Cosine Similarity of Multimodal Content Vectors for TV Programmes

Saba Nazir ¹  Taner Cagali ²  Chris Newell ³  Mehrnoosh Sadrzadeh ¹

Abstract

Multimodal information originates from a variety of sources: audiovisual files, textual descriptions, and metadata. We show how one can represent the content encoded by each individual source using vectors, how to combine the vectors via middle and late fusion techniques, and how to compute the semantic similarities between the contents. Our vectorial representations are built from spectral features and Bags of Audio Words, for audio, LSI topics and Doc2vec embeddings for subtitles, and the categorical features, for metadata. We implement our model on a dataset of BBC TV programmes and evaluate the fused representations to provide recommendations. The late fused similarity matrices significantly improve the precision and diversity of recommendations.

1. Introduction

Ideas put forwards by Firth and Harris in the 1930’s led to the development of vector representations for words. The original word vectors represented context of textual use and the cosine distances between them, semantic similarities (Turney & Pantel, 2010). Subsequent research extended the vector representation methods from words to sentences and documents; nowadays, these vectors are learnt using neural networks, for a survey see (Jurafsky & Martin, 2019). Recently, the textual vector representations have been enriched by other modes of information, such audio-visual and cognitive (E. Bruni & Baroni, 2014; Kiela & Clark, 2017). The enriched representations are also used in multimodal content-based and hybrid recommendation systems for problems such as cold-start (Oramas et al., 2017), (Barkan et al., 2019), e-commerce assortment (Iqbal et al., 2018b) and genre classification (Ekenel & Semela, 2013). A large body of work exists here, with none as extensive or conclusive: e.g. (Yang et al., 2007), only considers tags and titles for textual data, (Bougiatiotis & Giannakopoulos, 2018) does use full subtitles but does not improve on the metadata-only recommendations.

This paper works with multimodal vector representations for audio and text, and investigates their application to TV recommendations, based on a dataset of 145 BBC TV programmes. On the methodological side, this is the first time that neural (Doc2Vec) and topical (LSI) document vectors are combined with audio (BoAW) vectors and vector representations of metadata. On the experimental side, the late fused representations significantly improve the precision and diversity of the recommendations.

2. Multimodal Content Vectors

Our dataset contains 145 BBC TV programmes with their subtitle and audiovisual files and metadata information.

Subtitle Vectors. Latent Semantic Indexing (LSI) (Papadimitriou et al., 2000), a topic modelling technique, was applied to the subtitle files. LSI is a two-step procedure. Firstly, a document-term matrix is generated via a low-rank approximation obtained from the term vector space projections of the Bag of Words vectors. Secondly, Singular Value Decomposition (SVD) is applied to the document-term ma-
rix, where the newly created eigenvectors represent the concepts within the latent space. We worked with 50 dimensional spaces. LSI improves on the term-document matrices, but does not take word order into account. To deal with this, we worked with neural semantics embeddings Doc2vec (Le & Mikolov, 2014). Doc2vec is an extension of the neural semantic word embeddings Word2vec (T. Mikolov & Dean, 2013). We worked with Paragraph Vector Distributed Memory (PV-DM), which concatenates the unique document ID with the context words with respect to the specified context window over the text and preserves the order of words.

Audio Vectors. We extracted acoustic features including MFCCs, Spectral Centroid, Zero Crossing Rate, Spectral Flatness and Root Mean Square using LibROSA (McFee et al., 2015), keeping audio sampling rate of 22050 Hz and hop length of 512 samples, with variable lengths of audio tracks averaging on about 30 mins each for a detailed analysis. The extracted multiple acoustic features are concatenated, normalised and then used as audio vectors for each audio. We then followed (Kiela & Clark, 2017) and used a Bag of Audio Words (BoAW) model to learn abstract audio vector representations. BoAW is used in audio information retrieval recognition (Liu et al., 2010; Pancoast & Akbabak, 2012; Rawat et al., 2013) and acoustic event detection (Plinge et al., 2014; Grzeszick et al., 2015; Lim et al., 2015). They are learnt via mini-batch K-means clustering with $K = 50$.

Metadata Vectors. Metadata representations are based on the editorially-assigned attributes of the programmes. We worked with hierarchical genre information, e.g. "factual/scienceandnature/natureandenvironment", where a match can occur at any level. A categorical feature vector is created for each attribute by traversing the trees.

Fusion. Individual content vectors are ranked using cosine similarities and are fused with middle and late fusion techniques (Kiela & Clark, 2017; Atrey et al., 2010; Zhu et al., 2006). In middle fusion, we concatenated the different vectors representations. In late fusion, we first computed the cosine similarities of pairwise vectors, resulting in 3 symmetric $145 \times 145$ similarity matrices; then combined these with each other by weighted averaging. Figure 1 shows our late fusion framework.

3. Evaluation and Results

Performance of the singular and fused vectors is evaluated by a personalised Python-based recommender system evaluation framework, developed using MyMediaLite library (MyMediaLite). We calculated the Mean Average Precision (MAP) and Intra-list diversity (ILD) of the recommendations at ranks 10 and 20 obtained from cosine similarities, and compared these with a metadata-only recommenda-

| Model   | MAP@10  | ILD@10 | MAP@20  | ILD@20 |
|---------|---------|--------|---------|--------|
| LSI     | 11.30   | 69.89  | 13.40   | 76.79  |
| D2V     | 11.76   | 77.20  | 13.88   | 80.37  |
| AUD     | 06.67   | 77.96  | 8.11    | 81.38  |
| MD      | 10.78   | 35.52  | 12.77   | 52.72  |
| FUS     | 14.98   | 61.29  | 17.45   | 70.00  |
| USER    | 15.60   | 79.73  | 18.51   | 80.90  |

Table 1. Singular and fused model evaluations. The acronyms LSI, D2V, AUD, MD, and Fus are used for Latent Semantic Indexing, Doc2vec, Audios, metadata, respectively. User is the user-based behavioural similarity that we are trying to estimate.

4. Future Work

Our framework can easily be extended to other modalities. We worked with standard Python packages for sentiment and writing style, with format and service metadata, and with 200 scene images extracted from the video files of programmes, but did not obtain improvements. Working with more sophisticated attributes, and larger number of images and jointly learning multimodal representations, as in (Iqbal et al., 2018a), via neural nets is work in progress.
Cosine Similarity of Multimodal Content Vectors for TV Programmes

References

Atrey, P. K., Hossain, M. A., El Saddik, A., and Kankanahalli, M. S. Multimodal fusion for multimedia analysis: a survey. *Multimedia systems*, 16(6):345–379, 2010.

Barkan, O., Koenigstein, N., Yogev, E., and Katz, O. Ch2cf: a neural multiview content-to-collaborative filtering model for completely cold item recommendations. In *Proceedings of the 13th ACM Conference on Recommender Systems*, pp. 228–236, 2019.

Bougiatiotis, K. and Giannakopoulos, T. Enhanced movie content similarity based on textual, auditory and visual information. *Expert Systems with Applications*, 96:86 –102, 2018.

E. Bruni, N. T. and Baroni, M. Multimodal distributional semantics. *Journal of Artifical Intelligence Research*, 49: 1–47, 2014.

Ekenel, H. K. and Semela, T. Multimodal genre classification of tv programs and youtube videos. *Multimedia tools and applications*, 63(2):547–567, 2013.

Grzeszick, R., Plinge, A., and Fink, G. A. Temporal acoustic words for online acoustic event detection. In *German Conference on Pattern Recognition*, pp. 142–153. Springer, 2015.

Iqbal, M., Kovac, A., and Aryafar, K. A multimodal recommender system for large-scale assortment generation in e-commerce. In *The SIGIR 2018 Workshop On eCommerce co-located with the 41st International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR 2018)*, Ann Arbor, Michigan, USA, July 12, 2018, 2018a.

Iqbal, M., Kovac, A., and Aryafar, K. A multimodal recommender system for large-scale assortment generation in e-commerce. *arXiv preprint arXiv:1806.11226*, 2018b.

Jurafsky, D. and Martin, J. H. *Speech and Language Processing*. https://web.stanford.edu/~jurafsky/slp3/, 2019.

Kiela, D. and Clark, S. Learning neural audio embeddings for grounding semantics in auditory perception. *Journal of Artificial Intelligence Research*, 60:1003–1030, 2017.

Le, Q. and Mikolov, T. Distributed representations of sentences and documents. In *International conference on machine learning*, pp. 1188–1196, 2014.

Lim, H., Kim, M. J., and Kim, H. Robust sound event classification using lbp-hog based bag-of-audio-words feature representation. In *Sixteenth Annual Conference of the International Speech Communication Association*, 2015.

Liu, Y., Zhao, W.-L., Ngo, C.-W., Xu, C.-S., and Lu, H.-Q. Coherent bag-of audio words model for efficient large-scale video copy detection. In *Proceedings of the ACM international conference on image and video retrieval*, pp. 89–96, 2010.

McFee, B., Raffel, C., Liang, D., Ellis, D. P., McVicar, M., Battenberg, E., and Nieto, O. Librosa: Audio and music signal analysis in python. In *Proceedings of the 14th python in science conference*, volume 8, 2015.

MyMediaLite. Mymedialite recommender system library. [http://www.mymedialite.net/](http://www.mymedialite.net/). (Accessed on 02/20/2020).

Oramas, S., Nieto, O., Sordo, M., and Serra, X. A deep multimodal approach for cold-start music recommendation. In *Proceedings of the 2nd Workshop on Deep Learning for Recommender Systems*, pp. 32–37, 2017.

Pancoast, S. and Akbacak, M. Bag-of-audio-words approach for multimedia event classification. In *Thirteenth Annual Conference of the International Speech Communication Association*, 2012.

Papadimitriou, C. H., Raghavan, P., Tamaki, H., and Vempala, S. Latent semantic indexing: A probabilistic analysis. *Journal of Computer and System Sciences*, 61(2):217–235, 2000.

Plinge, A., Grzeszick, R., and Fink, G. A. A bag-of-features approach to acoustic event detection. In *2014 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pp. 3704–3708. IEEE, 2014.

Rawat, S., Schulam, P. F., Burger, S., Ding, D., Wang, Y., and Metze, F. Robust audio-codebooks for large-scale event detection in consumer videos. In *INTERSPEECH*, pp. 2929–2933, 2013.

T. Mikolov, K. Chen, G. C. and Dean, J. Efficient estimation of word representations in vector space. In *Proceedings of ICLR*, Scottsdale, AZ, 2013.

Turney, P. and Pantel, P. From frequency to meaning: vector space models of semantics. *Journal of Artificial Intelligence Research*, 37:141188, 2010.

Yang, B., Mei, T., Hua, X.-S., Yang, L., Yang, S.-Q., and Li, M. Online video recommendation based on multimodal fusion and relevance feedback. In *Proceedings of the 6th ACM International Conference on Image and Video Retrieval, CIVR 07*, pp. 7380, New York, NY, USA, 2007. Association for Computing Machinery.

Zhu, Q., Yeh, M.-C., and Cheng, K.-T. Multimodal fusion using learned text concepts for image categorization. In *Proceedings of the 14th ACM international conference on Multimedia*, pp. 211–220, 2006.