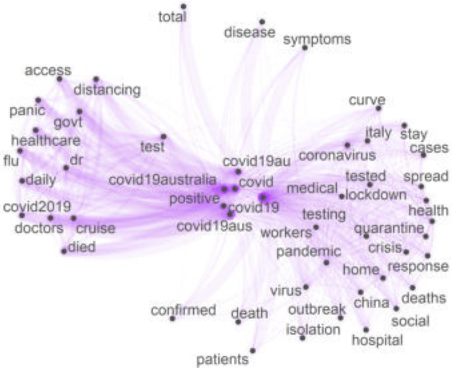
Text Mining the COVID-19 discourse in the Australian Twittersphere

Martin Schweinberger | Michael Haugh | Sam Hames



Why analyze COVID-19 discourse on Twitter?

- COVID-19 discourse treated as one big lump of words
- Focus on hashtags or use of small/unclean data sets

How can we as linguists improve text mining of discourse around COVID-19 on OzTwitter?

	Jan. - Apr. 2019		Jan. - Apr. 2020	
	Tweets	**Words/Elements**	**Tweets**	**Words/Elements**
Before processing	889,192	18,903,659	871,826	19,362,115
After processing	769,165	17,288,018	753,630	17,726,090
COVID-19 tweets			41,342	1,327,874

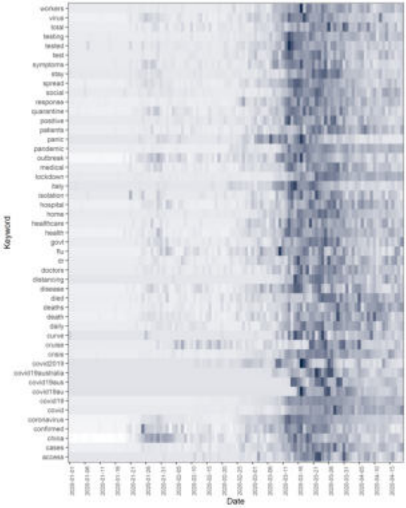


Figure 1: Heatmap of COVID19-related keywords

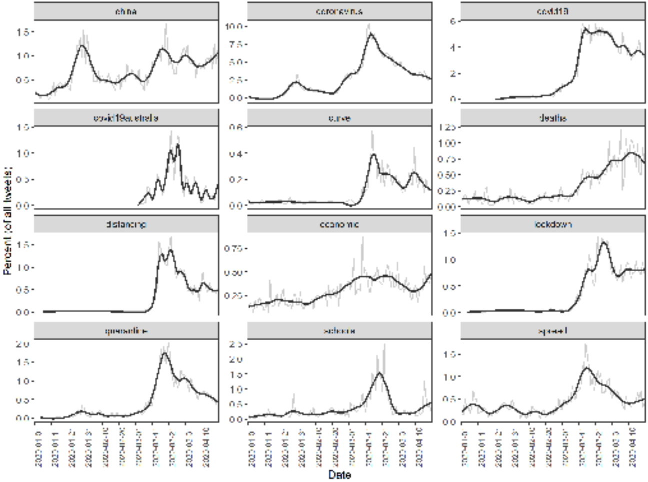


Figure 2: Linegraphs of selected COVID19-relates keyterms across time of COVID19-related keywords

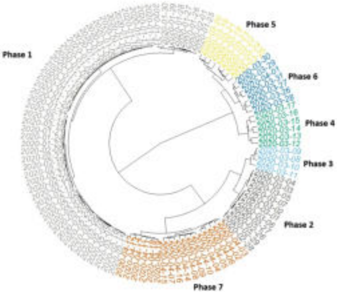


Figure 3: Results of the PAM clustering showing the data-driven periodization of the data

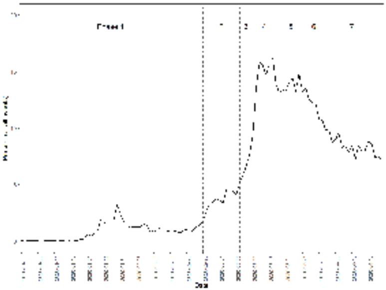


Figure 4: Percantages of COVID19-related tweets by period

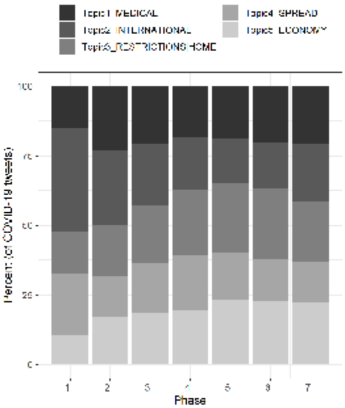


Figure 5: Distribution of topics across periods (bar plot)

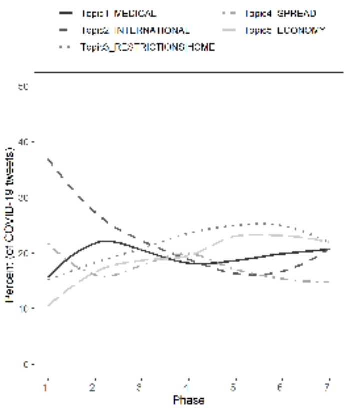


Figure 6: Distribution of topics across periods (loess smoothed)

Outlook

Aim: create a prototype of a text mining application that is both time-sensitive and differentiates between different sub-discourses (topics)

Moving forward

- Apply analysis to more data
- Apply same method to other phenomena (BLM, Bushfires)

Thank you very much!

Acknowledgements

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