a,” “the,” “and”).
  f) Stemming or lemmatization to reduce words to base form.

How Text Classification?

Step 2. Feature Representation

- **Bag-of-Words (BoW)**: simple word counts; ignores order.
- **TF-IDF**: weighs words by frequency vs. rarity.
- **Word Embeddings**: Word2Vec, GloVe, FastText capture semantic similarity.
- **Contextual Embeddings**: ELMo, BERT capture meaning depending on context.

Step 3. Dimensionality Reduction (optional)

- High-dimensional vectors are sparse and inefficient.
- Methods: PCA, LDA, NMF, Autoencoders, Random Projection.
- Benefit: faster training, less overfitting.

How Text Classification?

Step 4. Model Training

- **Traditional Models**:
  - Naïve Bayes (probabilistic).
  - Logistic Regression (linear).
  - Support Vector Machines (margin-based).
- **Neural Models**:
  - RNNs (capture sequential order).
  - CNNs (detect local patterns like n-grams).
  - Transformers (self-attention, contextual understanding).

How Text Classification?

Step 5. Evaluation

- Metrics depend on task:

  Accuracy (overall correctness), consider imbalanced datasets: accuracy may be misleading.

  Precision, Recall, F1 (balance false positives/negatives); ROC-AUC (ranking ability), etc.

Step 6. Deployment

- Integrate into applications:

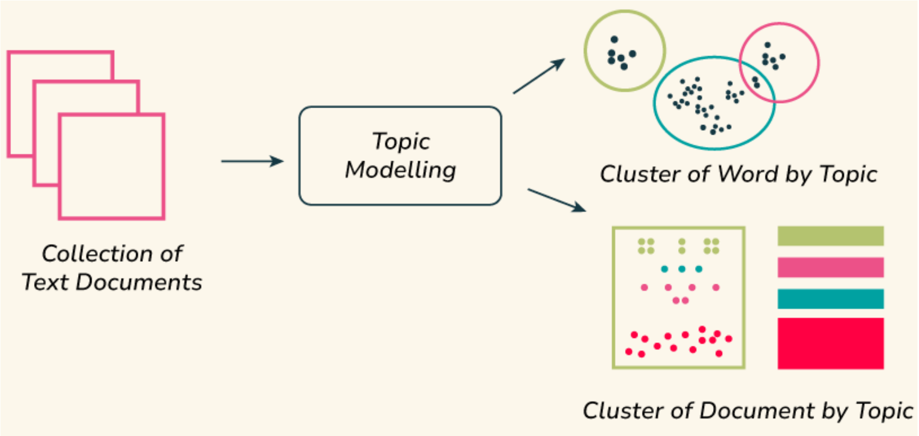
  Email spam filters; real-time recommendation engines.

  Customer service chatbots; healthcare diagnosis support tools, etc.

Models in Practice

Topic Models

- *Representative*: Latent Dirichlet Allocation (LDA).
- Learns hidden topics in a collection of documents.
- Each document is represented as a mixture of topics; each topic is a distribution over words.
- *Example*: News classification—documents mapped into topic space, then classified into categories.
- *Limitation*: Ignores word order; works better on long documents.



Models in Practice

Recurrent Neural Networks (RNN)

- *Representative*: Long Short-Term Memory (LSTM).
- Designed to capture sequential dependencies and long-term context.
- *Example*: Sentiment analysis of movie reviews—model understands word order ("not good" ≠ "good").
- *Strengths*: Handles variable-length sequences.
- *Limitations*: Training can be slow; hard to capture very long dependencies.

Models in Practice

Transformers

- *Representative*: BERT (Bidirectional Encoder Representations from Transformers).
- Based on self-attention mechanism; models relationships between all words in a sequence simultaneously.
- Pre-trained on massive corpora, fine-tuned for specific tasks.
- *Example*: Fine-tuning BERT on IMDB dataset for sentiment classification, achieving state-of-the-art accuracy.
- *Strengths*: Captures bidirectional context, efficient transfer learning.
- *Limitations*: Computationally expensive; large memory requirements.

Hands-on Session: Text Classification in Google Colab

Our Github page: https://github.com/DCS-training/Text-Calssification-in-Practice-From-Topic-Models-to-Transformers

Three tasks:

- **Topic Models – LDA for News Classification**

  Colab link: https://github.com/DCS-training/Text-Calssification-in-Practice-From-Topic-Models-to-Transformers/blob/main/Task1-LDA-News%20Classification/Task1_LDA_News_Classification.ipynb

- **Recurrent Neural Network – LSTM for Ecommerce Classification**

  Colab link: https://github.com/DCS-training/Text-Calssification-in-Practice-From-Topic-Models-to-Transformers/blob/main/Task2-LSTM-EcommerceClassification/LSTM.ipynb

Hands-on Session: Text Classification in Google Colab

Our Github page: https://github.com/DCS-training/Text-Calssification-in-Practice-From-Topic-Models-to-Transformers

Three tasks:

- **Transformer – BERT for Tweets Sentiment Classification**

  Colab link: https://github.com/DCS-training/Text-Calssification-in-Practice-From-Topic-Models-to-Transformers/blob/main/Task3-BERT-TweetsClassification/BERT.ipynb