Methodological issues in designing and evaluating a corpus to identify YouTube videos containing informal English speech.

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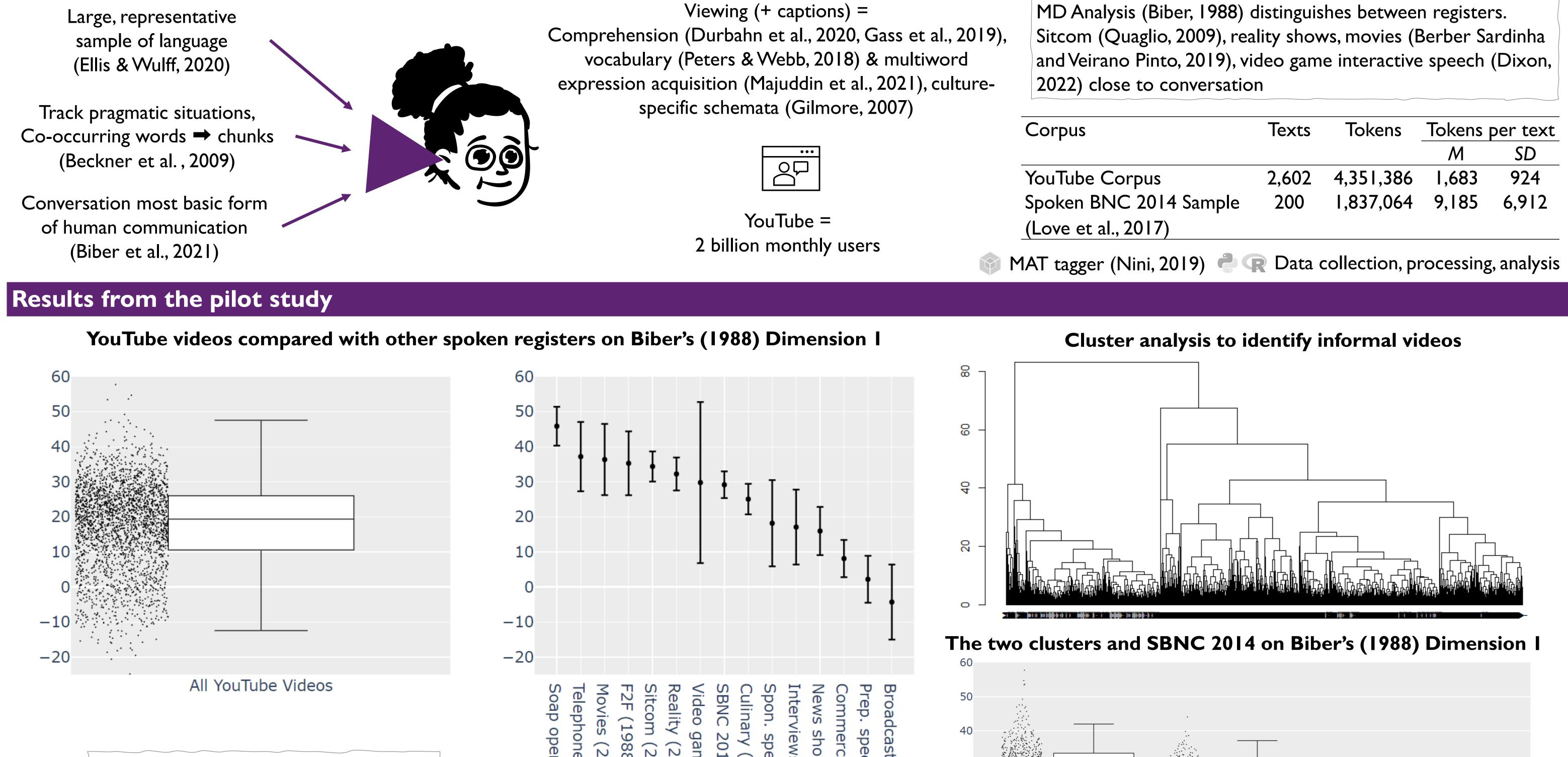
FLER

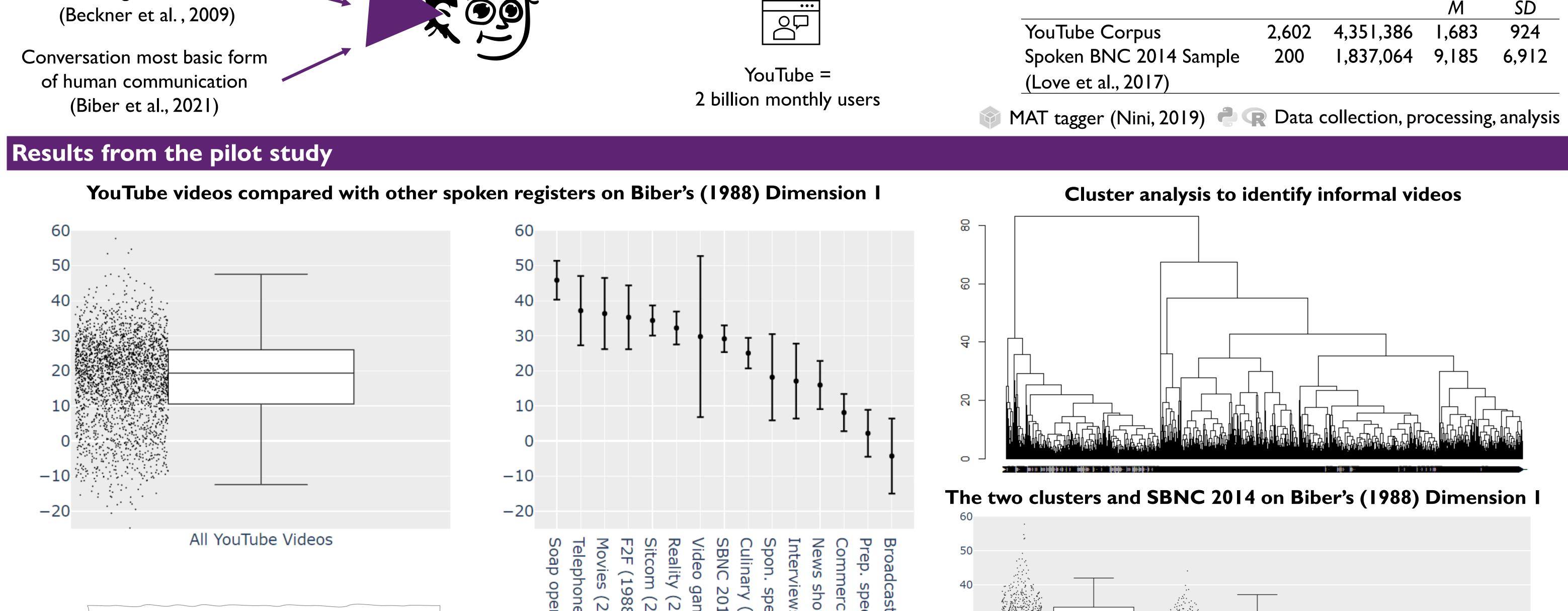
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Background

sample of language (Ellis & Wulff, 2020)

(Beckner et al., 2009)





Corpus	Texts	Tokens	Tokens per text	
			М	SD
YouTube Corpus	2,602	4,351,386	I,683	924
Saakan BNIC 2014 Samala	200			(01)

666 YouTube videos clustered with 171 Spoken BNC 2014 texts

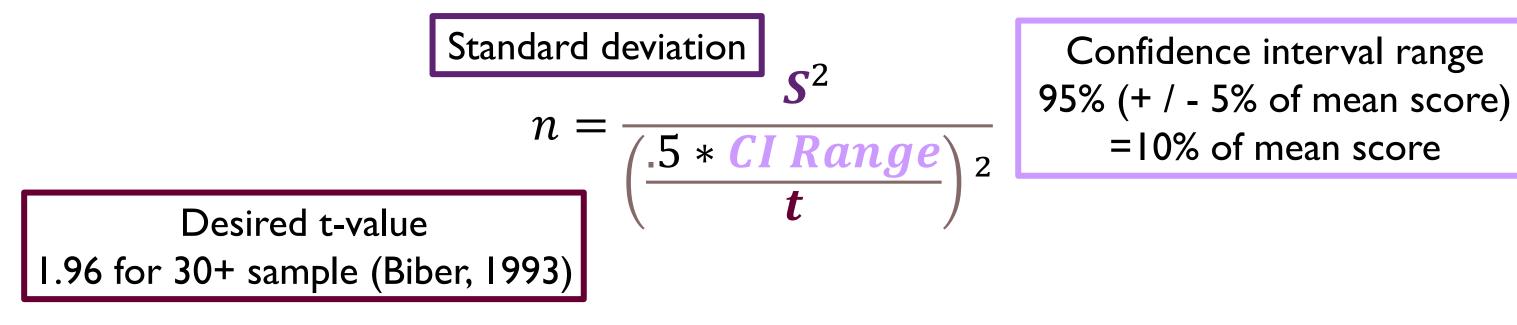
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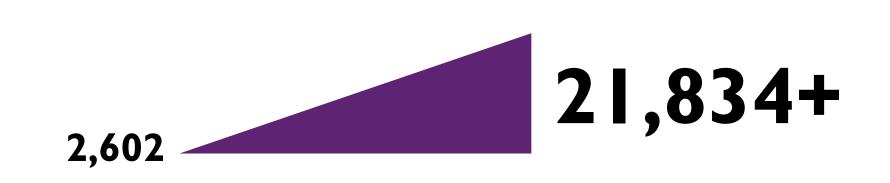
- Videos in both clusters seemed to have similar topics (but further analysis needed)
- Distinguishing features include 1st/2nd person pronouns, contractions, private & present tense verbs



Methodological issues for future research

Corpus size (Egbert et al., 2022) For each linguistic feature





95% (+ / - 5% of mean score)

Corpus evaluation Get to know the corpus with keyword analysis (Kilgariff, 2012)



Informal cluster as <u>target</u> Non-informal cluster as reference

Qualitatively sort words into categories, some examples from pilot study:

- Conservative estimate based on least frequent feature
- Past participle clauses (e.g. Built in a single week, the house would stand for fifty years)
- Not common in conversation

Informal	Non-informal
Informal (oh, stuff)	Sport (yard, touchdown)
Greetings (hey, bye)	Numbers (fourth, third)
Pronouns (me, my, y')	Function (its, by, from)
Private V (feel, guess)	Formal DM (however,
People (guys, bro, girl)	despite)

Identify 'topics' in the corpus with topic modelling (Murakami et al., 2017)

Several methods trialled on the main corpus (collected after the pilot study) using Python (BERTopic & Top2Vec)

Top2Vec (Word2Vec + Doc2Vec) seems to be more interpretable

- Can include 50 words in topic -
- Meaningful topics -
- E.g. self-improvement, songs, -European football, various specific video games, Christianity, cars, anime, junk food, pranks, Star Wars...



Search terms

(pilot) BNC top 200 includes: government, system, house, life, local, man, Mr...

→ Could influence the content



Stop words

Function words & highly frequent content words, little semantic weight (Juraksky & Martin, 2023) e.g. after too by, because should has

vlog + 3 stop words used in YouTube vlog corpus compilation (Egbert et al., 2022)

Optimal minimum text length 2,000 words+? (Biber, 1990, Thompson et al., 2017)

- Too strict for YouTube? - Many videos < 2,000 words
- MD Analysis of conversation (Biber, 2004)
- = 200+ words

'because of the difficulties in obtaining reliable rates of occurrence for linguistic features in shorter texts' (p. 18)





Machine Learning Linguistic features TAALES, TAALED, **C2** TAACO, TAASC CI (Kyle & Crossley) **B2** BI Random Forests Ordinal Logistic **A2** Regression ΑΙ Support Vector \uparrow Machines

So far low accuracy on CEFR labelled listening corpus ≈ 60%

LLMs BERT v. accurate (97%) at classifying learner writing with 50k-100k texts in training data (Schmalz & Brutti, 2021) ➡ fine-tune for listening?

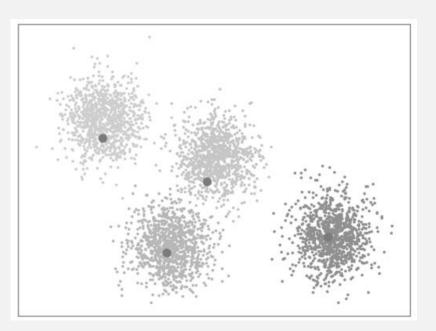
> CEFR descriptors seem to be too difficult for LLMs to classify accurately → LLM prompts + training

data?

Cluster Analysis Method

K-means?

- K chosen by researcher
- Hierarchical levels not analysed in this research



Poster / References 上

