Literature – Bachelor’s Thesis:

Domain Adapted Topic Modelling for Alt-tech Social Media

* Bachelor's Thesis BWL: Bodea, A. E. (2022b). From freedom of speech to the U.S. Capitol riots: Topic evolution of content on Parler. (Bachelor’s Thesis). Ludwig-Maximilians-Universität München, Institute of Artificial Intelligence (AI) in Management, Munich, Germany

@mastersthesis{BT\_BWL,

author = {Bodea, Andreea Elena},

title = {{From freedom of speech to the U.S. Capitol riots: Topic evolution of content on Parler.}},

school = {Ludwig-Maximilians-Universität München, Institute of Artificial Intelligence (AI) in Management},

year = {2022},

type = {Bachelor's Thesis},

address = {Munich, Germany},

month = {April}

}

* Bachelor's Thesis INFO GitHub Repo: Bodea, A. E. (2022a, 11). Domain adapted topic modelling for alt-tech social media [Computer software]. <https://github.com/andreea-bodea/bachelors-thesis-informatics>

@software{GitHub\_Repo,

author = {Bodea, Andreea Elena},

title = {{Domain adapted topic modelling for alt-tech social media}},

url = {<https://github.com/andreea-bodea/bachelors-thesis-informatics>},

year = {2022},

month = {11}

}

* Master's Thesis: Topic Modeling Evaluations: The Relationship Between Coherency and Accuracy

-> BERTopic vs LDA

-> evaluation metrics: topic coherence (UCI, Umass, NPMI, CV)

@mastersthesis{MT\_Topic Modeling Evaluations,

author = {Hadiat, Alfiuddin R.},

title = {Topic Modeling Evaluations: The Relationship Between Coherency and Accuracy},

school = {University of Groningen},

year = {2022},

month = {August},

type = {Master's Thesis}

}

**Topic Modelling:**

* Applications of topic models: Boyd-Graber, J., Hu, Y., & Mimno, D. (2017). Applications of topic models. Foundations and Trends in Information Retrieval, 11(2-3), 143-296.

@article{boyd2017applications,  
 title={Applications of topic models},  
 author={Boyd-Graber, Jordan and Hu, Yuening and Mimno, David and others},  
 journal={Foundations and Trends{\textregistered} in Information Retrieval},  
 volume={11},  
 number={2-3},  
 pages={143--296},  
 year={2017},  
 publisher={Now Publishers, Inc.}  
}

* Neural topic models: Zhao, H., Phung, D., Huynh, V., Jin, Y., Du, L., & Buntine, W. (2021). Topic modelling meets deep neural networks: A survey. arXiv preprint arXiv:2103.00498.

-> "We recommend transformer-based language models for the topic modelling, e.g., chapter 3.6"

-> evaluation metrics: perplexity, topic coherence (CV), topic diversity

@article{zhao2021topic,  
 title={Topic modelling meets deep neural networks: A survey},  
 author={Zhao, He and Phung, Dinh and Huynh, Viet and Jin, Yuan and Du, Lan and Buntine, Wray},  
 journal={arXiv preprint arXiv:2103.00498},  
 year={2021}  
}

* Neural vs non-neural topic models on COVID-19 Twitter data: Bennett, A., Misra, D., & Than, N. (2021). Have you tried Neural Topic Models? Comparative Analysis of Neural and Non-Neural Topic Models with Application to COVID-19 Twitter Data. arXiv preprint arXiv:2105.10165

-> results: neural topic models outperform classical topic models

-> evaluation metrics: perplexity, topic coherence (NPMI and CV), topic diversity

@article{bennett2021have,  
 title={Have you tried Neural Topic Models? Comparative Analysis of Neural and Non-Neural Topic Models with Application to COVID-19 Twitter Data},  
 author={Bennett, Andrew and Misra, Dipendra and Than, Nga},  
 journal={arXiv preprint arXiv:2105.10165},  
 year={2021}  
}

* BERTopic vs LDA vs NMF on Arabic data: Abuzayed, A., & Al-Khalifa, H. (2021). BERT for Arabic topic modeling: an experimental study on BERTopic technique. Procedia Computer Science, 189, 191-194. (paper + GitHub code)

-> evaluation metric: topic coherence with NPMI

@article{abuzayed2021bert,  
 title={BERT for Arabic topic modeling: an experimental study on BERTopic technique},  
 author={Abuzayed, Abeer and Al-Khalifa, Hend},  
 journal={Procedia Computer Science},  
 volume={189},  
 pages={191--194},  
 year={2021},  
 publisher={Elsevier}  
}

|  |
| --- |
| * LDA, NMF, Top2Vec vs. BERTopic on Twitter data: Egger, R., & Yu, J. (2022). A Topic Modeling Comparison Between LDA, NMF, Top2Vec, and BERTopic to Demystify Twitter Posts. Frontiers in Sociology, 7.   -> evaluation metric: only observation-based evaluation  @article{egger2022topic,  title={A Topic Modeling Comparison Between LDA, NMF, Top2Vec, and BERTopic to Demystify Twitter Posts},  author={Egger, Roman and Yu, Joanne},  journal={Frontiers in Sociology},  volume={7},  year={2022},  publisher={Frontiers Media SA} } |

* LDA vs. BERTopic on Coronavirus Corpus: Mifrah, S., & Benlahmar, E. H. (2022). Topic Modeling with Transformers for Sentence-Level Using Coronavirus Corpus. International Journal of Interactive Mobile Technologies, 16(17).

-> evaluation metrics: observation-based evaluation, topic coherence with CV

@article{mifrah2022topic,  
 title={Topic Modeling with Transformers for Sentence-Level Using Coronavirus Corpus.},  
 author={Mifrah, Sara and Benlahmar, El Habib},  
 journal={International Journal of Interactive Mobile Technologies},  
 volume={16},  
 number={17},  
 year={2022}  
}

* LDA, NMF vs neural topic models: Doan, T. N., & Hoang, T. A. (2021, August). Benchmarking neural topic models: An empirical study. In Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021 (pp. 4363-4368).

-> evaluation measure: perplexity, topic coherence with NPMI

-> "None of the neural topic models in our study outperforms the classical LDA on all the datasets and in all the metrics."

@inproceedings{doan2021benchmarking,  
 title={Benchmarking neural topic models: An empirical study},  
 author={Doan, Thanh-Nam and Hoang, Tuan-Anh},  
 booktitle={Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021},  
 pages={4363--4368},  
 year={2021}  
}

**Traditional Topic Models:**

* LDA: Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent dirichlet allocation. Machine Learning Research, 3, 993-1022.

@article{blei2003latent,  
 title={Latent dirichlet allocation},  
 author={Blei, David M and Ng, Andrew Y and Jordan, Michael I},  
 journal={Journal of machine Learning research},  
 volume={3},  
 pages={993--1022},  
 year={2003}  
}

* NMF: Lee, D., & Seung, H. S. (2000). Algorithms for non-negative matrix factorization. Advances in neural information processing systems, 13.

@article{lee2000algorithms,  
 title={Algorithms for non-negative matrix factorization},  
 author={Lee, Daniel and Seung, H Sebastian},  
 journal={Advances in neural information processing systems},  
 volume={13},  
 year={2000}  
}

**BERTopic:**

* BERTopic Paper: Grootendorst, M. (2022). BERTopic: Neural topic modeling with a class-based TF-IDF procedure. arXiv preprint arXiv:2203.05794.

-> evaluation metrics: topic coherence (NPMI) and topic diversity, both implemented through OCTIS

@article{grootendorst2022bertopic,  
 title={BERTopic: Neural topic modeling with a class-based TF-IDF procedure},  
 author={Grootendorst, Maarten},  
 journal={arXiv preprint arXiv:2203.05794},  
 year={2022}  
}

* BERTopic blog post: <https://maartengr.github.io/BERTopic/algorithm/algorithm.html>
* BERTopic GitHub repository: <https://github.com/MaartenGr/BERTopic>
* UMAP: McInnes, L., Healy, J., & Melville, J. (2018). Umap: Uniform manifold approximation and projection for dimension reduction. arXiv preprint arXiv:1802.03426.

@article{mcinnes2018umap,  
 title={Umap: Uniform manifold approximation and projection for dimension reduction},  
 author={McInnes, Leland and Healy, John and Melville, James},  
 journal={arXiv preprint arXiv:1802.03426},  
 year={2018}  
}

* HDBSCAN: McInnes, L., Healy, J., & Astels, S. (2017). hdbscan: Hierarchical density based clustering. J. Open Source Softw., 2(11), 205.

@article{mcinnes2017hdbscan,  
 title={hdbscan: Hierarchical density based clustering.},  
 author={McInnes, Leland and Healy, John and Astels, Steve},  
 journal={J. Open Source Softw.},  
 volume={2},  
 number={11},  
 pages={205},  
 year={2017}  
}

* Transformer: Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I. (2017). Attention is all you need. Advances in neural information processing systems, 30.

@article{vaswani2017attention,  
 title={Attention is all you need},  
 author={Vaswani, Ashish and Shazeer, Noam and Parmar, Niki and Uszkoreit, Jakob and Jones, Llion and Gomez, Aidan N and Kaiser, {\L}ukasz and Polosukhin, Illia},  
 journal={Advances in neural information processing systems},  
 volume={30},  
 year={2017}  
}

* BERT: Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2018). Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805.

@article{devlin2018bert,  
 title={Bert: Pre-training of deep bidirectional transformers for language understanding},  
 author={Devlin, Jacob and Chang, Ming-Wei and Lee, Kenton and Toutanova, Kristina},  
 journal={arXiv preprint arXiv:1810.04805},  
 year={2018}  
}

* Sentence-BERT: Reimers, N., & Gurevych, I. (2019). Sentence-bert: Sentence embeddings using siamese bert-networks. arXiv preprint arXiv:1908.10084.

@article{reimers2019sentence,  
 title={Sentence-bert: Sentence embeddings using siamese bert-networks},  
 author={Reimers, Nils and Gurevych, Iryna},  
 journal={arXiv preprint arXiv:1908.10084},  
 year={2019}  
}

* TSDAE: Wang, K., Reimers, N., & Gurevych, I. (2021). Tsdae: Using transformer-based sequential denoising auto-encoder for unsupervised sentence embedding learning. arXiv preprint arXiv:2104.06979.
* @article{wang2021tsdae,  
   title={Tsdae: Using transformer-based sequential denoising auto-encoder for unsupervised sentence embedding learning},  
   author={Wang, Kexin and Reimers, Nils and Gurevych, Iryna},  
   journal={arXiv preprint arXiv:2104.06979},  
   year={2021}  
  }
* SimCSE: Gao, T., Yao, X., & Chen, D. (2021). Simcse: Simple contrastive learning of sentence embeddings. arXiv preprint arXiv:2104.08821.

@article{gao2021simcse,  
 title={Simcse: Simple contrastive learning of sentence embeddings},  
 author={Gao, Tianyu and Yao, Xingcheng and Chen, Danqi},  
 journal={arXiv preprint arXiv:2104.08821},  
 year={2021}  
}

**Short text topic modelling**:

* GSDMM: Yin, J., & Wang, J. (2014, August). A dirichlet multinomial mixture model-based approach for short text clustering. In Proceedings of the 20th ACM SIGKDD international conference on Knowledge discovery and data mining (pp. 233-242). -> Gibbs Sampling algorithm for the Dirichlet Multinomial Mixture model for short text clustering (abbr. to GSDMM)

@inproceedings{yin2014dirichlet,  
 title={A dirichlet multinomial mixture model-based approach for short text clustering},  
 author={Yin, Jianhua and Wang, Jianyong},  
 booktitle={Proceedings of the 20th ACM SIGKDD international conference on Knowledge discovery and data mining},  
 pages={233--242},  
 year={2014}  
}

* BTM: Cheng, X., Yan, X., Lan, Y., & Guo, J. (2014). Btm: Topic modeling over short texts. IEEE Transactions on Knowledge and Data Engineering, 26(12), 2928-2941.

@article{cheng2014btm,  
 title={Btm: Topic modeling over short texts},  
 author={Cheng, Xueqi and Yan, Xiaohui and Lan, Yanyan and Guo, Jiafeng},  
 journal={IEEE Transactions on Knowledge and Data Engineering},  
 volume={26},  
 number={12},  
 pages={2928--2941},  
 year={2014},  
 publisher={IEEE}  
}

* Comparative analysis: Albalawi, R., Yeap, T. H., & Benyoucef, M. (2020). Using topic modeling methods for short-text data: A comparative analysis. Frontiers in Artificial Intelligence, 3, 42.

@article{albalawi2020using,  
 title={Using topic modeling methods for short-text data: A comparative analysis},  
 author={Albalawi, Rania and Yeap, Tet Hin and Benyoucef, Morad},  
 journal={Frontiers in Artificial Intelligence},  
 volume={3},  
 pages={42},  
 year={2020},  
 publisher={Frontiers Media SA}  
}

* Survey: Qiang, J., Qian, Z., Li, Y., Yuan, Y., & Wu, X. (2020). Short text topic modeling techniques, applications, and performance: a survey. IEEE Transactions on Knowledge and Data Engineering, 34(3), 1427-1445.

@article{qiang2020short,  
 title={Short text topic modeling techniques, applications, and performance: a survey},  
 author={Qiang, Jipeng and Qian, Zhenyu and Li, Yun and Yuan, Yunhao and Wu, Xindong},  
 journal={IEEE Transactions on Knowledge and Data Engineering},  
 volume={34},  
 number={3},  
 pages={1427--1445},  
 year={2020},  
 publisher={IEEE}  
}

* GPU-DMM: Li, C., Wang, H., Zhang, Z., Sun, A., & Ma, Z. (2016, July). Topic modeling for short texts with auxiliary word embeddings. In Proceedings of the 39th International ACM SIGIR conference on Research and Development in Information Retrieval (pp. 165-174).

@inproceedings{li2016topic,  
 title={Topic modeling for short texts with auxiliary word embeddings},  
 author={Li, Chenliang and Wang, Haoran and Zhang, Zhiqian and Sun, Aixin and Ma, Zongyang},  
 booktitle={Proceedings of the 39th International ACM SIGIR conference on Research and Development in Information Retrieval},  
 pages={165--174},  
 year={2016}  
}

* SeaNMF: Shi, T., Kang, K., Choo, J., & Reddy, C. K. (2018, April). Short-text topic modeling via non-negative matrix factorization enriched with local word-context correlations. In Proceedings of the 2018 World Wide Web Conference (pp. 1105-1114).

@inproceedings{shi2018short,  
 title={Short-text topic modeling via non-negative matrix factorization enriched with local word-context correlations},  
 author={Shi, Tian and Kang, Kyeongpil and Choo, Jaegul and Reddy, Chandan K},  
 booktitle={Proceedings of the 2018 World Wide Web Conference},  
 pages={1105--1114},  
 year={2018}  
}

**Evaluation of Topic Models:**

* OCTIS: Terragni, S., Fersini, E., Galuzzi, B. G., Tropeano, P., & Candelieri, A. (2021, April). Octis: comparing and optimizing topic models is simple!. In Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: System Demonstrations (pp. 263-270).

@inproceedings{terragni-etal-2021-octis,  
 title = {{OCTIS}: Comparing and Optimizing Topic models is Simple!},  
 author = {Terragni, Silvia and Fersini, Elisabetta and Galuzzi, Bruno Giovanni and Tropeano, Pietro and Candelieri, Antonio},  
 booktitle = {Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: System Demonstrations{,  
 month = {apr},  
 year = {2021},  
 publisher = {Association for Computational Linguistics},  
 url = {<https://aclanthology.org/2021.eacl-demos.31> <https://github.com/MIND-Lab/OCTIS>},  
 doi = {10.18653/v1/2021.eacl-demos.31},  
 pages = {263--270}  
}

* Perplexity/held out likelihood: Wallach, H. M., Murray, I., Salakhutdinov, R., & Mimno, D. (2009, June). Evaluation methods for topic models. In Proceedings of the 26th annual international conference on machine learning (pp. 1105-1112).

-> first topic coherence measure

@inproceedings{wallach2009evaluation,  
 title={Evaluation methods for topic models},  
 author={Wallach, Hanna M and Murray, Iain and Salakhutdinov, Ruslan and Mimno, David},  
 booktitle={Proceedings of the 26th annual international conference on machine learning},  
 pages={1105--1112},  
 year={2009}  
}

* Human judgement: Chang, J., Gerrish, S., Wang, C., Boyd-Graber, J., & Blei, D. (2009). Reading tea leaves: How humans interpret topic models. Advances in neural information processing systems, 22. (kick-off email)

-> perplexity negatively correlated with human judgement

@article{chang2009reading,  
 title={Reading tea leaves: How humans interpret topic models},  
 author={Chang, Jonathan and Gerrish, Sean and Wang, Chong and Boyd-Graber, Jordan and Blei, David},  
 journal={Advances in neural information processing systems},  
 volume={22},  
 year={2009}  
}

* PMI: Newman, D., Lau, J. H., Grieser, K., & Baldwin, T. (2010, June). Automatic evaluation of topic coherence. In Human language technologies: The 2010 annual conference of the North American chapter of the association for computational linguistics (pp. 100-108).

-> introduction of PMI as topic coherence measure

@inproceedings{newman2010automatic,  
 title={Automatic evaluation of topic coherence},  
 author={Newman, David and Lau, Jey Han and Grieser, Karl and Baldwin, Timothy},  
 booktitle={Human language technologies: The 2010 annual conference of the North American chapter of the association for computational linguistics},  
 pages={100--108},  
 year={2010}  
}

* PMI and NMPI vs Human judgement: Lau, J. H., Newman, D., & Baldwin, T. (2014, April). Machine reading tea leaves: Automatically evaluating topic coherence and topic model quality. In Proceedings of the 14th Conference of the European Chapter of the Association for Computational Linguistics (pp. 530-539).

-> introduction of NPMI as topic coherence measure

-> both PMI and NMPI positively correlated with human judgment

@inproceedings{lau2014machine,  
 title={Machine reading tea leaves: Automatically evaluating topic coherence and topic model quality},  
 author={Lau, Jey Han and Newman, David and Baldwin, Timothy},  
 booktitle={Proceedings of the 14th Conference of the European Chapter of the Association for Computational Linguistics},  
 pages={530--539},  
 year={2014}  
}

* CV: Röder, M., Both, A., & Hinneburg, A. (2015, February). Exploring the space of topic coherence measures. In Proceedings of the eighth ACM international conference on Web search and data mining (pp. 399-408).

-> comprehensive examination of different coherency measures including NPMI

-> introduction of CV as topic coherence measure

-> CV positively correlated with human judgement

@inproceedings{roder2015exploring,  
 title={Exploring the space of topic coherence measures},  
 author={R{\"o}der, Michael and Both, Andreas and Hinneburg, Alexander},  
 booktitle={Proceedings of the eighth ACM international conference on Web search and data mining},  
 pages={399--408},  
 year={2015}  
}

* Automated topic model evaluation for neural topic models: Hoyle, A., Goel, P., Hian-Cheong, A., Peskov, D., Boyd-Graber, J., & Resnik, P. (2021). Is automated topic model evaluation broken? the incoherence of coherence. Advances in Neural Information Processing Systems, 34, 2018-2033.

-> automated topic model evaluation needs reassessment especially for neural topic models

-> PMI and NMPI may not be positively correlated with human judgement (Limitations section)

@article{hoyle2021automated,  
 title={Is automated topic model evaluation broken? the incoherence of coherence},  
 author={Hoyle, Alexander and Goel, Pranav and Hian-Cheong, Andrew and Peskov, Denis and Boyd-Graber, Jordan and Resnik, Philip},  
 journal={Advances in Neural Information Processing Systems},  
 volume={34},  
 pages={2018--2033},  
 year={2021}  
}

* Human judgement example: Toetzke, M., Banholzer, N., & Feuerriegel, S. (2022). Monitoring global development aid with machine learning. Nature Sustainability, 1-9. (kick-off email)

-> validation through user study

@article{toetzke2022monitoring,  
 title={Monitoring global development aid with machine learning},  
 author={Toetzke, Malte and Banholzer, Nicolas and Feuerriegel, Stefan},  
 journal={Nature Sustainability},  
 pages={1--9},  
 year={2022},  
 publisher={Nature Publishing Group}  
}

**Pre-trainig/Domain adaptation:**

* Advantages of pre-training: Gururangan, S., Marasović, A., Swayamdipta, S., Lo, K., Beltagy, I., Downey, D., & Smith, N. A. (2020). Don't stop pretraining: adapt language models to domains and tasks. arXiv preprint arXiv:2004.10964.

@article{gururangan2020don,  
 title={Don't stop pretraining: adapt language models to domains and tasks},  
 author={Gururangan, Suchin and Marasovi{\'c}, Ana and Swayamdipta, Swabha and Lo, Kyle and Beltagy, Iz and Downey, Doug and Smith, Noah A},  
 journal={arXiv preprint arXiv:2004.10964},  
 year={2020}  
}

* MLM for stance detection: Kawintiranon, K., & Singh, L. (2021, June). Knowledge enhanced masked language model for stance detection. In Proceedings of the 2021 conference of the north american chapter of the association for computational linguistics: human language technologies. (kick-off email)

@inproceedings{kawintiranon2021knowledge,

title={Knowledge enhanced masked language model for stance detection},

author={Kawintiranon, Kornraphop and Singh, Lisa},

booktitle={Proceedings of the 2021 conference of the north american chapter of the association for computational linguistics: human language technologies},

year={2021}

}

* CLIMATEBERT: Webersinke, N., Kraus, M., Bingler, J. A., & Leippold, M. (2021). Climatebert: A pretrained language model for climate-related text. arXiv preprint arXiv:2110.12010. (kick-off email)

@article{webersinke2021climatebert,

title={Climatebert: A pretrained language model for climate-related text},

author={Webersinke, Nicolas and Kraus, Mathias and Bingler, Julia Anna and Leippold, Markus},

journal={arXiv preprint arXiv:2110.12010},

year={2021}

}

* FinBERT: Araci, D. (2019). Finbert: Financial sentiment analysis with pre-trained language models. arXiv preprint arXiv:1908.10063.

@article{araci2019finbert,  
 title={Finbert: Financial sentiment analysis with pre-trained language models},  
 author={Araci, Dogu},  
 journal={arXiv preprint arXiv:1908.10063},  
 year={2019}  
}

* BERTweet: Nguyen, D. Q., Vu, T., & Nguyen, A. T. (2020). BERTweet: A pre-trained language model for English Tweets. arXiv preprint arXiv:2005.10200.

@article{nguyen2020bertweet,  
 title={BERTweet: A pre-trained language model for English Tweets},  
 author={Nguyen, Dat Quoc and Vu, Thanh and Nguyen, Anh Tuan},  
 journal={arXiv preprint arXiv:2005.10200},  
 year={2020}  
}

**Parler:**

* Parler dataset + paper: A Large Open Dataset from the Parler Social Network - Aliapoulios Aliapoulios, M., Bevensee, E., Blackburn, J., Bradlyn, B., De Cristofaro, E., Stringhini, G., & Zannettou, S. (2021, May). A Large Open Dataset from the Parler Social Network. In ICWSM (pp. 943-951). (kick-off email BT BWL)

@inproceedings{aliapoulios2021large,  
 title={A Large Open Dataset from the Parler Social Network.},  
 author={Aliapoulios, Max and Bevensee, Emmi and Blackburn, Jeremy and Bradlyn, Barry and De Cristofaro, Emiliano and Stringhini, Gianluca and Zannettou, Savvas},  
 booktitle={ICWSM},  
 pages={943--951},  
 year={2021}  
}

* Parler vs Twitter Usage by USA Congress Members: M. Otala, J., Kurtic, G., Grasso, I., Liu, Y., Matthews, J., & Madraki, G. (2021, April). Political polarization and platform migration: a study of Parler and Twitter usage by United States of America Congress Members. In Companion Proceedings of the Web Conference 2021 (pp. 224-231). (kick-off email BT BWL)

@inproceedings{m2021political,  
 title={Political polarization and platform migration: a study of Parler and Twitter usage by United States of America Congress Members},  
 author={M. Otala, Jacqueline and Kurtic, Gillian and Grasso, Isabella and Liu, Yu and Matthews, Jeanna and Madraki, Golshan},  
 booktitle={Companion Proceedings of the Web Conference 2021},  
 pages={224--231},  
 year={2021}  
}

* Parler vs Twitter: Prabhu, A., Guhathakurta, D., Subramanian, M., Reddy, M., Sehgal, S., Karandikar, T., ... & Kumaraguru, P. (2021). Capitol (Pat) riots: A comparative study of Twitter and Parler. arXiv preprint arXiv:2101.06914. (kick-off email BT BWL)

@article{prabhu2021capitol,  
 title={Capitol (Pat) riots: A comparative study of Twitter and Parler},  
 author={Prabhu, Avinash and Guhathakurta, Dipanwita and Subramanian, Mallika and Reddy, Manvith and Sehgal, Shradha and Karandikar, Tanvi and Gulati, Amogh and Arora, Udit and Shah, Rajiv Ratn and Kumaraguru, Ponnurangam and others},  
 journal={arXiv preprint arXiv:2101.06914},  
 year={2021}  
}

* Parler community guidelines 11/02/2021. (2021). Retrieved from <https://www.parler.com/documents/guidelines.pdf>
* Parler - where free speech thrives. (2022). Retrieved from <https://parler.com/>
* Parler - wikipedia. (2022). Retrieved from <https://en.wikipedia.org/wiki/Parler>

**Gab:**

* Gab dataset + paper: Zannettou, S., Bradlyn, B., De Cristofaro, E., Kwak, H., Sirivianos, M., Stringini, G., & Blackburn, J. (2018, April). What is gab: A bastion of free speech or an alt-right echo chamber. In Companion Proceedings of the The Web Conference 2018 (pp. 1007-1014).

@inproceedings{zannettou2018gab,  
 title={What is gab: A bastion of free speech or an alt-right echo chamber},  
 author={Zannettou, Savvas and Bradlyn, Barry and De Cristofaro, Emiliano and Kwak, Haewoon and Sirivianos, Michael and Stringini, Gianluca and Blackburn, Jeremy},  
 booktitle={Companion Proceedings of the The Web Conference 2018},  
 pages={1007--1014},  
 year={2018}  
}

* Gab Hate Speech: Mathew, B., Dutt, R., Goyal, P., & Mukherjee, A. (2019, June). Spread of hate speech in online social media. In Proceedings of the 10th ACM conference on web science (pp. 173-182).

-> We observe that the content generated by the hateful users tend to spread faster, farther and reach a much wider audience as compared to the content generated by normal users.

-> An important finding is that the hateful users are far more densely connected among themselves.

@inproceedings{mathew2019spread,

title={Spread of hate speech in online social media},

author={Mathew, Binny and Dutt, Ritam and Goyal, Pawan and Mukherjee, Animesh},

booktitle={Proceedings of the 10th ACM conference on web science},

pages={173--182},

year={2019}

}

* Pittsburgh Synagogue Shooting: McIlroy-Young, R., & Anderson, A. (2019, July). From “welcome new gabbers” to the pittsburgh synagogue shooting: The evolution of gab. In Proceedings of the international aaai conference on web and social media (Vol. 13, pp. 651-654).

@inproceedings{mcilroy2019welcome,  
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