

NSTM: Real-Time Query-Driven News Overview Composition at Bloomberg

**Joshua Bambrick¹, Minjie Xu¹, Andy Almonte¹, Igor Malioutov¹,
Guim Perarnau¹, Vittorio Selo¹, Iat Chong Chan^{2,*}**

¹Bloomberg, London, United Kingdom

²OakNorth, London, United Kingdom

¹{jbambrick7, mxu161, aalmonte2, imalioutov, gperarnau, vselo}@bloomberg.net

²iat.chan@oaknorth.com

Abstract

Millions of news articles from hundreds of thousands of sources around the globe appear in news aggregators every day. Consuming such a volume of news presents an almost insurmountable challenge. For example, a reader searching on Bloomberg’s system for news about the U.K. would find 10,000 articles on a typical day. Apple Inc., the world’s most journalistically covered company, garners around 1,800 news articles a day.

We realized that a new kind of summarization engine was needed, one that would condense large volumes of news into short, easy to absorb points. The system would filter out noise and duplicates to identify and summarize key news about companies, countries or markets.

When given a user query, Bloomberg’s solution, Key News Themes (or NSTM), leverages state-of-the-art semantic clustering techniques and novel summarization methods to produce comprehensive, yet concise, digests to dramatically simplify the news consumption process.

NSTM is available to hundreds of thousands of readers around the world and serves thousands of requests daily with sub-second latency. At ACL 2020, we will present a demo of NSTM.

1 Introduction

In many domains, finding contextually-important news as fast as possible is a key goal. With millions of articles published around the globe each day, quickly finding relevant and actionable news can mean the difference between success and failure.

When provided with a search query, a traditional system returns links to articles sorted by relevance. However, users typically encounter (near) duplicate or overlapping articles, making it hard to quickly identify key events and easy to miss less-reported

*Order reflects writing contributions; M.X., I.C.C., and J.B. designed and developed a prototype of the system; All implemented the production system; A.A. managed the project. I.C.C. worked on the project while employed by Bloomberg.

stories. Moreover, news headlines are frequently sensational, opaque, or verbose, forcing readers to open and read individual articles.

For illustration, imagine an analyst sees the price of Amazon.com stock drop and wants to know why. With a traditional system, they would search for news on the company and wade through many stories (307 in this case¹), often with duplicate information or unhelpful headlines, to slowly build up a full picture of what the key events were.

By contrast, using *NSTM (Key News Themes)*, this same analyst can search for ‘Amazon.com’, over a given time horizon, and promptly receive a concise and comprehensive overview of the news, as shown in Fig. 1. We tackle the challenges involved with consuming vast quantities of news by leveraging modern techniques to semantically cluster stories, as well as innovative summarization methods to extract succinct, informational summaries for each cluster. A handful of *key stories* are then selected from each cluster. We define a (story cluster, summary, key stories) triple as one *theme* and an ordered list of themes as an *overview*.

NSTM works at web scale but responds to arbitrary user queries with sub-second latency. It is deployed to hundreds of thousands of users around the globe and serves thousands of requests per day.

2 Design Goals

We focus on the scenario where a news search query can render many matching news articles, from tens up to hundreds of thousands. The task is to create a succinct overview of the results to help our users to easily grasp the gist of them without combing through the individual articles.

Since the matching articles often cover various aspects and events, NSTM must first cluster related stories to form a clear separation among them.

Furthermore, the system must extract a concise

¹The corresponding overview can be found in Appendix C.

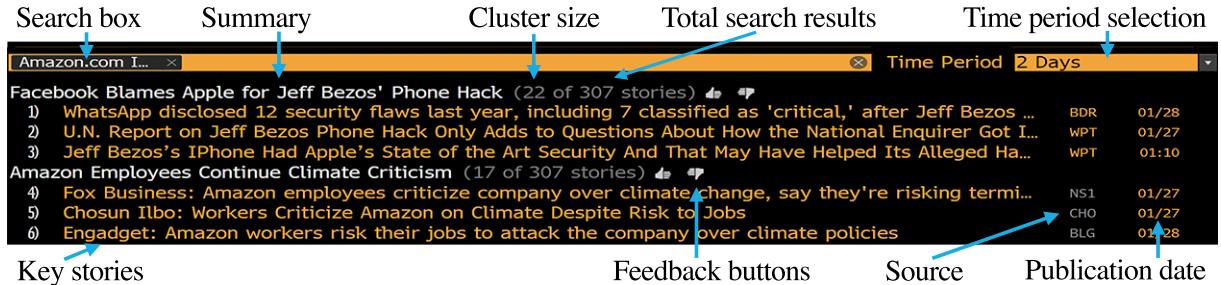


Figure 1: A query-based UI for NSTM showing two themes. The un-cropped screenshot is in Appendix C.

(up to 50 characters, or roughly 6 tokens) summary for each cluster. It needs to be short enough to be understandable to humans with a single glance, but also rich enough to retain critical details from a minimal ‘who-does-what’ stub, so the most popular noun phrase or entity alone will not suffice. Such conciseness also helps when screen space is limited (for context-driven applications or mobile devices).

From each cluster, NSTM must surface a few key stories to provide a sample of its contents. The clusters themselves should also be ranked to highlight the most important few in limited screen space.

Finally, the system must be fast. It may only take up to a few seconds for the slowest queries.

Main technical challenges: **1)** There is no public dataset corresponding to this overview composition problem with all the requirements set above, so we were required to either define new (sub-)tasks and collect new annotations, or select techniques by intuition, implement them, and iterate on feedback; **2)** Generating summaries which are simultaneously accurate, informational, fluent, and highly concise necessitates careful and innovative choices of summarization techniques; **3)** Supporting arbitrary user searches in real-time places significant performance requirements on the system whilst also setting a high bar for its robustness.

3 Related Work

A comparable system is Google News’ ‘Full Coverage’ feature², which groups stories from different sources, akin to our clustering approach. However, it doesn’t offer summarization and its clustered view is unavailable for arbitrary search queries.

SUMMA (Liepins et al., 2017) is another comparable system which integrates a variety of NLP components and provides support for numerous media and languages, to simultaneously monitor

several media broadcasts. SUMMA applies the online clustering algorithm by Aggarwal and Yu (2006) and the extractive summarization algorithm by Almeida and Martins (2013). In contrast to NSTM, SUMMA focuses on scenarios with continuous multimedia and multilingual data streams and produces much longer summaries.

4 Approach

4.1 Architecture

The functionality of NSTM can be formulated as: given a search query, generate a ranked list (*overview*) of the key *themes*, or (news cluster, summary, key stories) triples, that concisely represent the most important matching news events.

Fig. 2 depicts the system’s architecture. The *story ingestion service* processes millions of published news stories each day, stores them in a search index, and applies online clustering to them. When a search query is submitted via a user interface (① in the diagram), the *overview composition service* retrieves matching stories and their associated online cluster IDs from the search index (②). The system then further clusters the retrieved online clusters into the final clusters, each corresponding to one theme (③). For each such cluster, the system extracts a concise summary and a handful of key stories to reflect the cluster’s contents (④). This creates a set of themes, which NSTM ranks to create the final overview. Lastly, the system caches the overview for a limited time to support future reuse (⑤) before returning it to the UI (⑥).

4.2 News Search

The first step in the NSTM pipeline is to retrieve relevant news stories (① in Fig. 2), for which we leverage a customized in-house news search engine based on Apache Solr.³ This supports searches based on keywords, metadata (such as news source

²<https://www.blog.google/products/news/new-google-news-ai-meets-human-intelligence/>

³<http://lucene.apache.org/solr/>

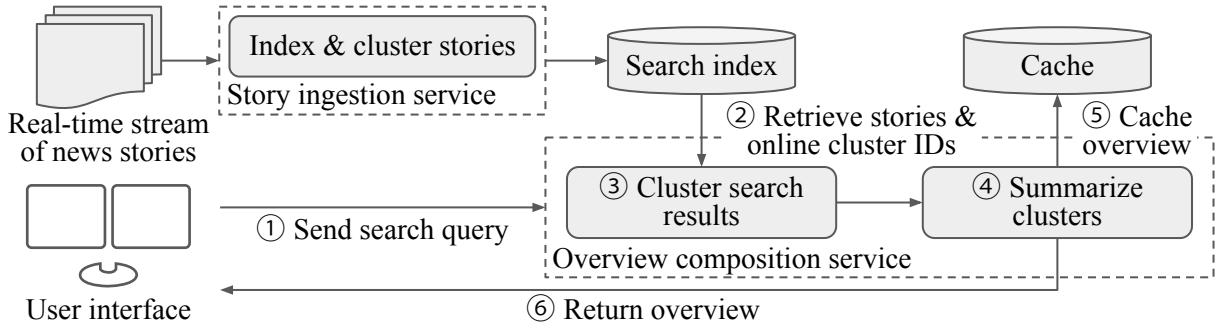


Figure 2: The architecture of NSTM. The digits indicate the order of execution whenever a new request is made.

and time of ingestion), and tags generated during ingestion (such as topics, regions, securities, and people). For example, TOPIC:ECOM AND NOT COMPANY:AMZN⁴ will retrieve all news about ‘E-commerce’ but exclude Amazon.com.

NSTM uses Solr’s *facet* functionality to surface the largest k online clusters (detailed in Sec. 4.3.2) in the search results, before returning n stories from each. This tiered approach offers better coverage and scalability than direct story retrieval.

4.3 Clustering

4.3.1 News Embedding and Similarity

At the core of any clustering system is a similarity metric. In NSTM, we define the similarity between two articles as the cosine similarity between their embeddings as computed by NVDM (Miao et al., 2016), i.e., $\tau(d_1, d_2) = 0.5(\cos(z_1, z_2) + 1)$, where $z \in \mathbb{R}^n$ denotes the NVDM embedding.

Our choice is motivated by two observations: **1**) The generative model of NVDM is based on bag-of-words (BoW) and $P(w|z) = \sigma(W^\top z)$ where σ is the softmax function, $W \in \mathbb{R}^{n \times V}$ is the word embedding matrix in the decoder and V is the size of the vocabulary. This resembles the latent topic structure popularized by LDA (Blei et al., 2003) which has proven effective in capturing textual semantics. Additionally, the use of cosine similarities is naturally motivated by the fact that the generative model is directly defined by the dot-product between the story embedding (z) and a shared vocabulary embedding (W). **2**) NVDM’s Variational Autoencoder (VAE) (Kingma and Welling, 2014; Rezende et al., 2014) framework makes the inference procedure much simpler than LDA and it also supports decoder customizations. For example, it allows us to easily integrate the idea of introducing

a learnable common background word distribution into the generative model (Arora et al., 2017).

We trained the model on an internal corpus of 1.85M news articles, using a vocabulary of size about 200k and a latent dimension n of 128.

4.3.2 Clustering Stages

We divide clustering into two stages in the pipeline, **1**) online incremental clustering at story ingestion time, and **2**) hierarchical agglomerative clustering (HAC) at query time (③ in Fig. 2). The former is used to produce query-agnostic *online clusters* at a relatively low cost to handle the daily influx of millions of news stories. These clusters reduce the computational cost at query time. However, due to its online nature, over-fragmentation, among other quality issues, occurs in the resulting clusters. This necessitates further refinement at query time when an offline HAC step is performed on top of the retrieved online clusters. A similar, but more complicated, design was adopted in Vadrevu et al. (2011) for clustering real-time news search results.

At both stages, we compute the cluster embedding $z_c \in \mathbb{R}^n$ as the mean of all the story embeddings therein, and evaluate similarities between clusters (individual stories are taken as singleton clusters) using the metric τ defined in Sec. 4.3.1.

For online clustering, we apply an in-house implementation which uses a distributed pool of workers to reduce latency and increase throughput. It merges each incoming story with the closest cluster if the similarity is within a parameterized threshold and otherwise creates a new singleton cluster.

For HAC, we apply `fastcluster`⁵ (Müllner, 2013) to construct the dendrogram. We use complete linkage to encourage more congruent clusters and then form flat clusters by cutting the dendrogram at the same (height) threshold. To further

⁴This is Bloomberg’s internal news search query syntax, which maps closely to the final query submitted to Solr.

⁵<https://www.jstatsoft.org/article/view/v053i09>

reduce fragmentation where similar clusters are left un-clustered, we apply HAC twice recursively.

To find a reasonable similarity threshold, we manually annotated just over 1k pairs of news articles. Each annotator indicated whether they would expect to see the articles grouped together or not in an overview. We then selected the threshold which achieved the highest F_1 score on this binary classification task, which was 0.86.

4.4 Summary Extraction

Clustering search results (Vadrevu et al., 2011) is a meaningful step towards creating a useful overview. With NSTM, we push this one step further by additionally generating a concise, yet still human-readable, summary for each cluster (④ in Fig. 2).

Due to the unique style of the summary explained in Sec. 2, the scarcity of training data makes it hard to train an end-to-end seq2seq (Sutskever et al., 2014) model, as is typical for abstractive summarization. Also, this technique would only offer limited control over the output. Hence, we opt for an extractive method, leveraging OpenIE (Banko et al., 2007) and a BERT-based (Devlin et al., 2019) sentence compressor (both illustrated in Fig. 3) to surface a pool of sub-sentence-level candidate summaries from the headline and the body, which are then scored by a ranker.

4.4.1 OpenIE-based Tuple Extraction

Open Domain Information Extraction (OpenIE) presents an unsupervised approach to extract summary candidates from an input sentence.

First, we construct a dependency parse tree of the sentence, using a model based on Kiperwasser and Goldberg (2016) (① in Fig. 3).

From this tree, we extract predicate-argument n -tuples using an adapted reimplementation of PredPatt (White et al., 2016) (②). The tuples represent nested proto-semantic parses of the sentence, and typically correspond to well-formed phrases. This method applies rules cast over Universal Dependencies (Nivre et al., 2016) so syntactic patterns are unlexicalized and language-neutral.

We then prune these tuples (③), applying rules which reduce the arguments to their syntactic heads, while heuristics keep named entities and multi-word expressions intact. We recursively intersect the resulting tuples to create more tuples.

Finally, to render summary candidates, we create a titlecased surface form of each tuple (④).

4.4.2 BERT-based Sentence Compression

In addition to the rule-based OpenIE system, we apply a Transfer Learning-based solution, using a novel in-house dataset specific to our sub-task. In particular, we model candidate summary extraction as a ‘sentence compression’ task (Filippova et al., 2015), where each story is split into sentences and tokens are classified as *keep* or *delete* to make each sentence shorter, while retaining the key message.

We oversaw the manual annotation of a dataset which maps sentences to compressed equivalents that correspond to summaries. When presented with a news story, annotators selected one sentence and deleted words to create a high quality summary. This rendered 10k annotations which we randomly partitioned into train (80%) and test (20%) sets.

The task is formulated as sequence tagging, whereby each sub-token (① in Fig. 3), defined using the BERT vocabulary, is classified as *keep* or *delete* (②). We implement this using a feedforward layer on top of a Bloomberg-internal pre-trained neural network, akin to the uncased English BERT-Base model, applying an adapted implementation.

To create a compression, we stitch sub-tokens labelled *keep* together (③). Lastly, we use postprocessing rules to improve formatting (④), such as titlecasing and fixing partial-entity deletion (where only some sub-tokens of a token/entity are deleted).

4.4.3 Summary Candidate Ranking

Tuple generation and sentence compression provide a pool of summary candidates for individual news stories. These are further aggregated across stories within a cluster to form the final pool. To identify the best summary for the cluster, we trained a sequence-pair model $s_\theta(a, c)$ to score each candidate c given an article a . Such article-level scores for a candidate are computed against all the stories in a cluster and then aggregated (e.g., averaged) to produce the final cluster-level scores, which we use for ranking.

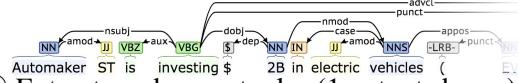
For this purpose, we collected an in-house annotated dataset. We sampled a few thousand news articles and generated 33k summary candidates from them using OpenIE.⁶ Then we asked internal annotators to label each as *Great*, *Acceptable* or *Terrible* were it to be used as a summary for the article, considering both readability and informativeness.

From this dataset, we constructed about 48k pairwise samples $(c, c')|a$ where c is labelled more

⁶At this time, we hadn’t considered sentence compression.

Automaker ST is investing \$2B in electric vehicles (EVs), atoning for the 2018 scandal

- ① Parse dependencies (shown cropped)



- ② Extract pred-arg n-tuples (1 output shown)

(atoning, Automaker ST, for the 2018 scandal)
PRED ARG ARG

- ③ Prune tuples (1 output shown)

(atoning, ST, for 2018 scandal)
PRED ARG ARG

- ④ Create surface form

ST Atoning For 2018 Scandal
OpenIE Pipeline

- ① Create sub-tokens

['automaker', 'ST', 'is', 'investing', '\$', '2', '#B', ...]

- ② Classify sub-tokens

[0.3, 0.8, 0.2, 0.8, 0.4, 0.6, 0.8, ...]

- ③ Stitch sub-tokens (with score greater than 0.5)

st investing 2b in evs

- ④ Postprocess

ST Investing \$2B in EVs

BERT-based Sentence Compression Pipeline

Figure 3: Illustrations of the symbolic OpenIE (left) and neural sentence compression (right) candidate extraction pipelines. We apply both, to render a diverse pool of candidate summaries, and use a ranker to select the best.

favorably than c' for a given common article a , and the model $s_\theta(a, c)$ was then trained to match such preferences using pairwise margin loss, i.e., $\max(0, 1 - s_\theta(a, c) + s_\theta(a, c'))$.

We considered a few models, including a parameter-free baseline which scores candidate-article pairs as the dot-product of their NVDM (Sec. 4.3.1) embeddings, i.e., $s = \mathbf{z}_a^\top \mathbf{z}_c$. We also considered this model’s bilinear extension $s = \mathbf{z}_a^\top W \mathbf{z}_c$ where W is the learnable weight matrix. Lastly, we tried neural network models, such as DecAtt (Parikh et al., 2016). We evaluated these models on a held-out test set with metrics such as pairwise ranking accuracy and NDCG. We opted to productionize the baseline model, since it was the simplest and performed on par with the others.⁷

Because NVDM uses a bag-of-words model, this ranker ignores syntax entirely. We believe that its empirical success owes to both the well-formedness of the majority of the candidates and the averaging effect that amplifies the ‘signal-noise ratio’ when the scores are averaged over the cluster.

Empirically, this approach tends to surface ‘informational’ summaries, in contrast to headlines which are often ‘sensational’. We posit that this is because high-ranked summaries must also be representative of story bodies, not just headlines.

4.4.4 Combining Summary Candidates

OpenIE and sentence compression offer distinct ways to extract candidates, and we experimented with each as the sole source of summary candidates in our pipeline. On the basis of ROUGE

scores (Lin and Hovy, 2003; Lin, 2004) (details in Appendix B), the latter provides superior results.

However, in a production system which informs business decisions, we must consider factors which aren’t readily captured by metrics which compare generated and ‘gold’ outputs. For example, changing a single word can reverse the meaning of a summary, with only a small change in such scores. Hence, we consider a range of pros and cons.

The sentence compression method is supervised and is trained to produce summaries which can take advantage of news-specific grammatical styles. However, the OpenIE system is much faster and offers greater interpretability and controllability.

Since the neural and symbolic systems provide different advantages, we apply both. This renders a diverse pool of candidate summaries from which the ranker’s task is to select the best. At the pooling stage we also impose a length constraint of 50 characters and exclude any longer candidates.

4.5 Key Story Selection

As a sample from the full story cluster, NSTM selects an ordered list of *key stories* which are deemed to be *representative*. We select these using a heuristic based on intuition and client feedback.

Our approach is to re-cluster all stories in the cluster using HAC (see Sec. 4.3.2), to create a parameterized number of sub-clusters. For each sub-cluster, we select the story that has maximum average similarity τ (as per Sec. 4.3.1) to the other sub-cluster stories. This strategy is intended to select stories which represent each cluster’s diversity.

We sort the key stories by sub-cluster size and time of ingestion, in that order of precedence.

⁷E.g., with NDCG₅, the (untrained) NVDM dot-product yields 0.61, while the bilinear model and DecAtt yield 0.64.

4.6 Theme Ranking

We have described how (story cluster, summary, key stories) triples, or *themes*, are created. However, some themes are considered to be more *important* than others since they are more useful to readers. It is tricky to define this concept concretely but we apply proxy metrics in order to estimate an importance *score* for each theme. We rank themes by this score and, in order to save screen space, return only the top few ('key') themes as an *overview*.

The main factor considered in the importance score is the size of the story cluster – the larger the cluster, the larger the score. This heuristic corresponds to the observation that more important themes tend to be reported on more frequently. Additionally, we consider the entropy of the news sources in the cluster, which corresponds to the observation that more important themes are reported on by a larger number of publishers and reduces the impact of a source publishing duplicate stories.

4.7 Caching

Since many user requests are the same or use similar data, caching is useful to minimize response times. When NSTM receives a request, it checks whether there is a corresponding overview in the cache, and immediately returns it if so. 99.6% of requests hit the cache and 99% of requests are handled within 215ms.⁸ In the event of a cache miss, NSTM responds in a median time of 723ms.⁹

We apply two mechanisms to ensure cache freshness. Firstly, we preemptively invoke NSTM using requests that are likely to be queried by users (e.g., most read topics) and re-compose them from scratch at fixed intervals (e.g., every 30 min). Once computed, they are cached. The second mechanism is user-driven: every time a user requests an overview which is not cached, it will be created and added to the cache. The system will subsequently preemptively invoke NSTM using this request for a fixed period of time (e.g., 24 hours).

5 Demonstration

NSTM was deployed to our clients in 2019. Using the UI depicted in Fig. 1, users can find overviews for customized queries to help support their work. From this screen, the user can enter a search query using any combination of Boolean logic with tag- or keyword-based terms. They may also alter the

⁸Computed for all requests over a 90-day period.

⁹Computed for the top 50 searches over a 7-day period.

Summary	Size
1 Facebook to Settle Recognition Privacy Lawsuit	90
2 Facebook Warns Revenue Growth Slowing	79
3 Facebook Stock Drops 7% Despite Earnings Beat	70
4 Facebook to Remove Coronavirus Misinformation	49
5 Mark Zuckerberg to Launch WhatsApp Payments	19

Table 1: Ranked theme summaries and cluster sizes for 'Facebook' (1,176 matching stories) from 31 Jan. 2020.

Summary	Size
1 Britain to Leave the EU	459
2 Bank of England Would Keep Interest Rate Unchanged	141
3 Sturgeon Demands Scottish Independence Vote	71
4 Pompeo in UK for Trade Talks	45
5 Boris Johnson Hails 'Beginning' on Brexit Day	63

Table 2: Ranked theme summaries and cluster sizes for 'U.K.' (13,858 matching stories) from 31 Jan. 2020.

period that the overview is calculated over (this UI offers 1 hour, 8 hour, 1 day, and 2 day options).

This interface also allows users to provide feedback via the 'thumb' icons or plain-text comments. Of several hundred per-overview feedback submissions, over three quarters have been positive.

Tables 1 and 2 show example theme summaries generated for the queries 'Facebook' and 'U.K.'. Note that the summaries are quite different from what has previously been studied by the NLP community (in terms of brevity and grammatical style) and that they accurately represent distinct events.

In addition to user-driven settings, NSTM can be used to supplement context-driven applications. One example, demonstrated in Appendix D, uses themes provided by NSTM to help explain why companies or topics are 'trending'.

6 Conclusion

We presented NSTM, a novel and production-ready system that composes concise and human-readable news overviews given arbitrary user search queries.

NSTM is the first of its kind; it is query-driven, it offers unique news overviews which leverage clustering and succinct summarization, and it has been released to hundreds of thousands of users.

We also demonstrated effective adoption of modern NLP techniques and advances in the design and implementation of the system, which we believe will be of interest to the community.

There are many open questions which we intend to research, such as whether autoregressivity in neural sentence compression can be exploited and how to compose themes over longer time periods.

References

- Charu C Aggarwal and Philip S Yu. 2006. A framework for clustering massive text and categorical data streams. In *Proceedings of the 2006 SIAM International Conference on Data Mining*, pages 479–483. SIAM.
- Miguel Almeida and André Martins. 2013. **Fast and robust compressive summarization with dual decomposition and multi-task learning.** In *Proceedings of the 51st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 196–206, Sofia, Bulgaria. Association for Computational Linguistics.
- Sanjeev Arora, Yingyu Liang, and Tengyu Ma. 2017. **A simple but tough-to-beat baseline for sentence embeddings.** In *Proceedings of the 5th International Conference on Learning Representations*, ICLR’17. OpenReview.net.
- Michele Banko, Michael J. Cafarella, Stephen Soderland, Matt Broadhead, and Oren Etzioni. 2007. Open information extraction from the web. In *Proceedings of the 20th International Joint Conference on Artificial Intelligence*, IJCAI’07, page 2670–2676, San Francisco, CA, USA. Morgan Kaufmann Publishers Inc.
- David M. Blei, Andrew Y. Ng, and Michael I. Jordan. 2003. **Latent dirichlet allocation.** *J. Mach. Learn. Res.*, 3:993–1022.
- Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. **BERT: Pre-training of deep bidirectional transformers for language understanding.** In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.
- Katja Filippova, Enrique Alfonseca, Carlos A. Colmenares, Lukasz Kaiser, and Oriol Vinyals. 2015. **Sentence compression by deletion with LSTMs.** In *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing*, pages 360–368, Lisbon, Portugal. Association for Computational Linguistics.
- Diederik P. Kingma and Max Welling. 2014. **Auto-encoding variational bayes.** In *2nd International Conference on Learning Representations, ICLR 2014, Banff, AB, Canada, April 14-16, 2014, Conference Track Proceedings*.
- Eliyahu Kiperwasser and Yoav Goldberg. 2016. **Simple and accurate dependency parsing using bidirectional LSTM feature representations.** *Transactions of the Association for Computational Linguistics*, 4:313–327.
- Renars Liepins, Ulrich Germann, Guntis Barzdins, Alexandra Birch, Steve Renals, Susanne Weber, Peggy van der Kreeft, Hervé Bourlard, João Prieto, Ondřej Klejch, Peter Bell, Alexandros Lazaridis, Alfonso Mendes, Sebastian Riedel, Mariana S. C. Almeida, Pedro Balage, Shay B. Cohen, Tomasz Dwojak, Philip N. Garner, Andreas Giefer, Marcin Junczys-Dowmunt, Hina Imran, David Nogueira, Ahmed Ali, Sebastião Miranda, Andrei Popescu-Belis, Lesly Miculicich Werlen, Nikos Papasaran-topoulos, Abiola Obamuyide, Clive Jones, Fahim Dalvi, Andreas Vlachos, Yang Wang, Sibo Tong, Rico Sennrich, Nikolaos Pappas, Shashi Narayan, Marco Damonte, Nadir Durrani, Sameer Khurana, Ahmed Abdelali, Hassan Sajjad, Stephan Vogel, David Sheppey, Chris Hernon, and Jeff Mitchell. 2017. **The SUMMA platform prototype.** In *Proceedings of the Software Demonstrations of the 15th Conference of the European Chapter of the Association for Computational Linguistics*, pages 116–119, Valencia, Spain. Association for Computational Linguistics.
- Chin-Yew Lin. 2004. **ROUGE: A package for automatic evaluation of summaries.** In *Text Summarization Branches Out*, pages 74–81, Barcelona, Spain. Association for Computational Linguistics.
- Chin-Yew Lin and Eduard Hovy. 2003. **Automatic evaluation of summaries using n-gram co-occurrence statistics.** In *Proceedings of the 2003 Human Language Technology Conference of the North American Chapter of the Association for Computational Linguistics*, pages 150–157.
- Yishu Miao, Lei Yu, and Phil Blunsom. 2016. **Neural variational inference for text processing.** In *Proceedings of the 33rd International Conference on International Conference on Machine Learning - Volume 48*, ICML’16, pages 1727–1736. JMLR.org.
- Daniel Müllner. 2013. **fastcluster: Fast hierarchical, agglomerative clustering routines for R and Python.** *Journal of Statistical Software, Articles*, 53(9):1–18.
- Joakim Nivre, Marie-Catherine De Marneffe, Filip Ginter, Yoav Goldberg, Jan Hajic, Christopher D Manning, Ryan McDonald, Slav Petrov, Sampo Pyysalo, Natalia Silveira, et al. 2016. Universal dependencies v1: A multilingual treebank collection. In *Proceedings of the Tenth International Conference on Language Resources and Evaluation (LREC’16)*, pages 1659–1666.
- Ankur Parikh, Oscar Täckström, Dipanjan Das, and Jakob Uszkoreit. 2016. **A decomposable attention model for natural language inference.** In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, pages 2249–2255, Austin, Texas. Association for Computational Linguistics.
- Danilo Jimenez Rezende, Shakir Mohamed, and Daan Wierstra. 2014. **Stochastic backpropagation and approximate inference in deep generative models.** In *Proceedings of the 31th International Conference on Machine Learning, ICML 2014, Beijing, China, 21-26 June 2014*, pages 1278–1286.

Ilya Sutskever, Oriol Vinyals, and Quoc V. Le. 2014. [Sequence to sequence learning with neural networks](#). In *Advances in Neural Information Processing Systems 27: Annual Conference on Neural Information Processing Systems 2014, December 8-13 2014, Montreal, Quebec, Canada*, pages 3104–3112.

Srinivas Vadrevu, Choon Hui Teo, Suju Rajan, Kunal Punera, Byron Dom, Alexander J. Smola, Yi Chang, and Zhaohui Zheng. 2011. [Scalable clustering of news search results](#). In *Proceedings of the Fourth ACM International Conference on Web Search and Data Mining*, WSDM’11, pages 675–684, New York, NY, USA. ACM.

Aaron Steven White, Drew Reisinger, Keisuke Sakaguchi, Tim Vieira, Sheng Zhang, Rachel Rudinger, Kyle Rawlins, and Benjamin Van Durme. 2016. [Universal Decompositional Semantics on Universal Dependencies](#). In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, pages 1713–1723, Austin, Texas. Association for Computational Linguistics.

A Acknowledgements

This has been a multi-year project, involving contributions from many people at different stages.

In particular, we thank Miles Osborne, Marco Ponza, Amanda Stent, Mohamed Yahya, Christoph Teichmann, Prabhanjan Kambadur, Umut Topkara, Ted Merz, Sam Brody, and Adrian Benton for reviewing and commenting on the manuscript; We further thank Adela Quinones, Shaun Waters, Mark Dimont, Ted Merz and other colleagues from the News Product group for helping to shape the vision of the system; We also thank José Abarca and his team for developing the user interface; We thank Hady Elsahar for helping to improve summary ranking during his internship; Finally, we thank all colleagues (especially those in the Global Data department) who helped to produce high quality in-house annotations and all others who contributed valuable thoughts and time into this work.

B End-To-End Evaluation

We evaluate the end-to-end NSTM system when using the OpenIE (Sec. 4.4.1) and the BERT-based sentence compression (Sec. 4.4.2) algorithms as the sole source of candidate summaries. We also conducted one experiment where both were used to create a shared pool of candidates (as per Sec. 4.4.4).

We test the system end-to-end using the manually-annotated Single Document Summarization (SDS) test set described in Sec. 4.4.2. To implement SDS, our experimental setup assumes that only one story was returned by a search request (as per Sec. 4.2). We evaluate the output from each system with ROUGE (Lin and Hovy, 2003; Lin, 2004)¹⁰. The results are presented in Table 3.

Metric	OpenIE	BSC	Both
ROUGE-1 F ₁	0.831	0.863	0.851
ROUGE-2 F ₁	0.609	0.701	0.667
ROUGE-3 F ₁	0.530	0.640	0.599
ROUGE-4 F ₁	0.492	0.603	0.562
ROUGE-L F ₁	0.621	0.706	0.670

Table 3: ROUGE scores for the Single-Document Summarization task in the end-to-end system, when using OpenIE, BERT-based sentence compression (BSC) and both to construct the pool of candidate summaries.

¹⁰<https://github.com/google/seq2seq/blob/master/seq2seq/metrics/rouge.py>

C Screenshots of A Query-Driven User Interface

Key News Themes

Amazon.com I... Time Period 2 Days

Facebook Blames Apple for Jeff Bezos' Phone Hack (22 of 307 stories)

- 1) WhatsApp disclosed 12 security flaws last year, including 7 classified as 'critical,' after Jeff Bezos ... BDR 01/28
- 2) U.N. Report on Jeff Bezos Phone Hack Only Adds to Questions About How the National Enquirer Got I... WPT 01/27
- 3) Jeff Bezos's iPhone Had Apple's State of the Art Security And That May Have Helped Its Alleged Ha... WPT 01:10

Amazon Employees Continue Climate Criticism (17 of 307 stories)

- 4) Fox Business: Amazon employees criticize company over climate change, say they're risking termi... NS1 01/27
- 5) Chosun Ilbo: Workers Criticize Amazon on Climate Despite Risk to Jobs CHO 01/27
- 6) Engadget: Amazon workers risk their jobs to attack the company over climate policies BLG 01/28

Amazon to Open Fulfillment Center in Memphis (10 of 307 stories)

- 7) Area Development: Amazon Plans Fulfillment Center in Memphis, Tennessee NS1 01/28
- 8) Air Cargo [Reg]: Amazon expands MEM presence with fulfillment center NS1 01/28
- 9) Local Memphis: As Amazon holds groundbreaking for Memphis fulfillment center, company reacts to... NS1 01/28

Spyware Group Denies Role in Jeff Bezos Hack (10 of 307 stories)

- 10) Saudi-backed Spyware Group Denies Role in Jeff Bezos Hack And Says It Plans to Restructure Owne... TEL 06:04
- 11) Senator Asks Pompeo for Details on Saudi Links to Bezos Hack BFW 01/27
- 12) Saudi Gazette: UN's role in the Bezos 'hack' story faces scrutiny NSB 01/27

MacKenzie Bezos Sells \$400 Million Amazon Shares (18 of 307 stories)

- 13) MacKenzie Bezos Shrinks Her Amazon Stake by About \$400 Million BN 01/27
- 14) Market Chatter: Mackenzie Bezos Stake In Amazon Believed To Have Been Reduced By 200,000 Shar... MTN 01/27
- 15) Yahoo! India: MacKenzie Bezos, Amazon CEO's ex-wife, sells \$400M in stock after pledge to give a... NS6 01/28

Are these themes useful?

Yes No Tell us why (optional) Submit

Themes are machine-generated. Data may not be accurate.

Figure 4: Screenshot (taken on 29 January 2020) of a query-driven interface for NSTM showing the overview for the company ‘Amazon.com’.

Key News Themes

EVs - Electric ... Time Period 2 Days

Tata Motors Has Launched Electric SUV Nexus EV (118 of 1,002 stories)

- 1) BGR: Tata's first electric SUV 'Nexus EV' launched in India at starting Rs 13.99 lakh WE6 08:22
- 2) BusinessWorld.in: Tata Launches 'Ecosystem' To Kickstart Indian Clean Vehicles NS6 01/28
- 3) News 18: Ather 450X Electric Scooter Launched in India at Rs 99,000 NS6 04:36

GM Build Electric Vehicles at Detroit Plant (153 of 1,002 stories)

- 4) GM to Invest \$2.2B in Detroit to Build Electric Vehicles APW 01/27
- 5) Leb Dem [Reg]: GM commits to \$2.2 billion investment, 2,200 jobs at Detroit plant NS1 01/28
- 6) FMT: Maserati to unveil first model with electric powertrain soon NS6 01/28

2020 Ioniq Electric, Its Compact All-Electric Car (23 of 1,002 stories)

- 7) Malta Ind Dly: Strong early consumer demand for fully electric Volvo XC40 Recharge P8 AWD NSS 01/28
- 8) SlashGear: 2020 Hyundai Ioniq Electric rises in range, power and price BLG 01/28
- 9) Irish Times: Opel's introduces new plug-in hybrid SUV - but is the price right? NSS 01/28

Honda to Launch 2 Electrified Vehicles (17 of 1,002 stories)

- 10) Bus Insider.au: All the things carmakers say they will accomplish with their future electric vehicle... NS6 01/28
- 11) Times Now: Auto Expo 2020 electric vehicles: Evere to showcase a high-performance e-scooter pr... NS6 06:23
- 12) Digital Trends: Fisker vs. Canoo: Are subscriptions the future of electric cars? BLG 01/27

What to Expect in Tesla's 4Q 2019 Earnings Results (17 of 1,002 stories)

- 13) Elon's Encore: Predicting the Surprises Tesla Has in Store Next BN 01/28
- 14) Street Insider: High expectations for Tesla, and a long way to go to match rivals' steady profit NS1 01/28
- 15) CNBC: Jim Cramer: Expect Tesla's stock to fall hard on an earnings miss NS1 01:12

Are these themes useful?

Yes No Tell us why (optional) Submit

Themes are machine-generated. Data may not be accurate.

Figure 5: Screenshot (taken on 29 January 2020) of a query-driven interface for NSTM showing the overview for the topic ‘Electric Vehicles’.

Key News Themes

Canada × Time Period 2 Days

First Coronavirus Case in Canada Confirmed (111 of 7,835 stories) ↗ ↘		
1) First Canadian coronavirus case officially confirmed, second is presumptive, 19 people under invest...	NPW	01/27
2) Ontario confirms second coronavirus case, the wife of the first case	NPW	01/27
3) Wife of Canada's first coronavirus patient tests positive; 19 under investigation	NPW	01/27
MP Erin O'Toole Joins Conservative Leadership Race (30 of 7,835 stories) ↗ ↘		
4) Taking shots at Peter MacKay, Erin O'Toole enters Conservative leadership race	NPW	01/28
5) Conservative leadership campaign trail adds one more: MP Erin O'Toole	CNP	01/27
6) More John A. and a little less Charest: Why conservatives should reclaim the Red Tory banner	NPW	01/27
Ontario School Teachers to Hold Strike Next Week (26 of 7,835 stories) ↗ ↘		
7) CTV.ca: Ontario elementary school teachers to hold province-wide one-day strike next week	NS2	01/27
8) Ottawa Citizen: Catholic school teachers plan one-day strike next week; public elementary teacher...	NS2	01/28
9) CTV.ca: EFTO to escalate rotating strikes across the province	NS2	01/27
Declining Oil Prices Weigh on Canadian Dollar (17 of 7,835 stories) ↗ ↘		
10) Ottawa Citizen: Canadian dollar drops to 7-week low as virus fears grow	NS2	01/27
11) Prince Geo Citz: Stock markets tumble on coronavirus fears, loonie falls against U.S. dollar	NS2	01/27
12) Baystreet.ca: USD/CAD - Canadian Dollar Suffering from Oil Price Blues	WE2	01/27
Venezuelan President Thanks Canada (19 of 7,835 stories) ↗ ↘		
13) Canada Vows to Revive Talks With Cuba on Ending Venezuela Crisis	BN	01/27
14) 'We thank Canada' for support, says Venezuela's Guaidó; Embattled president seeks support	NPW	01/28
15) Scotiabank CEO Seeks Help for Troubled Venezuela in Op-Ed (1)	BN	01/28

Are these themes useful?

Yes No Tell us why (optional) Submit

Themes are machine-generated. Data may not be accurate.

Figure 6: Screenshot (taken on 29 January 2020) of a query-driven interface for NSTM showing the overview for the region ‘Canada’.

Key News Themes

Match All × Canada × "coronavirus" × Time Period 2 Days

First Coronavirus Case in Canada Confirmed (167 of 755 stories) ↗ ↘		
1) Ontario confirms second coronavirus case, the wife of the first case	NPW	01/27
2) Coronavirus live updates: B.C. officials 'confident' man who visited China is province's first case	NPW	01/28
3) CKNW Vancouver: Health officials continue to test for coronavirus; still no Alberta cases	NS2	01/28
Canada to ‘Avoid All Travel’ to Hubei Province (26 of 755 stories) ↗ ↘		
4) Canadians stuck in China's coronavirus quarantine zones seek government help to return home	NPW	01/28
5) Sputnik LatAm: Canadian Govt Issues ‘Avoid All Travel’ Alert For China’s Hubei Province Due to Viru...	NS7	01/27
6) CKNW Vancouver: Canada still assessing needs as U.S., France, Japan begin to evacuate citizens fro...	NS2	01/28
Schools Reassure Parents About Coronavirus (18 of 755 stories) ↗ ↘		
7) Coronavirus live updates: Ontario parents petition schools to ‘quarantine’ students whose families ...	NPW	01/28
8) Globe Mail [Reg]: Fear over coronavirus prompts school board in Ontario to warn parents about rac...	GLO	01/28
9) CTV.ca: Chinese-Canadians speak out against racism in light of coronavirus fears	NS2	01/28
TSX Has Worst Day in Nearly Four Months on Fears (15 of 755 stories) ↗ ↘		
10) TSX has worst day in nearly four months on concerns about coronavirus impact	CNP	01/27
11) Virus Fallout Hits Canadian Stocks After Second Confirmed Case	BN	01/27
12) UPDATE: 5 reasons coronavirus fears are overblown -- and 14 stocks to buy now	DJ	01/28
Flight Leaving Center Bound for Ontario Airport (14 of 755 stories) ↗ ↘		
13) ABC Los Angeles: Jet carrying US consulate employees from Wuhan, China headed to Ontario amid c...	NS1	01/28
14) OC Register: Flight leaving center of coronavirus outbreak in China bound for Ontario airport, repor...	NS1	01/27
15) CBC: Toronto opens hotline for passengers on flight with Canada’s first coronavirus patient	CBC	01/28

Are these themes useful?

Yes No Tell us why (optional) Submit

Themes are machine-generated. Data may not be accurate.

Figure 7: Screenshot (taken on 29 January 2020) of a query-driven interface for NSTM showing the overview for a complex query, including a keyword.

D Screenshots of A Context-Driven User Interface

Companies Security List Topics				Region Worldwide	Trend Period 1 Day	News Trends
News Reader Activity		News Sentiment	Twitter Sentiment	News Volume	Twitter Volume	Social Velocity
Largest Increase Largest Total						
Security	Δ Act.	↓ GN	Δ Price	Δ AVAT	News Summary	
1) General Electric Co	[blue]	[yellow]	+10.44%	+662.40%	GE Beats Profit, Cash Flow Estimates on Aviation	
2) AT&T Inc	[blue]	[yellow]	-2.46%	+121.37%	HBO Max Squeezes AT&T Revenue	
3) Intelsat SA	[blue]	[yellow]	-22.10%	+921.85%	U.S. Senate Proposal Limit C-Band Payout	
4) Advanced Micro Devi...	[blue]	[yellow]	-7.98%	+254.18%	AMD Revenue Forecast Disappoints	
5) Apple Inc	[blue]	[yellow]	+2.26%	+108.73%	Record Apple Q1 2020 Revenue and Profit Apple	
6) Starbucks Corp	[blue]	[yellow]	-3.06%	+89.65%	Starbucks Closed Half Stores in China Coronavirus	
7) Tesla Inc	[blue]	[yellow]	+0.67%	-25.75%	Tesla Earnings Are Coming	
8) Deutsche Bank AG	[blue]	[yellow]	+1.65%	-6.28%	Deutsche Bank Delays Raises to Fixed Pay	
9) LVMH Moet Hennessy ...	[blue]	[yellow]	-1.19%	+37.84%	Luxury Group LVMH Posts Record Sales	
10) Walt Disney Co/The	[blue]	[yellow]	-1.22%	-3.20%	Loki Marvel in Disney+ Series	
11) Goldman Sachs Grou...	[blue]	[yellow]	-0.46%	+42.35%	Term YORK The Goldman Sachs Group, Inc.	
12) Anthem Inc	[blue]	[yellow]	-5.24%	+304.44%	Insurer Anthem Misses 4Q Earnings Forecasts	
13) McDonald's Corp	[blue]	[yellow]	+2.69%	+154.75%	McDonald's Quarterly Sales Growth, Profit	
14) American Airlines Gr...	[blue]	[yellow]	+2.14%	-4.24%	American Airlines Suspending Flights to China	
15) L Brands Inc	[blue]	[yellow]	+13.35%	+1.27%	Talks to Sell the Victoria's Secret Brand	
16) JPMorgan Chase & Co	[blue]	[yellow]	+0.67%	-35.11%	JPMorgan Keeps Bonuses Flat for Bankers, Traders	
17) Credit Suisse Group ...	[blue]	[yellow]	+0.75%	-26.61%	Credit Suisse Shed U.S. Private Bank With Eye	
18) Novartis AG	[blue]	[yellow]	+1.26%	+71.34%	Novartis Delivered Sales Growth	
19) Mastercard Inc	[blue]	[yellow]	-0.19%	+57.71%	Mastercard Earnings, Revenue Beat in Q4	
20) Boeing Co/The	[blue]	[yellow]	+2.77%	+264.12%	Boeing Posts Loss Since 1997 Max Costs Skyrocket	

Figure 8: Screenshot (taken on 29 January 2020) of a context-driven application of NSTM. In the ‘Security’ column are the companies that have seen the largest increase in news readership over the last day. Each entry in the ‘News Summary’ column is the summary of the top theme provided by NSTM for the adjacent company.

Companies Security List Topics				Trend Period 8 Hours	News Trends	
News Reader Activity		News Sentiment	Twitter Sentiment	News Volume	Twitter Volume	Social Velocity
Largest Increase Largest Total						
News Topic	Act.	↓ NT	News Summary			
1) Communications	[blue]	[yellow]	Apple Posts iPhone Sales in Quarter			
2) Securities Firms	[blue]	[yellow]	Follow Goldman Sachs First-Ever Investor Day			
3) Banking	[blue]	[yellow]	Suncrest Bank Reports Fourth Quarter Earnings			
4) Legal Affairs, Litigation	[blue]	[yellow]	Votes to Block Trump Impeachment Trial Witnesses			
5) Hedge Funds	[blue]	[yellow]	Regulations Could Favor Oil Speculators			
6) Crude Oil	[blue]	[yellow]	Oil Prices OPEC Could Extend Oil Output Cuts			
7) Central Bank Interest Rates	[blue]	[yellow]	Fed Leaves Key Interest Rate Unchanged at Low			
8) Gold	[blue]	[yellow]	Osisko Mining Have Completed Drill Hole			
9) First Word Credit News	[blue]	[yellow]	Tata Capital to Sell INR2b			
10) BFW U.S. Credit News	[blue]	[yellow]	Lender Demand for Boeing Loan Grows to \$14 Billion			
11) Oil	[blue]	[yellow]	Oil Prices Rise as Oversupply Worries Ease			
12) Credit Analysis, Markets	[blue]	[yellow]	That's IT for Markets Live for Tuesday, Jan. 28			
13) Telecom	[blue]	[yellow]	Apple Quarterly Sales Expectations			
14) Litigation	[blue]	[yellow]	Votes to Halt Witnesses in Trump Impeachment Trial			
15) Utilities	[blue]	[yellow]	OVO Energy Fined £8.9M for Overcharging Customers			
16) Electricity Generation	[blue]	[yellow]	Spanish Power Sector Cuts CO2 Emissions			
17) BFW Europe Credit News	[blue]	[yellow]	Austria in Demand Nears 250 Tranches			
18) U.S. Federal Funds	[blue]	[yellow]	US Federal Reserve Hold Rates Steady			
19) Airlines	[blue]	[yellow]	Airlines Halt China Flights			
20) Trials	[blue]	[yellow]	Votes to Block Trump Impeachment Trial Witnesses			

Figure 9: Screenshot (taken on 29 January 2020) of a context-driven application of NSTM. In the ‘News Topic’ column are the topics that have seen the largest volume of news readership over the past 8 hours. Each entry in the ‘News Summary’ column is the summary of the top theme provided by NSTM for the adjacent topic.