Corpus Analysis
A case study on the use of 'conspiracy theory'

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Abstract

Corpus Analysis allows researchers to inform, illuminate and investigate many problems. This chapter provides easy access to some of the central tools commonly used in corpus linguistics. After a short exploration of pre-built corpora and a brief literature review surveying corpus-analytic studies in philosophy, we illustrate these tools by running several corpus analyses on the term 'conspiracy theory'. These analyses show that 'conspiracy theory' is a strongly evaluative term. The reader of this article can follow each of the steps of the corpus analyses using the online material that is freely available.

1 Introduction

Corpus Analysis allows philosophers to tackle philosophical problems in a way that was near impossible fifteen years ago. Until recently, we simply did not have the computer power and algorithms to effectively analyse large amounts of texts in a reasonable amount of time. Nowadays, using corpus-analytical methods yourself is easy (at least some of it) and just a few clicks away, as we will demonstrate in this chapter.

In order to make this chapter as accessible and intuitive as possible, we use a rather idiosyncratic approach. We start in Section 2 with some examples and small exercises that we encourage newcomers to corpus analysis to do while going through these pages. Consequently, Section 2 of this chapter is aimed at beginners with none or little experience in analyzing words and phrases in corpora. However, we hope that even those more familiar with corpus analysis will find some aspects helpful too. In Section 3, we then take a step back from the data, provide a brief introduction to corpus analysis and present some studies to illustrate what philosophers have used corpus-linguistic methods for. We pay specific attention to how a specific philosophical research question was transformed into a hypothesis suitable to be investigated with corpus analysis, because we believe that developing suitable corpus hypotheses might be the most difficult part when aiming to do corpus analysis.

In Section 4 and Section 5, we then do a corpus analysis of the composite term 'conspiracy theory'. Thus, readers who are mostly interested in how the term 'conspiracy theory' is used, might want to jump straight ahead to Section 4. We start with some analyses using pre-built corpora, the results of which indicate that

- 'conspiracy theory' is a strongly evaluative term;
- the use of 'conspiracy theory' has undergone substantial changes during the last 15 years;
- conspiracy theories are promoted and spread like false theories, and not discussed and tested like scientific theories.

In Section 5, we then show how to built a corpus from scratch, collecting texts, compiling and annotating the corpus, and running some analyses on the self-built corpus. While our analysis on pre-built corpora (Section 2 and Section 4) use freely accessible online corpora (https://www.english-corpora.org), we provide links to all material necessary for researchers to follow each of the steps in Section 5.

2 Exploration, Examples, and Exercises

The main purpose of this section is to make beginners to corpus analysis familiar with a few basic tools for searching pre-built corpora via a web-based interface.[1] Perhaps the most frequently used corpus is the Corpus of Contemporary American English, known as COCA (Davies, 2008-). To access COCA, please go to https://www.english-corpora.org/coca/.

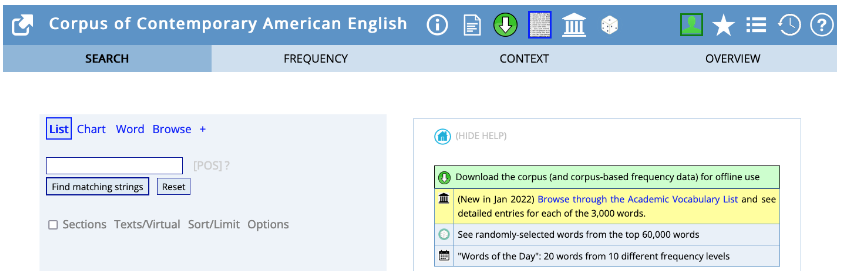


Figure 1: The starting page of COCA. The left hand side allows users to put in terms or phrases and select various search functions.

Figure 1 depicts the starting page. You can now enter any word or phrase into the textfield on the left. When you enter a word and click on "Find matching strings", you are likely to be asked to register first. If you haven't registered so far, please do so. It will only take you a minute or two.

Let's say we are interested in the term 'thinking' (something not too unfamiliar to philosophers). Type in <thinking> (without the brackets) and hit enter or "Find matching strings". The next page displays the frequency for the term of interest. There are 189'904 hits for 'thinking'. In this case, we are not primarily after the frequency of that term, but rather in how it is used. If you now click on "Context" on the top, COCA provides you with the context of all the 189'904 instances (see Figure 2).

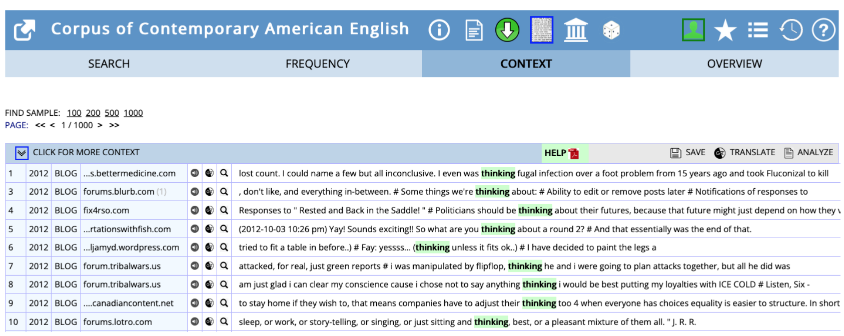


Figure 2: List of hits for 'thinking'. The right hand side displays the context in which the term is used. On the left hand side, meta-information about each use of the term is provided, such as year and source of the text.

If you would like to know the wider context of one of the uses, you can click on the source, e.g., "forums.blurb.com" of the second hit, to get the expanded context. The context option is very useful for exploratory purposes to figure out the various different uses and syntactical structures with which terms or phrases are used.

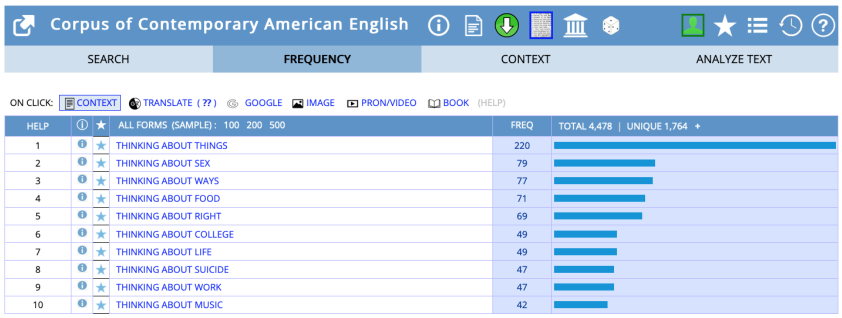
Exercise 1

- How many hits are there for the phrase 'experimental philosophy'?[2]

[1] As this section is meant to be purely exploratory, we refrain from a scientific approach. Thus, we will not state possible hypotheses that may either drive a corpus analysis or that can be inferred from the results.

[2] The answers to the questions from the exercises can be found in the Appendix (Section 7).

In most cases, researchers investigate more specific questions. For example, we might be interested in finding out what people say they most commonly think about. Go back to the search function, and instead of entering merely <thinking>, we now type in <thinking about *>. The asterisk is a placeholder (also known as "wildcard") for any term. The results are rather disappointing, because the most common terms after 'thinking about' are terms such as 'the', 'it', 'what' and 'how'. Thus, we need to be more specific about our search. Luckily, many corpora not only contain large amounts of text, the text also contains information about what *part of speech* the term belongs to, like noun, adjective, adverb, etc. The process of assigning part-of-speech information is also known as PoS-tagging. To specify that you are only interested in nouns, we now simply enter <thinking about NOUN>.


Corpus of Contemporary American English

SEARCH | FREQUENCY | CONTEXT | ANALYZE TEXT

ON CLICK: CONTEXT TRANSLATE (??) GOOGLE IMAGE PRON/VIDEO BOOK (HELP)

HELP			ALL FORMS (SAMPLE): 100 200 500	FREQ	TOTAL 4,478 | UNIQUE 1,764 +
1			THINKING ABOUT THINGS	220	
2			THINKING ABOUT SEX	79	
3			THINKING ABOUT WAYS	77	
4			THINKING ABOUT FOOD	71	
5			THINKING ABOUT RIGHT	69	
6			THINKING ABOUT COLLEGE	49	
7			THINKING ABOUT LIFE	49	
8			THINKING ABOUT SUICIDE	47	
9			THINKING ABOUT WORK	47	
10			THINKING ABOUT MUSIC	42	

Figure 3: List of nouns that appear most frequently after 'thinking about'. For example, COCA contains 220 hits for "thinking about things".

The outcome of this search is much more interesting (Figure 3). People write that they or others think a lot about sex, food, life, suicide, work, music, etc.

Exercise 2

- What things do people seem to be 'talking about' the most?
- What are the most frequent adjectives appearing before 'thinking'? (hint: try ADJ)

Next, we are looking at three further functions that come in very handy for many purposes. We start with the "Chart" function, which is situated right next to the "List" function. Let's explore some more technical terminology of philosophers. For instance, researchers often state that they are interested in the normative aspects of x. You might wonder though whether the term 'normative' is used outside of academia, and whether it was commonly used in the past.

To answer these questions, click on "Chart", type <normative> into the textfield and hit enter. You can now see in which section or genres (blog, web, TV, spoken, fiction, magazine, newspaper, academic) the term is frequently used, and its development over the last few decades. In this case, the term seems to occur only rarely outside of academia, and gained in popularity during the last two decades.

The Corpus of Historical American English (Davies, 2010), also known as COHA, gives you an insight into the use of terms over the last two *centuries*. Just go to https://www.english-corpora.org/coha/, select "Chart" and enter <normative>. The results displayed (see also Figure 4), confirm the trend seen on COCA. Before the 1980s the term was hardly ever used.[3]

[3] A further great tool for investigating the development of terms over time is Google's NGRAM viewer: https://books.google.com/ngrams. Just search for 'descriptive' and 'normative', and observe how the use of 'normative' has overtaken 'descriptive' around the turn of the millenium.

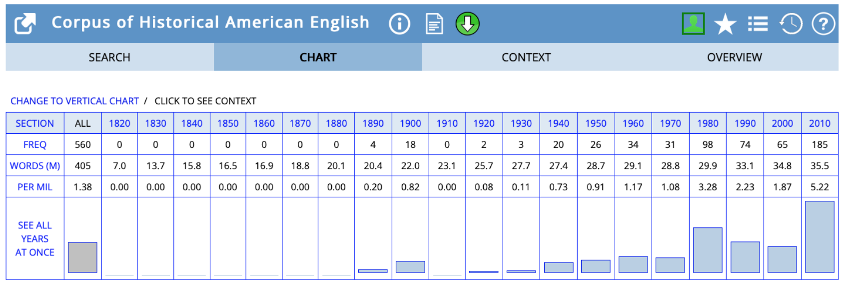


Figure 4: Development of the frequency of the use of the term 'normative' from the 1820s till now.

Exercise 3

- How has the term 'robot' developed over the last 20 years?
- How have the terms 'conservative' and 'liberal' developed over the last 200 years?

Moving back to COCA, another great tool is the "Collocates" function. In order to see the "Collocates" button, click on the + sign next to "Browse". Collocates are words that occur more frequently with a target term than what can be expected. Just put in the term 'vague'. Then click on "Find Collocates". You can now see (see also Figure 5) the most frequently occurring terms in the vicinity of the target term 'vague', sorted by different parts of speech. If you are interested in narrowing down or expanding the window in which your collocates search is done, the numbers underneath the entry field allow you to do so. The default is 4 words to the left and 4 words to the right of the target term.

Figure 5: Lists of the most frequent collocates of the word 'vague', separated into different parts of speech. For example, the left-most column lists the most frequent nouns that occur together with the term 'vague'.

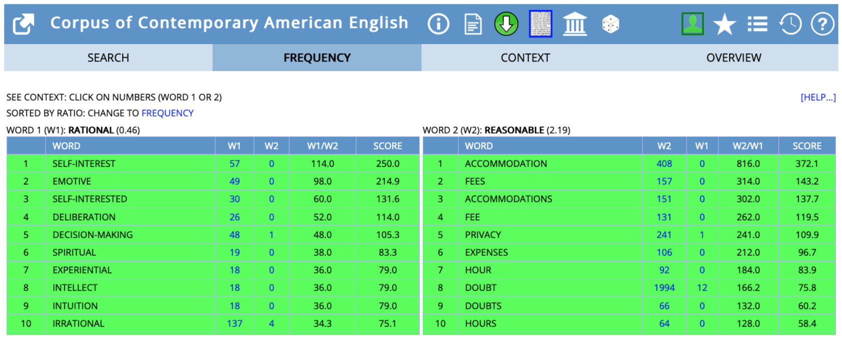
There are two numbers to the left of each term. The first tells you the frequency with which the term appears within the specified span of the target term. The second number is the mutual information score (MIT). Some terms are, of course, much more frequent than others, so it is no surprise that they occur more frequently as collocates. The mutual information score takes this into account and thus indicates relative collocation of the two terms. For instance, although the adjective 'broad' occurs more often together with 'vague', 'ambiguous' is more strongly tied to the term given its lower overall use, and thus has a higher MIT score (6.92).

Exercise 4

- Which fives adjectives occur most often together with 'happiness'?

We end this exploratory section of COCA by examining the "Compare" function (like the "Collocates" function, you need to click on the + sign to make it available). "Compare" allows you to compare the collocates of two expressions, thereby investigating both differences and similarities between them.

For example, enter the terms 'rational' and 'reasonable' into the placeholders and click on "Compare words". Although the two terms can be used interchangeably in some contexts, the results reveal important differences between them, even in everyday talk (see Figure 6). The standard search by ratio lists the terms that have the greatest ratio, i.e., terms that are used with one of the terms, but hardly with the other. As Figure 6 demonstrates, 'decision making', 'self-interest', and 'intuition' are commonly used with 'rational' but not 'reasonable'. In contrast, people talk about reasonable fees, reasonable doubts, but not rational fees and rational doubts.


Corpus of Contemporary American English

SEARCH | FREQUENCY | CONTEXT | OVERVIEW

SEE CONTEXT: CLICK ON NUMBERS (WORD 1 OR 2) [HELP...]
SORTED BY RATIO: CHANGE TO FREQUENCY

WORD 1 (W1): **RATIONAL** (0.46)

	WORD	W1	W2	W1/W2	SCORE
1	SELF-INTEREST	57	0	114.0	250.0
2	EMOTIVE	49	0	98.0	214.9
3	SELF-INTERESTED	30	0	60.0	131.6
4	DELIBERATION	26	0	52.0	114.0
5	DECISION-MAKING	48	1	48.0	105.3
6	SPIRITUAL	19	0	38.0	83.3
7	EXPERIENTIAL	18	0	36.0	79.0
8	INTELLECT	18	0	36.0	79.0
9	INTUITION	18	0	36.0	79.0
10	IRRATIONAL	137	4	34.3	75.1

WORD 2 (W2): **REASONABLE** (2.19)

	WORD	W2	W1	W2/W1	SCORE
1	ACCOMMODATION	408	0	816.0	372.1
2	FEES	157	0	314.0	143.2
3	ACCOMMODATIONS	151	0	302.0	137.7
4	FEE	131	0	262.0	119.5
5	PRIVACY	241	1	241.0	109.9
6	EXPENSES	106	0	212.0	96.7
7	HOUR	92	0	184.0	83.9
8	DOUBT	1994	12	166.2	75.8
9	DOUBTS	66	0	132.0	60.2
10	HOURS	64	0	128.0	58.4

Figure 6: Comparison of the term 'reasonable' with 'rational'. If a term appears high-up on the list, it means that it frequently occurs with one but not the other of the two terms.

Exercise 5

- Compare the term 'blaming' with 'praising'. Which differences are specifically noteworthy?
- Which nouns have the greatest ratio when comparing what people are 'afraid of' and what they are 'frightened of'?

3 Corpus analysis and philosophy: Why, who, and how?

3.1 Why do corpus analysis?

In many fields of the Arts & Humanities, as well as the Social Sciences, researchers are active in using corpus-linguistic tools. Not so much in philosophy—so far. Judging by the philpapers:corpusanalysis page,[4] around 60 corpus-analytic papers have been published by philosophers (as we write in Summer 2022). However, most of them have been published during the last 5 years, so the corpus train is gaining steam.

It seems that corpus methods are specifically suited to philosophers. Most philosophers are interested in identifying the meaning and structure of concepts, either as the primary target of investigation or at least as a starting point for theory-construction. By doing corpus analysis, they can gain valuable insights in how terms that express these concepts are used. From data about a term's usage, further inferences about the content and structure of concepts can be made.[5]

And, so, we have something of a conundrum: On the one hand, corpora are (i) highly accessible, (ii) big, (iii) (relatively) unbiased, and (iv) suited for philosophical investigation. On the other hand, corpus data is hardly used to investigate philosophical research questions. Compare this with standard experimental philosophy: Experimental data needs to be generated, is often limited, and often biased, *but still*, experimental data is frequently used to investigate philosophical research questions.

Let us say a bit more about the just mentioned positive characteristics. First, **corpora are highly accessible**. The previous section was intended to give you a glimpse of what you can do with pre-built corpora that are freely available for anybody to use on the internet. We hope you agree that it could not

[4] https://philpapers.org/browse/experimental-philosophy-corpus-analysis

[5] This is not to say that we do not need to be cautious about moving from claims about the use of a term to claims about its meaning.

be much easier to find out how frequent terms are, how their use developed over the decades and centuries, in which contexts they occur, which terms they co-occur with, etc. We did an exploratory tour of COCA[6] in the last section using its web-interface. If you go to the parent link[7] of COCA, you see that many more corpora are freely available through that site. The NOW and iWeb corpora are the largest ones, but come with some restrictions. There are also more specialized corpora like the Coronavirus Corpus or the Corpus of US Supreme Court Opinions. Some of them can be highly useful if you have research questions that are suited to be investigated in specialized corpora. As the name of the website indicates, www.english-corpora.org only features English-language corpora. However, there exist many corpora containing texts from other languages that are also available through websites. For instance, a large German-language corpus is available through COSMAS II.[8] And the Childes[9] database features large amounts of conversations with children. For a list of corpora featuring a wide variety of languages you might want to go to this wikipedia page: https://en.wikipedia.org/wiki/List_of_text_corpora.

The second and third characteristic we mentioned are that **corpora are big and (relatively) unbiased**. The two aspects, of course, are not independent of each other. The larger the corpus the less biased it will be (ceteris paribus) in regards to over- and underrepresenting specific uses of terms, contexts in which they are used, and topics of discussion.[10] Just how large are some of these corpora? COCA contains around 1 billion words from around 485,000 texts.[11] That sounds a lot, and it surely is. In the end, however, the overall amount of words is less decisive than the frequency of specific words and phrases. For example, there are 6182 hits for 'irrational' in COCA, which seems plenty if you are interested in finding out how the term is used. If, however, you would like to study how the phrase 'irrational choice' is used, then COCA yields only 4 hits; too little for a comprehensive analysis. In that case, you will probably need to look at other corpora, or build your own, something we will discuss in Section 5 of this chapter.

Given these positive characteristics of corpora, why then do most experimental philosophers generate their own data through tiresome and costly experiments? The answer, we believe, is, at least partly, that it is often not easy to translate a philosophical research question into a hypothesis that can be investigated by doing corpus analysis. We therefore decided in the next subsection to review the literature on existing philosophical corpus analysis by stating both the research question with which the philosopher(s) started as well as the hypothesis that lent itself to doing corpus analysis.

3.2 A somewhat different literature review

Although the philosophical literature using corpus analysis is still relatively small, it is too big to be fully covered here.[12] As stated above, we would like to encourage more philosophers to use corpus analysis for their own research. Therefore, we review 12 studies and state in a rather brief manner (a) the research question, (b) the corpus hypothesis the researchers worked with, (c) the corpus used, and (d) the results. We selected those 12 studies for two reasons. First, these studies show the large variety of different corpora that can and have been used in the last 15 years. Second, the research question with which the authors started are anchored in very different philosophical fields and, hence, demonstrate the usefulness and applicability of corpus analysis for many different areas. Most of the papers below included more than just one hypothesis that were investigated. For simplicity, however, we stick to a single hypothesis per paper covered.

Study 1: Prinz & Knobe, 2008

Philosophical Research Question: Do people ascribe phenomenally conscious states to group agents?

Corpus Hypothesis: People do not use phrases like "Microsoft feels pain" and "Microsoft feels happy".

[6] https://www.english-corpora.org/coca
[7] https://www.english-corpora.org
[8] https://cosmas2.ids-mannheim.de/cosmas2-web/
[9] https://childes.talkbank.org
[10] Of course, often researchers are specifically interested in biased corpora. For instance, Willemsen et al. (forthcoming) contrast laypeople's use of thick terms with those of judges. In such a case, the Corpus of US Supreme Court Opinions might be exactly what you are after.
[11] For more details see this overview document (www.english-corpora.org/coca/help/coca2020_overview.pdf).
[12] Chartrand (2022) provides a more comprehensive and rather critical review of the current state of corpus analysis in philosophy. Bluhm (2016) sketches various paths in which philosophy can benefit from corpus analysis. See also the blog entry of Ulatowski et al. (2020) on the merits of and challenges for corpus analysis in philosophy.

Corpus Used: World Wide Web

Summary of Results: Very few uses for phrases of the kind described above.[13]

Study 2: Reuter, 2011

Philosophical Research Question: Are pains the same as feelings of pain?

Corpus Hypothesis: People use 'feeling a pain' primarily with low-intensity pains and 'having a pain' primarily with high-intensity pains.

Corpus Used: World Wide Web

Summary of Results: People distinguish 'feeling a pain' from 'having a pain' in using 'feeling of pain' primarily for mild, small, and no pains, and vice versa for severe pains.

Study 3: Fischer, Engelhardt, & Herbelot, 2015

Philosophical Research Question: Does appearance language primarily serve to indicate a doxastic or an experiential attitude?

Corpus Hypothesis: Terms like 'seem' and 'appear' are strongly associated, i.e., distributionally similar, with epistemic terms like 'know'.

Corpus Used: Wikiwoods corpus

Summary of Results: The doxastic verbs 'believe', 'think', and 'find' are among the nearest neighbours of 'appear', 'look', and 'seem'.

Study 4: Andow, 2015

Philosophical Research Question: How central was and is the notion of intuition in philosophy?

Corpus Hypothesis: The term 'intuition' is more frequently used in recent decades.

Corpus Used: NGram and JSTOR

Summary of Results: Intuition-talk in philosophy has steadily increased between the 1950's and 2000.

Study 5: Wright et al., 2016

Philosophical Research Question: Are moral concerns ontogenetically driven by feelings and values (good/bad), or by rules and standards (right/wrong)?

Corpus Hypothesis: Young children primarily use the terms 'good' and 'bad', but not 'right' and 'wrong' to make moral evaluations.

Corpus Used: Childes

Summary of Results: While 'good' was used for moral evaluation 14.4% of the time, 'right' was used 0.1% of the time by children.

[13] For Study 1, as well as with the other studies, the corpus hypotheses have all been largely confirmed.

Study 6: Nichols & Pinillos, 2018

Philosophical Research Question: Is the ordinary notion of knowledge infallibilist?

Corpus Hypothesis: Children are not exposed to fallibilist uses of 'know' (used as a propositional attitude).

Corpus Used: Childes

Summary of Results: Of the 802 items, coders identified no cases in which the knowledge attribution was coupled with an expression of fallibility.

Study 7: Alfano, 2018

Philosophical Research Question: How strongly are the conceptions of drive (Trieb), instinct (Instinkt) and virtue (Tugend) related in Nietzsche's thinking?

Corpus Hypothesis: The terms 'drive', 'instinct', and 'virtue' co-occur strongly in text sections of the Nietzsche Corpus.

Corpus Used: Self-built Corpus assembled from www.nietzschesource.org

Summary of Results: The probability of one of these terms occurring in a passage is more than doubled if at least one of the other terms occurs in the same passage.

Study 8: Sytsma, Bluhm, Willemsen & Reuter, 2019

Philosophical Research Question: Is causation a descriptive concept or similar to the normative notion of responsibility?

Corpus Hypothesis: Nouns appearing after 'caused the' are primarily negative, indicating a normative use of 'caused' and similar to nouns occurring after 'responsible of the'.

Corpus Used: COCA

Summary of Results: 17 of the 20 most frequent nouns occurring after 'caused the' are negative terms.

Study 9: Mizrahi, 2020

Philosophical Research Question: What is the role of case studies in philosophy of science over the years?

Corpus Hypothesis: The terms 'case study' and 'case studies' are prevalent in philosophy of science articles.

Corpus Used: JSTOR database

Summary of Results: There is an upward trend in appeals to case studies in many philosophy of science journals.

Study 10: Tobia, 2020

Philosophical Research Question: Does corpus data capture the ordinary meaning of the term 'vehicle'?

Corpus Hypothesis: Corpus data fails to deliver useful information about non-prototypical members of the set of vehicles.

Corpus Used: COCA & NOW

Summary of Results: Corpus data provides little information on vehicles such that bicycle, airplane, and golf cart cannot be inferred to be among its members.

Study 11: Hansen, Porter, & Francis, 2021

Philosophical Research Question: Is 'I know' more frequently used to make non-assurances or assurances?[14]

Corpus Hypothesis: Occurrences of 'I know' that are non-assurances are higher compared to those that are assurances.

Corpus Used: COCA

Summary of Results: A random sample from COCA revealed 62% of uses of 'I know' that are non-assurances.

Study 12: Reuter, Willemsen, Baumgartner, 2022

Philosophical Research Question: How can we differentiate evaluative from value-associated adjectives?

Corpus Hypothesis: The modifier 'truly' precedes evaluative adjectives more frequently compared to value-associated adjectives.

Corpus Used: COCA and Reddit

Summary of Results: Evaluative adjectives are more frequently used with the intensifiers 'truly' compared to descriptive and value-associated adjectives.

3.3 Common patterns and doing it yourself

This quick "tour" of 12 studies reveals two interesting points. First, the use of corpus analysis is not restricted to philosophy of language, as one might initially think given its popularity in linguistics and its focus on language use. Instead, we find researchers taking corpus analyses to illuminate questions in (a) history of philosophy (Alfano), (b) metaphilosophy (Andow), epistemology (Nichols & Pinillos, Hansen et al.), philosophy of mind (Prinz & Knobe, Reuter), philosophy of language (Fischer et al.), philosophy of science (Mizrahi), metaphysics (Sytsma et al.), legal philosophy (Tobia), and moral philosophy (Wright et al., Reuter et al.). Now, in a very real sense, many of these 12 studies touch on issues in the philosophy of language. Importantly though, the central questions raised by the researchers of these papers are not primarily philosophy of language questions, but firmly rooted in a wide variety of philosophical areas.

Second, while there are many differences to be found between the 12 studies covered, there are also important commonalities. Very roughly, we suggest that those studies investigate terms or phrases in one of the following *three* ways:

- They investigate how frequent a term or phrase occurs (in some context or at some time): Prinz & Knobe, Reuter, Andow, Hansen et al., Mizrahi, Reuter et al.
- They investigate which other terms or phrases occur with the target term: Fischer et al., Alfano, Sytsma et al., Tobia
- They investigate the contexts in which certain terms or phrases occur: Wright et al., Nichols & Pinillos

[14] If a person states "I know that COCA contains over a billion words", she gives an assurance that COCA is such-and-so. In contrast, we also use 'know' merely to "share a reaction to a piece of purported news" (Baz, 2012, pp. 38–39), e.g., Person A: "Corpus Analysis is great!" Person B: "I know!"

Obviously, we do not claim that all corpus analyses fall within those three categories. But many studies, and very likely most corpus studies in *philosophy* do. Once we see these recurring patterns of approaches that researchers have used, it becomes easier to see how to translate a research question into a corpus-based hypothesis that can be investigated through corpus analysis. While there is no blueprint or recipe for such a translation, thinking about what the frequency of a certain phrase (in a certain context) and/or its co-occurrence with other terms might tell you, gets you a long way to your corpus-based hypothesis. Some of these translations are easier to see, others a bit more difficult.

The translation is easy (relatively speaking) if what you start with is already a question about the use of a term. For example, Knobe and Nichols (Study 1) more or less have their corpus question on the table, given their interest in whether we ascribe phenomenal consciousness to group agents. Similarly, Andow (Study 4) in asking about the prevalence of the term 'intuition' for philosophical theorizing across the last 100 years, *simply* needs to observe the use of the term over time.

In other cases, an important side-question needs to be answered first: What are the relevant contexts for which the frequency of a term or its co-occurrence with other terms matter. Sytsma et al. (Study 8), for instance, needed to check the frequency with which *bad outcomes* are specified after the phrases 'caused the' and 'responsible for the'. Once they had figured out which contextual information would tell them when a certain phrase was used normatively, the corpus hypothesis was as easy as pie: You collect data, analyze the frequency or co-occurrence, run your analysis, and verify or falsify your hypothesis.

Importantly, some studies cannot (yet) dispense with human thinkers at an important stage of the process. Both in Studies 5 & 6, as well as to a lesser extent in Studies 3 & 10, the researchers needed to find out (or code) whether certain uses of a phrase belong to a certain category. Wright et al. (Study 5) needed people to read the larger context in which a term like 'good' or 'right' was used in order to determine whether its use was moral. Nichols & Pinillos (Study 6) needed to code whether the use of 'know' was indeed infallibilist. Similar tasks were needed in Fischer et al. (Study 3) and Hansen, Porter, & Francis (Study 10).

These at times tedious human tasks should not discourage anyone running their own corpus analysis.[15] Thus, don't despair if the hypothesis is too complex to be analyzed fully computerized (without human involvement). Corpus data might still provide you with a new window into your research question, even if you need to look at the data qualitatively yourself.

Before we move on to our corpus analyses of 'conspiracy theory', we should highlight that whereas corpus analysis is empirical but often non-experimental—in the sense of using data but not generating new data—some of the same scientific standards hold for both experimental as well as corpus studies. First, a thorough corpus analysis should include proper control conditions wherever possible to make sure that the effects that were found cannot easily be accounted for by other factors (see also Chartrand (2022) for a discussion of the need and prevalence of control conditions in philosophical corpus studies). While including control conditions can be very laborious, some controls can be easily incorporated into your corpus design. We will show in the next section using the example of 'conspiracy theory', how control conditions can and should be part of one's corpus study. Second, corpus data should not speak for itself, but statistical analyses of the data should be done wherever possible. This, of course, makes many corpus analyses more tedious and complex, just as about any well-designed experimental study. In many cases, however, the statistical tests are similar to those used in vignette studies. Third, just as with experimental studies, ethical standards need to be adhered to (only make anonymized data publicly available, etc.). We will repeatedly touch on some of these issues in the next two sections. Now on to conspiracy theories.

4 A corpus analysis of 'conspiracy theory' with pre-built corpora

The term 'conspiracy theory' was hardly used before the second half of the 20th century. It gained popularity in the 60s and 70s in the wake of the Kennedy assassination (deHaven-Smith (2013), but see Butter (2021), and McKenzie-McHarg (2018)). Since the 80s we see a sharp rise in its use (see, e.g., the profiles in COHA and NGRAM). Nowadays, terms like 'conspiracy theory' and 'fake news' are part and parcel of the stock of concepts we use on a very regular basis. Unsurprisingly, philosophers are increasingly interested in understanding what we mean when we say that something is a conspiracy theory.

[15] Often what starts as a human classification task, can be automatized later, through classifiers etc. (supervised and unsupervised machine learning).

The dominant view in analytic philosophy is that conspiracy theories are theories about conspiracies (see, e.g., Basham & Dentith 2016, Cassam 2019, Coady 2008, Cohnitz 2018, Feldman 2011, Harris 2018, Keeley 1999, Pigden 2007, Räikkä 2018).[16] That sounds a bit like a truism, but, of course, while the meaning of composite terms is often made up of the meanings of its parts, that is not always the case: The rainbow press is not the press about rainbows, and cloud computers have nothing to do with raindrops in the air. That said, without evidence to the contrary, we might simply assume the standard view to be correct, according to which *conspiracy theory* refers to a theory that features a conspiracy.

Empirical evidence against the standard view in philosophy has been put forward by Napolitano & Reuter (2021). The results of their experiments reveal a double dissociation of *conspiracy* and *conspiracy theory*: Not only are people willing to call a claim or an explanation a conspiracy theory even though no conspiracy has taken place (their Study 4), they also show that even if a conspiracy is part of the explanation that is put forward, laypeople are not inclined to call the explanation a conspiracy theory if the conspiracy has indeed taken place (their Study 5).

The central aim of Napolitano & Reuter's paper, however, is to investigate whether the term 'conspiracy theory' has an inherently negative evaluative nature, i.e., whether the term only refers to bad, false, or unjustified theories. That research question can be roughly put as follows:

Research Question: Is 'conspiracy theory' an evaluative term?

How can we investigate this research question with the means of corpus linguistics? Napolitano and Reuter conjecture that if 'conspiracy theory' is indeed an evaluative term, people will frequently use evaluative adjectives before the term 'conspiracy theory'. When looking at the way people use 'conspiracy theory', we should then find frequent uses for 'stupid conspiracy theory' and 'wild conspiracy theory', and less frequently phrases like 'interesting conspiracy theory' or 'complex conspiracy theory'. Thus, we can formulate a more specific corpus-based hypothesis in the following way:

Corpus Hypothesis 1: The most frequent adjectives before 'conspiracy theory' are predominantly negative.

Of course, without a suitable control condition, we cannot make reliable inferences about the evaluative dimension of 'conspiracy theory'. It might, for example, be the case that many other terms are preceded by many negative adjectives without themselves being evaluative. Napolitano and Reuter use the term 'theory' as a control condition. Based on their corpus analysis[17] they note that among the 50 most frequent adjectives preceding 'conspiracy theory' 25 were negative, compared to merely 6 negative adjectives in the top 50 for 'theory'. While the results suggest 'conspiracy theory' to be an evaluative term and thus support Corpus Hypothesis 1, one might wonder:

(i) Aren't there further control conditions (e.g., how does the term 'conspiracy' function?) that need to be checked to draw more reliable conclusions about the evaluative nature of the term 'conspiracy theory'? Do the results only hold for 'conspiracy theory' or also for agents labeled 'conspiracy theorists'?

(ii) Has the use of the term 'conspiracy theory' changed during the last years and decades?

(iii) Can we investigate the evaluate nature of 'conspiracy theory' using a different corpus strategy?

In the remainder of Section 4, we investigate these questions with the help of pre-built corpora, such as COCA and NOW. In Section 4.1, we provide evidence that 'conspiracy theory' is indeed a strongly evaluative term, thereby tackling the questions stated in (i). In Section 4.2, we provide an affirmative answer to question (ii), and in Section 4.3, we respond to (iii) by demonstrating that theories that are labelled 'conspiracy theories' are treated like false and baseless theories by investigating verbs that occur before 'conspiracy theories'.

We will also show that corpus analyses based on pre-built corpora are limited in important respects. More specifically, we will argue that the results we present are

16 This is, of course, not to say that all these theorists agree on what the proper definition of conspiracy theory is. In fact, they disagree quite a lot. For example, some theorists include a conflict criterion or some other additional element; some define conspiracy theories to be epistemically evaluative. They do agree, however, that a theory cannot be a conspiracy theory if it does not refer to a conspiracy.

17 Their corpus analysis was based on a corpus featuring 68'640 texts from the social media website Reddit.

- often based on too few data points;
- do not provide a comprehensive picture of a term's usage;
- are not representative of ordinary usage;
- are too strongly reliant on people's intuitions.

A discussion of these limitations will serve as our motivation for building our own corpus, and for digging deeper into more complex corpus-analytic tools in Section 5.

4.1 The evaluative nature of 'Conspiracy theory' and 'Conspiracy theorist'

Napolitano & Reuter's corpus study shows that many of the most frequent adjectives before 'conspiracy theory' are evaluative terms. In contrast, the term 'theory' is preceded by a different set of mostly neutral or positive adjectives. These results suggest 'conspiracy theory' to be a strongly evaluative term. However, one might object that an important control condition is missing, namely the term 'conspiracy'. If 'conspiracy' were as evaluative as 'conspiracy theory', then we could not conclude that the composite term 'conspiracy theory' is used more evaluatively than its individual parts. Instead, it would then seem that the evaluativity of the term 'conspiracy theory' is likely derived from 'conspiracy'. Some of the more recent literature has not only asked what counts as a conspiracy theory, but also who counts as a conspiracy theorist (Klein et al., 1918; Tsapos, forthcoming). We therefore decided to include in our corpus study the term 'conspiracy theorist'.

In order to find the most frequent adjectives before 'conspiracy theory', we go to the COCA website and enter <ADJ conspiracy theory> into the search field and hit enter. The results can also be found in Table 1 (two most left columns) but are somewhat disappointing. While the list of the 15 most frequent terms indeed contains several evaluative terms, the overall number of hits is fairly low (N=330, and N=111 for the top 15), certainly too low to make robust claims about the use of 'conspiracy theory'. Perhaps we can boost the number by searching for <ADJ conspiracy theories> (plural), but the numbers are not much higher (see also Table 1). Our initial worry was that perhaps the term 'conspiracy' is already predominantly negative. Searching for <ADJ conspiracy> and <ADJ theories> certainly yields higher numbers overall. The results are also displayed in Table 1. Finally, we have also listed the results for <ADJ conspiracy theorist>. As the results in the middle of the table show, there are too few hits to make any reliable conclusions about its evaluative use.

Conspiracy Theory		Conspiracy Theories		Conspiracy Theorist		Conspiracy		Theories	
Term	N	Term	N	Term	N	Term	N		
good	14	wild	24	right-wing	9	criminal	230	scientific	326
crazy	13	crazy	13	crazy	8	right-wing	193	other	290
new	13	various	13	anti-muslim	4	grand	92	new	239
latest	8	paranoid	11	favorite	3	vast	87	different	194
debunked	7	right-wing	11	crazed	2	big	72	various	158
rich	7	bizarre	10	lunar	2	alleged	68	economic	152
baseless	6	new	9	long-time	2	international	67	current	140
bizarre	6	elaborate	8	paranoid	2	jewish	61	implicit	124
big	6	other	8	real	2	communist	54	competing	110
wild	6	outlandish	7	full-on	2	global	49	alternative	91
grand	5	specific	7	resident	1	larger	47	psychological	86
other	5	baseless	6	unhelpful	1	crazy	46	legal	83
paranoid	5	anti-semitic	4	ultimate	1	federal	44	political	67
racist	5	colorful	4	total	1	liberal	43	existing	63
silly	5	good	4	strong	1	massive	42	modern	63
Total Top 15	111	Total Top 15	139	Total Top 15	41	Total Top 15	1195	Total Top 15	2186
All uses	330	All uses	428	All uses	83	All uses	3892	All uses	7065

Table 1: A list of the 15 most frequent adjectives in front of 'conspiracy theory', 'conspiracy theories', 'conspiracy', and 'theories' on COCA. Derogatory terms are highlighted in orange, and negative epistemic terms in yellow.

Let's set aside the problem of low numbers for the moment. The results show that the term 'conspiracy' is preceded mostly (at least when we glimpse at the top 15) by descriptive terms. 'Crazy conspiracy' seems to be the only exception of a clearly negative evaluative adjective. Once we look more closely at the results for 'crazy conspiracy', however, we find that of the 46 hits, most uses are about 'crazy conspiracy *theory*', 'crazy conspiracy *theories*', and 'crazy conspiracy *theorist*'. In other words, 'crazy' is only one of top hits for 'conspiracy' because it is used with 'conspiracy theory/ies/ist/ists'.[18] In summary, our analysis does provide additional evidence that 'conspiracy theory/ies' is used often in a negative evaluative way, and, that its negative use can hardly be explained by a negative use of 'conspiracy' or 'theory'.

One way to get a greater number of results for <ADJ conspiracy theory> is to use different pre-built corpora like iWEB and NOW, each of which contain between 14–15 billion words compared to COCA's 1 billion words (e.g., NOW contains 7839 hits for <ADJ conspiracy theory> compared to COCA's 330). The downside of using these other corpora is that they are not well-balanced corpora. NOW, for instance, is a collection of texts from news on the web and thus certainly not representative of laypeople's use of language. Consequently, in order to get a higher number of uses that allows for a more quantitative analysis *and also* to have data representative of ordinary usage, we would need to built our own corpus (see Section 5).

There are (at least) three further difficulties with our corpus analysis in Section 4.1. First, we only examined the top 15 hits for our searches. Second, we relied on *intuitive* classification of the adjectives into derogatory, negative epistemic evaluative terms and descriptive terms. Third, we did not do any proper statistical analysis but made inferences merely by looking at the data and counting the number of evaluative adjectives.

In principle, nothing prevents us from classifying all adjectives preceding our target structure. It is simply fairly tedious work. The intuitive classification we used might be more of a problem though. One way to tackle researcher bias would be to ask several independent coders to categorize the adjectives into derogatory, epistemically evaluative and descriptive terms.

In terms of running a statistical analysis, we could, for example, run a t-test comparing differences in the occurrence of evaluative terms among the most frequent terms.[19] Fisher's Exact test reveals a significant difference between the test condition (Conspiracy Theory) and the control condition (Conspiracy): $\chi^2 = 7.194; p = 0.015$. Of course, we could take more adjectives into account, and also weigh the frequency with which they occur. The overall fairly low numbers, however, do not lend themselves for a robust statistical analysis. We will get back to this issue, once we have compiled our own corpus for which we have a much greater number of target adjectives.

4.2 How has the meaning of 'conspiracy theory' developed over time?

Many philosophers have argued that 'conspiracy theory' is a *descriptive* term referring to a theory featuring a conspiracy of some sort. The results of the experimental studies in Napolitano & Reuter as well as the corpus analysis of Section 4.1 suggest instead that 'conspiracy theory' is a negative evaluative term. How can we explain this contrast? Have those philosophers been simply out of touch with reality? Perhaps a different explanation is available. While the term 'conspiracy theory' has hardly been used by the folk before 2010, nowadays it is a highly popular term among laypeople. It is thus not unlikely that the term has changed its meaning during the last 10–15 years.[20] From this observation, we can state our second corpus hypothesis:

Corpus Hypothesis 2: The most frequent adjectives occurring before 'conspiracy theory' were less negative 10–12 years ago than they are now.

The corpus COCA features too few hits to do an analysis of the term 'conspiracy theory' over time. The corpus NOW with its 15 billion words, however, does allow us to compare the adjectives preceding 'conspiracy theory' in the timespan 2010–2016 with those in the time span of 2019–2021.[21]

[18] Unfortunately, COCA does not allow you to exclude phrases that are followed by certain terms. In order to do this, you need to check by hand, or, even better, run your own computer code.

[19] For more on the assumptions for running t-tests, on effect sizes, on p-values, etc., please see Sytsma's Chapter ("Pain Judgments and T-Tests") in this book.

[20] Terms like 'naughty', 'gay', 'nice' and 'silly' all have changed their meanings over decades and centuries. Perhaps 'conspiracy theory' went through a similar change, albeit on a much smaller time scale.

[21] We only selected the last three years (2019, 2020, 2021, excluding 2022) as a snapshot of its current use. We then selected the years 2010–2016 as the contrasting time span. The less frequent use of the term 'conspiracy theory' in the early 10's made it necessary to extend the time frame up to the year 2016.

In order to investigate the hypothesis that the use of 'conspiracy theory' has changed during the last 10–15 years, we go to https://www.english-corpora.org/now/, enter <ADJ conspiracy theory> into the search field, click on sections, select the years between 2010 and 2016 in the left column by holding down the shift button, and then hit enter. The left hand side of Table 2 lists the most frequent adjectives occurring before 'conspiracy theory'. In order to get the data from the last three years, we simply select 2019–2021 and hit enter again. The results are listed on the right hand side of Table 2.

2010–2016		2019–2021	
Term	Number	Term	Number
good	43	baseless	475
popular	28	debunked	368
bizarre	27	far-right	317
new	26	right-wing	204
online	21	unfounded	184
big	15	false	180
particular	14	anti-semitic	131
elaborate	13	new	130
paranoid	13	pro-trump	121
racist	12	bizarre	115
grand	10	racist	113
latest	10	popular	108
ridiculous	10	discredited	97
right-wing	10	wild	95
false	9	online	93
crazy	9	crazy	68
baseless	9	dangerous	66
great	8	bogus	54
political	8	good	51
weird	8	latest	51

Table 2: List of the 20 most frequent terms occurring before 'conspiracy theory' for the years 2010–2016 (left-hand side) and 2019–2021 (right-hand side) of the NOW corpus. We color-coded positive and neutral terms in cyan, derogatory terms in orange, and negative epistemic terms in yellow. Terms left uncolored are primarily descriptive albeit often carrying a negative connotation.

The results clearly suggest quite a dramatic change in its use during the last 10 years, providing positive evidence for Corpus Hypothesis 2. While the most frequent adjectives preceding 'conspiracy theory' in the years 2010–2016 have been either positive or neutral ('good', 'popular', 'new', 'online', 'big', 'particular', 'elaborate', 'grand', 'latest'), these terms are not as often used (relatively speaking) in the last few years. Instead, we see a rise of mostly negative epistemic terms: Among the six most common adjectives, we find 'baseless', 'debunked', 'unfounded', and 'false'.

Perhaps surprisingly, the data does not reveal an observable difference in the use of derogatory adjectives. Of course, the top 20 most frequent terms provide an incomplete picture of all the adjectives. However, the increase in negative epistemic terms as well as the decrease in positive and neutral terms is remarkable. Although we do not have any data to support this view,[22] we might want to speculate that going back in time even further, say to the beginning of the century or even to the 80s and 90s of the 20th century, we find an even more neutral picture of the use of 'conspiracy theory' (see also McKenzie-McHarg, 2018).

If these two lists do reflect the meaning of 'conspiracy theory' at different times, then purely descriptive definitions of philosophers might indeed reflect the dominant meaning of the term in previous times. In other words, the evaluative meaning of *conspiracy theory* that was recorded by Napolitano & Reuter (2021) might be a more recent phenomenon. We need to be careful in not overinterpreting our data, though. The NOW corpus reflects the language use in media, and hence differs in important respects from everyday use. The rise in negative epistemic terms might reflect a bias in the media sector. For instance, journalists might increasingly feel the need to highlight that current conspiracy theories are baseless, debunked, false, unfounded, and discredited.[23]

22 Although the data on COCA is very sparse, there seem to be only four negative uses of the term 'conspiracy theory' of the 166 hits from the 90s of the 20th century.

23 It is also not implausible to think that the nature of conspiracy theories has changed over the last decades, i.e., whereas conspiracy theories of the past were more often based on facts and well-argued for, nowadays, conspiracy theories are more often epistemically deficient (we thank Giulia Napolitano for this suggestion).

4.3 Conspiracy theories are treated like false theories

Before we conclude this section, we would like to introduce and discuss a further approach to investigate the meaning of the term ‘conspiracy theory’. While we believe the *adjectival* method to be a robust means to examine the evaluative dimension of ‘conspiracy theory’, it would certainly be more convincing to have additional corpus data that does not rely on an analysis of preceding adjectives.

By analyzing preceding verbs instead of adjectives, we can find out what people *do* with conspiracy theories. If our inferences from the corpus data are correct, the meaning of ‘conspiracy theory’ is not a theory about a conspiracy. Instead, the term ‘conspiracy theory’ is considered equivalent to a false theory, wild theory, or baseless theory. So, let us examine the verbs people use before ‘false theories’, ‘wild theories’, and ‘baseless theories’ in the NOW Corpus.[24] Thus, let us enter <VERB false theories> into the search field of the NOW corpus, as well as <VERB wild theories> and <VERB baseless theories>. As you can see for yourself, people seem to be primarily talking about *promoting*, *spreading*, and *pushing* false, wild, and baseless theories. Consequently, we might develop the following corpus hypothesis:

Corpus Hypothesis 3: The composite term ‘conspiracy theories’ is frequently preceded by verbs indicating their promotion and spread.

Again, before we investigate this hypothesis, we need proper control conditions that will also allow us to run some statistical analysis. It might be helpful to include both ‘theories’ as well as ‘critical race theory’ as controls. While it will be useful to contrast ‘conspiracy theories’ with ‘theories’, ‘critical race theory’ is at least in conservative circles considered very critically, and thus might deliver similar results to ‘conspiracy theories’. In order to get the respective data, we enter <VERB conspiracy theory> etc. into the search field of the NOW corpus. Table 4 shows the most frequent verbs preceding the three composite terms.

Conspiracy Theories		Critical Race Theory		Theories	
Term	Number	Term	Number	Term	Number
promote	738	teach	767	testing	291
spread	493	ban	415	develop	166
believe	403	say	119	discuss	108
push	396	promote	114	debunk	89
peddle	346	oppose	113	offer	85
embrace	183	push	104	support	82
debunk	125	use	82	promote	79
share	124	mention	76	share	79
amplify	118	define	59	learn	77
fuel	101	embrace	52	apply	68
Total Top 10	3027	Total Top 10	1901	Total Top 10	1124
All uses	7315	All uses	3553	All uses	4890

Table 3: A list of the 10 most frequent verbs in front of ‘conspiracy theories’, ‘critical race theories’, and ‘theories’. Terms that are synonymous with ‘spreading’ are color-coded in cyan.

A look at the ten most common verbs preceding ‘conspiracy theory’ reveals a highly frequent use of verbs referring to the spreading of information. 7 out of 10 verbs in the top 10 (or 2316 out of 3027 uses (76.5%)) belong to that category. In contrast, we find only 2 out of 10 ‘spreading-verbs’ in the top 10 (or 1683 out of 1901 uses (11.5%)) for ‘critical race theory’, and 2 out of 10 ‘spreading-verbs’ in the top 10 (or 966 out of 1124 uses (14.1%)) for ‘theories’.

While we need to stress again that focusing on the 10 most frequent verbs preceding ‘conspiracy theory’ comes with its limits, the results nonetheless clearly demonstrate that people speak highly often about conspiracy theories being promoted, spread and pushed. This provides substantial evidence in favor of Corpus Hypothesis 3. In other words, conspiracy theories seem to be commonly treated like false, baseless theories, but not like theories that have an epistemically more respected standing.

This last corpus analysis concludes our investigation of the term ‘conspiracy theory’ using *pre-built corpora*. In this section, we have learned about the way we talk about conspiracy theories by running corpus analyses. However, we often noticed that we need to be cautious with our corpus data. Here are six limitations and problems we faced:

[24] The COCA corpus once more is too small to explore the use of verbs before these composite terms.

- The corpora were at times too small to deliver enough data points to make reliable inferences.
- Focusing on the most common terms preceding the target term does not reveal a complete picture of the use of the target term.
- We often relied on our own intuitions in regards to whether certain terms belong to a certain category.
- Statistical analyses are often not easy to do on data from pre-built corpora.
- The corpora we used are often not representative of the ordinary use among laypeople.

In the next section, we run some corpus analyses on ‘conspiracy theory’ using a corpus that we build ourselves, and thereby show how at least some of these limitations can be tackled.

5 Building your own corpus and analyzing ‘conspiracy theory’

Given the drawbacks and limitations we faced in Section 4, we now show how to build your own corpus, and how to run simple analyses with the data in R (also see Chapter 2). Before embarking on this endeavor, however, we highly encourage you to take a look at the multitude of pre-existing corpora which have wide applications in computational corpus linguistics. Among the most well known are the Brown Corpus, the Gutenberg Corpus, the Reuters Corpus, and the Penn Treebank—just to name a few.[25] These corpora are pre-annotated but require additional software for analysis, and most of these resources are structured for very specific tasks.

5.1 Prerequisites

This section assumes that the reader is familiar with the basics of the programming language R. For this chapter, we use R version 4.1.0 and RStudio version 1.4.1106. The full code script and data for this chapter is available on our OSF repository.[26] We highly recommend working through the example script parallel to reading the code explanations. If you are relatively new to R, working with the provided script and data is essential. The line numbering in the code chunks follows the line numbering in the original script, which allows for seamless navigation between the two resources. We also provide pre-compiled data-objects for each step in the data collection and analysis, which can be loaded directly into the workspace, in case you want to skip one of the steps. The code blocks’ headers also detail the estimated runtime, which is *significant* in places. Note that there are two scripts and two output folders: `/script.R` and `/output/` contain the code and data to process the full data, while `/script_subsample.R` and `/output_subsample/` only uses a subsample of the data. This chapter details the code in `/script.R`, but `/script_subsample.R` is identical (including the line numbering), except for different filepaths and a few additional lines for the subsampling.

> If you intend to run the whole script on your local machine, **we highly recommend processing only the subsample**—the total runtime with the full data is more than a day. Please install all the packages specified in the script. If you skip certain code blocks, make sure to still **load all packages mentioned earlier in the script** as they might be needed later on as well. Lastly, please note that this script is optimized for Unix systems; on Windows, the parallelization used does not work and will lead to a significant increase in runtime.[27]

Before we start, please set the working directory to the downloaded folder for every new session (l.15-18), since the code in this chapter loads external objects:

[25] The corpora are freely available, for instance at http://www.nltk.org/nltk_data/. Many more can be found in the catalogue of the Linguistic Data Consortium (https://catalog.ldc.upenn.edu/).

[26] https://osf.io/abkm3/?view_only=189759a7dd2e407581bed5641e273c52

[27] That said, the code will still run on a Windows machine. Due to the lack of the `fork()`-functionality on Windows, parallelized vectorized R functions (`mc*apply()`) will simply default to single-threaded computing. Check out the `parallelsugar`-package (https://github.com/nathanvan/parallelsugar) if you are interested in a parallel computing application on Windows with a similar syntax to the one used in this chapter.

```
15 setwd(dirname(rstudioapi::getActiveDocumentContext()$path)) # set working directory
16 getwd() # print working directory
17
18 rm(list = ls()) # clear workspace
```

On l.15, we set the working directory to the folder in which the code file is located at. The location can be printed by invoking l.16. On l.18, we clear the workspace to ensure there is no leftover data from previous sessions. Now, we are all set up!

5.2 Why APIs are your new best friends

For our current purposes, we decided to collect Reddit comments containing mentions of 'conspiracy theory'. Reddit is probably *the* biggest online forum, with thousands of submissions and comments every day, and it is well known to host very controversial opinions, among them also conspiracy theories. As such, Reddit comments provide us with a presumably very large pool of natural language data on conspiracy theories, which can be mined for scientific interests. This data can easily be accessed via a so-called Application Programming Interface (API). APIs allow external entities (e.g. a software application on your mobile phone) to send queries to the API-provider, which then sends an automated response back. In our case, we want to send a query for comments containing the phrase 'conspiracy theory'; the Reddit API will then send us these comments back as a response. This service is free and open to the public. There are plenty of APIs available, including for services like Twitter, Google Maps,Google Translate, Skyscanner Flight Search, etc. Some of these require prior registration and subsequent authentication, others can be used (mostly) anonymously. In sum, APIs allow access to large amounts of structured data, which are just a query away, without all the hassle related to more extensive web scraping.

APIs are highly regulated and come with their own query language. The Pushshift Reddit API (Baumgartner et al. 2020) can easily be accessed via your browser. Here is a sample query:

```
https://api.pushshift.io/reddit/search/comment/?q=%22conspiracy%20theory%22
```

With this query, we tell the API that we want to search Reddit data, specifically comments. The actual query parameter is `<q=>`, for which we provide the phrase we are looking for, namely `<"conspiracy theory">` (the quotes are translated to `<%22>`, the spaces to `<%20>`, which is called percent encoding). If we type this into our browser, we get a response back, which looks analogous to this:


```
{
"data": [
    {
        "all_awardings": [],
        "archived": false,
        "associated_award": null,
        "author": "TaroProfessional6141",
        "author_flair_background_color": null,
        "author_flair_css_class": null,
        "author_flair_richtext": [],
        "author_flair_template_id": null,
        "author_flair_text": null,
        "author_flair_text_color": null,
        "author_flair_type": "text",
        "author_fullname": "t2_crckblfb",
        "author_patreon_flair": false,
        "author_premium": false,
        "body": "Their idea of research is simply to search for anyone who confirms their biases and/or
        ↪  offers them an alternative reality conspiracy theory.  They find this and act like their
        ↪  super Google typing skills are proof of their innate genius LMFAO!",
        "body_sha1": "54259c88fec0d7c428e38a1ff34719ed0643a679",
        "can_gild": true,
        "collapsed": false,
        "collapsed_because_crowd_control": null,
        "collapsed_reason": null,
        "collapsed_reason_code": null,
        "comment_type": null,
        "controversiality": 0,
```

```
        "created_utc": 1647512281,
        "distinguished": null,
        "gilded": 0,
        "gildings": {},
        "id": "i102192",
        "is_submitter": false,
        "link_id": "t3_tfiisq",
        "locked": false,
        "no_follow": true,
        "parent_id": "t1_i0y1ixy",
        "permalink":
        ↪  "/r/ParlerWatch/comments/tfiisq/this_dude_on_my_friends_list_that_just_got_removed/i102192/",
        "retrieved_utc": 1647512295,
        "score": 1,
        "score_hidden": false,
        "send_replies": true,
        "stickied": false,
        "subreddit": "ParlerWatch",
        "subreddit_id": "t5_3dw7go",
        "subreddit_name_prefixed": "r/ParlerWatch",
        "subreddit_type": "public",
        "top_awarded_type": null,
        "total_awards_received": 0,
        "treatment_tags": [],
        "unrepliable_reason": null
    },...
]
}
```


The data we get back comes in the JSON-format, which is—simply put—the enhanced cousin of your standard CSV or Excel file. The JSON-response contains lots of information with which the regular Reddit user might be familiar, but for us the most interesting variable is <body>, i.e. the text of the comment. Now, the goal is to collect all these comments in an orderly fashion. Currently, the API limits your queries to 25 comments per response—not quite the number we have in mind. In order to get more responses, we will have to send the same query multiple times. If you try this in your browser, you will get different responses back every time. But how can we ensure that we do not get the same responses back among our several thousand queries? The Reddit API allows you to specify a time frame, within which the query will be computed. Hence, we will select a start date and work our way back in time to the desired end date.

In theory, this seems like an easy task. But how do we send automated queries and store each response? For this, we use the programming software R. Now, here is how formulating a query and saving the response in R looks like:

```
23 library(jsonlite)
24 library(tidyverse)
25 response <- fromJSON("https://api.pushshift.io/reddit/search/comment/?q=%22conspiracy%20theory%22")
26 response <- as_tibble(response$data)
```

To read in the response from the query within R, we can use the `fromJSON()`-function from the `jsonlite`-package (Ooms et al. 2020; l.23) and assign the output to the object <response> (l.25). Then, we use the `as_tibble`-function to coerce the <data>-element of the response into a special kind of dataframe, called tibble (l.26).[28] In sum, two lines of code already get us the desired data in a form that can easily be manipulated further down the line.

> The `jsonlite`-package (Ooms et al. 2020; l.23) is used to import, handle, and write data in JSON-format. For more information visit https://cran.r-project.org/web/packages/jsonlite/index.html. The `as_tibble`-function is loaded using the `tidyverse`-package (Wickham 2021; l.24), which is an opinionated collection of R-packages for data science (https://www.tidyverse.org/). Please make sure to load these packages, even if you skip this step.

[28] For more on tibbles, visit https://tibble.tidyverse.org/.

Now, we want to send multiple queries to get all data for a specific time period, which can be achieved by *looping* the query process. In our case, we would like to get Reddit comments from 01.10.2021 to 31.12.2021. Since we do not know how many iterations of the query are necessary to get all the data, we use a while-loop, which just continues the query process as long as we do not have all the data, and stops as soon as we do. **Please note that this is an *open-ended* process, and due to the amount of data available it will take multiple hours to complete. We thus recommend to use the pre-compiled data-objects on our OSF repository, in order to continue without delay.**[29] Here is the example code for 'conspiracy theory':

```
32 library(utc)
33 container <- list()
34 query.root <- "https://api.pushshift.io/reddit/search/comment/?q=%22conspiracy%20theory%22&before="
35 time.index <- as.numeric(toUTC(as.Date("31-12-2021", '%d-%m-%Y')))
36 time.end <- as.numeric(toUTC(as.Date("30-09-2021", '%d-%m-%Y')))
37 while(time.index>time.end){ # outer loop
38   query <- paste0(query.root, time.index)
39   print(time.index)
40   TRYING <- T
41   while(TRYING){ # inner loop
42     response <- try(fromJSON(query))
43     TRYING <- "try-error" %in% class(response)
44     #Sys.sleep(1) #uncomment this line if you get 429 and 403 errors
45   }
46   df <- as_tibble(response$data)
47   container[[as.character(time.index)]] <- df
48   time.index <- min(df$created_utc)
49 }
50 save(container, file = "./output/api-calls/conspiracy_theories.RDS")
```

First, we specify a list, the <container>-object on l.33, which serves to collect each response.[30] On l.34, you will find a slightly changed API query string, which is assigned to <query.root>. It contains a new parameter (the suffix <&before=>) which controls that the query is restricted to the newest comments *prior to* the specified time point. Said time point will be specified anew for every iteration, as we will see later. The start date for the query is assigned to <time.index> (l.35), the end date is assigned to <time.end> (l.36). The dates are provided in UTC epoch date format, an unambiguous machine-readable date format.

> Epoch time is the number of seconds that have elapsed since the Unix epoch (excl. leap seconds), which is 00:00:00 UTC on 1 January 1970. To get our start date, the 31 December 2021, in Epoch time, we can use an online converter such as https://www.epochconverter.com/. On l.35–36 in the code, we instead use the toUTC()-function from the utc-package (Segura 2019; loaded on l.32) to convert the respective date object to UTC format and subsequently coerce it to numeric, which gives us the Epoch time.

In the code above, there are two while-loops, an inner (l.41–45) and an outer (l.37–49) one. The outer one gets evaluated first and controls that our time period is respected: as long as <time.index> is still bigger than <time.end>, the queries continue on. For each iteration in the outer while-loop, we formulate a new query by appending <time.index> to <query.root> (l.38).[31] For the actual query, we then enter the inner while-loop on l.41. The reason why we need this inner loop is that the query relies on your internet connection which might not be stable at all times. If the connection breaks during a query, the outer while-loop breaks because of a no-connection error. To prevent this, we add some simple error handling: the inner while-loop will try over and over to perform the query, *if* the connection throws an error.[32] If there is *no* error, the loop stops and we proceed to coercing the response to a tibble (l.46), which is subsequently stored in our <container> (l.47). Finally, we extract the timestamp of the last comment and assign it as the new

[29] This also applies to the code in /script_subsample.R.

[30] Alternatively, one could also save each response locally (as a RDS-file, for instance).

[31] Our start date, the 31 December 2021, is 1640908800 in epoch format. Hence, the query would read as https://api.pushshift.io/reddit/search/comment/?q=%22conspiracy%20theory%22&before=1640908800.

[32] If you make too many queries, the server will throw the error codes 429 or 403. In that case, simply uncomment the code on l.44, which introduces a pause of 1 second between each query.

`<time.index>` (l.48). By doing so, we always take the timestamp of the last comment as the new time point for the next query on l.38, and thus continually go back in time. If the timestamp of the last comment is later than 01.10.2021 (our `<time.end>`), the outer `while`-loop stops, and the data collection is completed. Lastly, `<container>` can be saved to your working directory, e.g. as a RDS-file (l.50). Congrats, you just collected your first corpus data!

For our project, we repeat the data collection process for 'conspiracy theories', 'conspiracy theorist(s)', 'conspiracy' (without the mention of 'theory'), and 'theory', to have comparison sets and control conditions.[33] Next, we will analyze which adjectives are most often attributed to conspiracy theory.

5.3 Corpus annotation

We want to investigate whether 'conspiracy theory' is a descriptive term or whether it communicates a negative evaluation. In the following we will walk you through the following steps:

1. Compiling the API responses into a single corpus
2. Syntactic annotation of the data
3. Extracting target constructions (adjectives preceding 'conspiracy theory', 'theory', etc.)
4. Sentiment annotation of the extracted adjectives

5.3.1 Compiling the corpus

At this point in the process, the API data is saved as separate RDS-files in the folder `"./output/api-calls/"` (one file for each target phrase, e.g. `"./output/api-calls/%22conspiracy%20theory%22.RDS"`). We recommend to pool the data into a single corpus, as this will make the data processing easier (even though decentralized pipelines might be faster). To better understand this process, the data structure is illustrated in Figure 7:

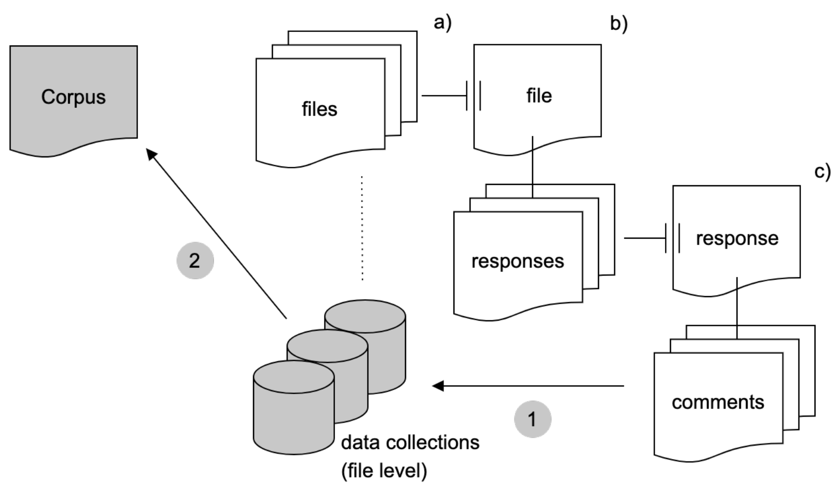


Figure 7: The data is stored in multiple files (a); each file consists of multiple responses (b). Each response, in turn, consists of multiple comments (c). The task is to collect the comments for each file (1), and then compile them into a single corpus (2).

The current data structure is depicted in white, the desired output is depicted in grey. Each file is essentially a list containing all API responses as its elements; each element in turn contains the desired comments. So, how do we reduce these data chunks into a single corpus? This is a two-step process:

33 The corresponding code is detailed on l.55–76 in the script.

1. We need to open each file, which is essentially a list of single API responses. We then *collapse the data for each file into a dataframe*.

2. Once each file corresponds to a single dataframe, *we pool these dataframes into a single object*, and finalize the corpus.

Here is how we go about the first step: First, we assign a list with all the files we want to combine to <files> (l.83). We then use the lapply()-function—a so-called *wrapper*—to apply a custom function to all elements in <files> (l.84–91). The custom function first loads the first element in <files> (l.86), i.e. "./output/api-calls/conspiracy.RDS", which adds the object <container> to the workspace, viz. the list-object containing the API responses from above. The API data has a very complex and slightly heterogeneous structure, which cannot be *directly* compiled into a single dataframe. The code on l.87–90 takes care of these issues, for which we require functionalities from the plyr-package (Wickham 2020; loaded on l.81). This treatment gets repeated for every element in <files>, compiling all the API responses for an element in a single dataframe. The result of this process is a list of dataframes we assigned to <dfl> and corresponds to the elements in <files>.

```
81  library(plyr)
82  rm(list = ls())
83  files <- list.files("./output/api-calls/", pattern = "*\\.RDS", full.names = T)
84  dfl <- lapply(files, function(x){
85    print(paste0("currently loading: ", x))
86    load(x)
87    container <- lapply(container, function(y){
88      select(y, !where(is.data.frame))
89    })
90    do.call(rbind.fill, container)
91  })
```

In the second step, we collapse <dfl>, the list of dataframes, to a single dataframe (l.92). Then, we annotate each comment (i.e. each row) with the target phrase it contains according to the API, and assign it to the variable <df$target_phrase (l.93–94).[34] Finally, we coerce the comments' timestamp to integers (l.95), make sure that there are no comments prior to October 1, 2021 (l.96), arrange the data by date and ID (l.97), and save the dataframe (l.101).

```
92  df <- as_tibble(do.call(rbind.fill, dfl))
93  target_phrases <- c("conspiracy", "theory", "conspiracy theories", "conspiracy theorist", "conspiracy
    ↪  theory") # follows the order in <files>
94  df$target_phrase <- rep(target_phrases, sapply(dfl, nrow))
95  df$created_utc <- as.numeric(df$created_utc)
96  df <- filter(df, created_utc>=1633046401)
97  df <- arrange(df, created_utc, id)

101 save(df, file = paste0("./output/api-calls/combined/combined_api_responses.RDS"), compress = "gzip")
102 detach("package:plyr", unload=TRUE)
```

Now that we have a single corpus object, we can annotate the data and isolate the phenomena we are interested in.

> Text data is inherently multidimensional: it has a syntax, encodes semantic information, is written on different topics, contains coreferences, etc. But these dimension are *latent* rather than explicitly available. This means that the data has to be prepared in such a way that it can be used for computational analysis. This is usually done by adding relevant metadata to the data, a process which is often referred to as *data annotation*. This labeling process is typically performed by means of pre-trained NLP classifiers. In certain cases it might be beneficial or even necessary to train your own classifiers for your specific purposes, but generally it is advised to rely on the standard annotators for the task at hand.

[34] Note that the order in <target_phrases> (l.93) follows the order in <files> (l.83).

5.3.2 Syntactic annotation

In order to extract our target adjectives, we first have to annotate the syntactic structure of the comments. Syntactic annotation is often referred to as part-of-speech tagging (henceforth: PoS-tagging), which makes use of pre-trained syntactic dependency parsers. These parsers are used to decompose and convert text strings (i.e. our Reddit comments) into a structural representation, in this case syntactic dependency trees. There are several dependency parsers available for R, such as `udpipe` (Wijffels et al. 2022), `spacyr` (Benoit and Matsuo 2020), `openNLP` (Hornik 2019), etc. In this chapter, we use **`spacyr`**, which **needs a separate installation**. Please follow the installation instructions in the package vignette.[35] **Please note that the PoS-tagging takes several hours with the full data and several minutes with the subsample.** This is how the syntactic annotation works:

```
107 library(spacyr)
108 library(stringi)
109 library(pbmcapply)
110 rm(list = ls())
111 #spacy_install() # only run if you do not have spacyr language models installed yet
112 spacy_initialize()
113 load("./output/api-calls/combined/combined_api_responses.RDS")
114 ## Please subset the corpus if you want to run the whole annotation:
115 #df <- sample_n(group_by(df, target_phrase), 50)
116 alist <- pbmclapply(1:nrow(df), function(x){
117   annot <- spacy_parse(df$body[x])
118   return(paste0(tolower(annot$token), "__", annot$pos, collapse = " "))
119 }, mc.cores = 3)
```

On l.113, we load the data, which is stored in the object `<df>` (for 'data frame'). The functions on l.114–115 parse each comment into PoS-tags, which are assigned to `<annot>`. If we take the sentence "I hate these stupid conspiracy theories.", its annotation will look like this:

```
> spacy_parse("I hate these stupid conspiracy theories.")
  doc_id sentence_id token_id      token      lemma   pos entity
1  text1           1        1          I     -PRON-  PRON
2  text1           1        2       hate       hate  VERB
3  text1           1        3      these      these   DET
4  text1           1        4     stupid     stupid   ADJ
5  text1           1        5 conspiracy conspiracy  NOUN
6  text1           1        6   theories     theory  NOUN
7  text1           1        7          .          . PUNCT
```

As we can see, the data structure of `<annot>` differs from the one in our corpus (`<df>`): `<df>` has one *comment* per row in the data frame, whereas `<annot>` contains one *token* (i.e. one syntactic component of a comment) per row. In other words, the latter is a long version of the former, which means that their respective formats are *incompatible*. Hence, we need to re-aggregate the token-level PoS-tags back to comment-level, in order to ensure that we can join the PoS-tags back to our corpus (l.115): First, we paste together the lower case tokens (`<annot$token>`) with their respective PoS-tag (`<annot$pos>`) and a double underscore as delimiter, and subsequently collapse those compounds on comment level, introducing whitespace between each of the token–PoS-tag compounds. Finally we return the annotated comments, which are automatically collected in a list by the wrapper function, and assign said list to the new object `<alist>`. The end result will look analogous to this:

```
I__PRON hate__VERB these__DET stupid__ADJ conspiracy__NOUN theories__NOUN .__PUNCT
```

> The syntactic annotation is wrapped by the `pbmclapply()`-function (l.116–119) from the `pbmcapply`-package (Kuang et al. 2019; loaded on l.109). The `pbmclapply()`-function is a wrapper that tracks the progress of `mclapply()` which is a parallelized version of the `lapply()`-function we used earlier. The `mclapply()`-function allows us to compute several tasks at the same time and thus significantly reduces computation time, all the while its wrapper (i.e. `pbmclapply()`) tracks and visualizes the progress.

[35] https://cran.r-project.org/web/packages/spacyr/readme/README.html

5.3.3 Extracting target structures

Next, we need to extract all the adjectives preceding our target phrases. For this, we can use so-called *regular expressions* or *regex*. Regex is used to describe a chain of signs using syntactic rules.[36] In our case, we are looking for one of more lower case letters (`<[a-z]+>`) followed by a the suffix `<__ADJ>` (viz. *adjectives*), which precede our target phrases.[37] As we only want to extract the adjective rather than the whole target structure, we use a so-called *positive lookahead* expression (i.e. `<(?=...)>`), which only *looks* at what comes after the precedent expression, without actually evaluating or extracting it.[38] Here is an abstract example for 'conspiracy theory':

```
[a-z]+(?=__ADJ\\sconspiracy__NOUN\\stheory__NOUN)
```

On l.118, below, we coerce `<alist>` to the vector `<astring>`. Then, we define all regex expressions based on the target phrases, analogous to above (l.119). The `stri_extract()`-function (from the `stringi`-package[39] (Gagolewski & Tartanus 2019) loaded on l.108) extracts exactly what is specified in the regex from the annotated token strings in `<astring>`, and assigns it to the new object `<adj>` (l.120). After checking that `<adj>` and our corpus `<df>` have the same length, we add `<adj>` and `<astring>` to our corpus, as `<df$adj>` and `<df$body_pos>` respectively (l.121–124).

```
118 astring <- unlist(alist)
119 regex <- paste0("[a-z]+(?=__ADJ\\s", gsub("\\s", "__NOUN\\\\s", df$target_phrase), "__NOUN)")
120 adj <- stri_extract(str = astring, regex = regex)
121 if(length(adj) == nrow(df)){
122   df$adj <- adj
123   df$body_pos <- astring
124 }
125 save(df, file = "./output/annotation/syntactically_annotated_corpus.RDS", compress = "gzip")
```

Our corpus now has two new variables: `<df$adj>`, the adjectives preceding our target phrases, and `<df$body_-pos>`, the PoS-tagged comments.

5.3.4 Sentiment annotation

Sentiment annotation is usually dictionary-based or uses pre-trained classifiers (or a combination of both). For this project, we use the VADER (for Valence Aware Dictionary for sEntiment Reasoning) dictionary (Hutto et al. 2014, Roehrick 2020).[40] VADER annotates tokens based on their embedding and calculates the sentiment value of the whole text string based on the word scores. The word scores are retrieved from a dictionary that contains pairs of tokens and decontextualized sentiment scores. VADER then weighs these lexical scores by taking into account negations as well as the wider context of tokens (to a limited degree). For example, the word score for 'crazy' in "This is crazy!" is -1.4, the one in "This is not crazy!" is 1.036. This means that we do not have to treat negations separately, as VADER takes care of it. Furthermore, VADER is specifically attuned to sentiments expressed in social media (Hutto et al. 2014), which means that we can expect adequate results for Reddit data.[41]

Sentiment annotation is very similar to syntactic annotation. Before starting, we remove all objects from the workspace (l.132) and load the data (l.133), viz. `<df>`. Then, we remove all comments which do *not* have an adjective preceding our target phrases (i.e. they have a missing value [`<NA>`] instead of a character string) and create our `<corpus>` (l.134). Hence, we can remove the now obsolete `<df>` (l.135).

```
130 library(vader)
131 library(quanteda)
132 rm(list=ls())
```

36 For more resources on regex, consult: https://www.regular-expressions.info/.
37 Our target phrases look as follows: `<conspiracy__NOUN\\stheories__NOUN>`; where `<\\s>` stands for whitespace)
38 For more on lookaround expressions, see: https://www.regular-expressions.info/lookaround.html.
39 For an extensive documentation on the `stringi`-package, see: https://stringi.gagolewski.com/.
40 More information on the VADER implementation in R can be found at: https://cran.r-project.org/web/packages/vader/index.html.
41 For recent applications of sentiment analysis to philosophical corpus studies, see Baumgartner 2022, Willemsen et al. 2022, Meylan & Reuter ms, Messerli & Reuter ms

```
133 load("./output/annotation/syntactically_annotated_corpus.RDS")
134 corpus <- filter(df, !is.na(adj))
135 rm(df)
```

We also need to ensure that our comments only contain the target phrase they are supposed to contain. More specifically, the API queries for ‘conspiracy’ might include results for the composita ‘conspiracy theories’, ‘conspiracy theorist’, or ‘conspiracy theory’. Since we are interested in the differences between these target phrases, though, we need to filter out these overlapping observations (l.136).

```
136 corpus <- filter(corpus, !(target_phrase == "conspiracy" &
    ↪  grepl("[a-z]+__ADJ\\sconspiracy__NOUN\\s(?=theories|theorist|theory)", body_pos, perl = T)))
```

Now, we can begin the actual sentiment analysis. We decided to perform the sentiment annotation on sentence-level, rather than taking into account the whole comment, because the length of comments varies a lot.[42] Accordingly, we break the comments down to sentences[43] (l.137) and only retain the sentences which actually contain our target structures (l.138–142). Next, we use the vader_df()-function to annotate the sentiment of the remaining sentences (l.143), and collapse the <sentiment>-list to a dataframe (l.144).

```
137 text <- tokenize_sentence(corpus$body, remove_url = TRUE)
138 regex <- paste0(corpus$adj, " ", corpus$target_phrase)
139 sentences <- pbmclapply(1:length(text), function(x) text[[x]][stri_detect(tolower(text[[x]]), regex =
    ↪  regex[x])], mc.cores = 3)
140 corpus <- corpus[lengths(sentences)==1,]
141 sentences <- sentences[lengths(sentences)==1]
142 sentences <- unlist(sentences)
143 sentiment <- pbmclapply(sentences, vader_df, mc.cores = 3)
144 sentiment <- do.call(rbind, sentiment)
```

The process to extract the sentiment score of the adjectives preceding our target phrases as well as of the target phrases themselves is analogous to the extraction of syntactic target structures in Section 5.3.3. The sentiment annotation data contains the sentences (<sentiment$text>) and the sentiment scores of all tokens in the corresponding sentence (<sentiment$word_scores>). Thus, if we tokenize the sentences (l.145) and split the sentiment scores (l.146), this yields vectors of equal length. The idea behind that is to be able to paste the two vectors together and extract the target structures using regex. On l.147–156, we specify the regex (<regex_adj> and <regex_tphrase>) and extract the corresponding token-sentiment score compounds. The result is the dataframe <token_sentiment> which contains the sentiment score of the adjectives (<token_sentiment$adj_sent>) as well as of the target phrases (<token_sentiment$tphrase_-sent>), and a variable which checks that the token vector and the sentiment score vector have equal length (<token_sentiment$check>). We join this annotation data back to the corpus (l.157) and filter out all instances where the aforementioned sanity check fails (l.158).

```
145 toks <- strsplit(sentiment$text, "\\s+")
146 sents <- strsplit(sentiment$word_scores, "\\,\\s|\\{|\\}")
147 regex_adj <- paste0(corpus$adj, "__(-)?[0-9.]+(?=\\s", gsub("\\s", "__(-)?[0-9.]+\\\\s",
    ↪  corpus$target_phrase), "__(-)?[0-9.]+)")
148 regex_tphrase <- paste0(gsub("\\s", "__(-)?[0-9.]+\\\\s", corpus$target_phrase),  "__(-)?[0-9.]+")
149 token_sentiment <- pbmclapply(1:length(toks), function(x){
150   body_sent_annot <- paste0(paste0(sub("[[:punct:]]+", "", toks[[x]]), "__", sents[[x]][-1]), collapse = " ")
151   adj_sent <- stri_extract(tolower(body_sent_annot), regex = regex_adj[x])
152   tphrase_sent <- stri_extract(tolower(body_sent_annot), regex = regex_tphrase[x])
153   check <- length(toks[[x]]) == length(sents[[x]][-1])
154   return(tibble(adj_sent, tphrase_sent, body_sent_annot, check))
155 }, mc.cores = 3)
156 token_sentiment <- do.call(rbind, token_sentiment)
157 corpus <- cbind(corpus, token_sentiment)
158 corpus <- filter(corpus, check)
```

The newly integrated sentiment scores are still concatenated with their corresponding token, e.g. "crazy__-1.4". Hence, on l.159-164, the scores are extracted and coerced to numeric values. We also code the polarity of adjective sentiment and calculate the sum of the word scores of the adjectives and the target phrases for each observation. With this, the annotation step is completed.

[42] Note that for other applications you might want to chose another annotation level, e.g. tokens, n-grams, or complete texts.
[43] For this, we use the functionality from the quanteda-package (Benoit et al. 2021).

```
corpus <- mutate(corpus,
     sentiment = as.numeric(stri_extract(adj_sent, regex = "(-)?[0-9.]+")),
     sentiment_target = as.numeric(stri_extract(tphrase_sent, regex = "(-)?[0-9.]+")),
     polarity = ifelse(sentiment >= 0, "positive", "negative"),
     sent_aggr = sentiment + sentiment_target
)
save(corpus, file = "./output/annotation/complete_corpus.RDS", compress = "gzip")
```

5.4 How crazy are conspiracy theories?

At the end of Section 4, we raised several problems with using data from pre-built corpora in order to investigate the putative evaluative character of 'conspiracy theory'. First, our pre-built corpora are either too small (e.g., COCA) or too specialized (e.g., NOW) to reliably reveal the ordinary use of 'conspiracy theory'. Second, the coding of preceding adjectives into various categories by experts or non-experts is either limited (because not all adjectives are coded) or very resource-consuming, as well as subject to biases. Third, and connected to the other two points, the statistical analysis we did was rather unsatisfactory and not up to the standards of experimental science.

With the collection of a large amount of data from Reddit and the sentiment annotation of the sentences containing '[adj] + [target term]', we are now in a position to correct for these limitations. Obviously, the improvement is mostly gradual and it is almost always possible to get more data from better sources and use better annotation procedures. Nonetheless, we hope the following section will convince even skeptical readers of the enormous scientific and philosophical potential of corpus analysis that is done with self-built corpora.

5.4.1 Hypotheses

The hypotheses we used in the last section will no longer do, given our different approach in this section. As we are now dealing with sentiment scores, we will investigate the following hypotheses:

Hypothesis 1 The term 'conspiracy theory' has significantly lower adjectival sentiment scores than 'theory'.

Hypothesis 2 The terms 'conspiracy theory', 'conspiracy theories', and 'conspiracy theorist' each have significantly lower adjectival sentiment scores than 'conspiracy'.

Hypothesis 3 The average adjectival sentiment scores for the terms 'conspiracy theory', 'conspiracy theories', and 'conspiracy theorist' are each significantly below the midpoint of 0; the one for 'theory' is significantly above the midpoint.

5.4.2 Descriptive statistics

The first step in any analysis is to familiarize yourself with the data. Most often, what is meant by that is simply to look at different measures of the data distribution. The ones most readers might be familiar with include the average (or mean), median, standard error of the mean, the number of observations, as well as skewness and kurtosis. In our case, we are mostly interested in the sentiment distribution of our different target phrases. After grouping the corpus by target phrase (l.176), we can compute the different measures as follows (l.177):[44]

```
172 library(e1071)
173 rm(list = ls()) # clear workspace
174 load("./output/annotation/complete_corpus.RDS")
175 corpus <- filter(corpus, !sentiment==0)
176 dfx <- group_by(corpus, target_phrase)
177 dfx <- dplyr::summarise(dfx, mean = mean(sentiment, na.rm = T), se = sd(sentiment)/sqrt(length(sentiment)),
    ↪ median = median(sentiment, na.rm = T), skewness = skewness(sentiment), kurtosis = kurtosis(sentiment),
    ↪ n = n())
```

[44] The functions `skewness()` and `kurtosis()` are provided by the `e1071`-package (Meyer et al. 2021; loaded on l.172).

```
> dfx
# A tibble: 5 x 7
  target_phrase          mean      se median skewness kurtosis     n
  <chr>                 <dbl>   <dbl>  <dbl>    <dbl>    <dbl> <int>
1 conspiracy          -0.0558 0.0168    -0.7   0.0584   -1.36  15032
2 conspiracy theories -1.26   0.0198    -1.5   1.15      0.937  5400
3 conspiracy theorist -1.03   0.0326    -1.4   0.894     0.478  1949
4 conspiracy theory   -0.504  0.0258    -1.3   0.414    -1.11   5049
5 theory               0.943  0.00780    1.7  -0.815    -0.181 44624
```

The majority of the sentiment averages is clustered very closely around the midpoint ($\bar{x}$: -1.26 – 0.94). All target phrases except for 'theory' have a right skew (`skewness` > 0), which means the distribution is skewed towards negative adjectival sentiment scores. This is what we expect according to Hypothesis 3. The target phrases 'conspiracy' 'conspiracy theory', and 'theory' have negative kurtosis, which means that the distribution is more homogenous and dispersed; 'conspiracy theories' and 'conspiracy theorist', on the other hand, have positive kurtosis, which means that their distribution is less dispersed than under the assumption of a normal distribution. These findings can be illustrated by a boxplot in Figure 8.

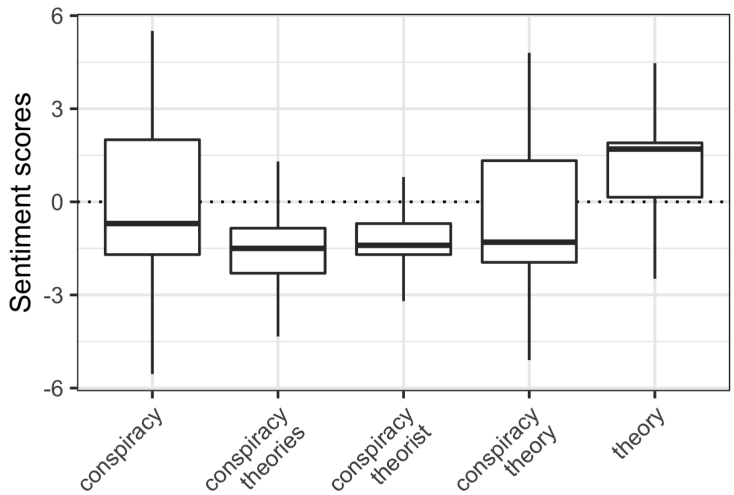


Figure 8: Boxplot of the sentiment distribution for the different target phrases.

For the boxplot, we can use the `ggplot2`-package (Pedersen et al. 2020).[45] On l.182. we specify the data and the axes. Then, we add a horizontal dotted line (l.183), the boxplot elements (l.184), specify the axes' names (l.185), apply a pre-defined theme to the plot (l.186), and finally change the alignment and orientation of the labels on the x-axis (l.187).

```
181 library(ggplot2)
182 > p <- ggplot(data = group_by(corpus, target_phrase), aes(y = sentiment, x = gsub("\\s", "\n",
    ↪  target_phrase))) +
183   geom_hline(aes(yintercept = 0), lty = "dotted") +
184   geom_boxplot(outlier.alpha = 0) +
185   labs(y = "Sentiment scores", x = "") +
186   theme_bw() +
187   theme(axis.text.x = element_text(angle = 45, hjust=1))
188 p
189 ggsave(p, file = "./output/plots/boxplot.png", width = 4, height = 3, dpi = 300)
```

It is also important to check whether the text data *makes sense*, qualitatively speaking. In our case, it is advised to review the adjectives most associated with each target phrase. For this, we first group the data by target phrase and adjective (l.192), and then calculate the number of observations per pair of target

[45] For more resources on `ggplot2`, consult: https://ggplot2.tidyverse.org/index.html.

phrase and adjective, as well as their average sentiment (l.193). Then, we arrange the data by the number of observations (l.194), retain the top 50 adjectives per target phrase (l.195), and write out the list as CSV (l.196). Table 4 shows the top 20 adjectives per target phrase.

```
192 topw <- group_by(corpus, target_phrase, adj)
193 topw <- dplyr::summarise(topw, n = n(), avg_sentiment = mean(sentiment))
194 topw <- arrange(topw, desc(n))
195 topw <- slice(topw, 1:50)
196 write_csv(topw, file = "./output/topw.csv")
```

Conspiracy Theory		Conspiracy Theories		Conspiracy Theorist		Conspiracy		Theory	
Term	Number	Term	Number	Term	Number	Term	Number	Term	Number
crazy	818	crazy	1036	crazy	756	grand	3261	interesting	8137
good	367	insane	630	paranoid	124	crazy	1418	good	6616
insane	295	stupid	455	insane	120	criminal	954	critical	2829
stupid	270	ridiculous	413	racist	63	huge	942	popular	2055
weird	240	weird	260	huge	57	weird	568	great	2031
ridiculous	237	dumb	174	stupid	49	best	557	nice	1818
favorite	229	dangerous	161	weird	43	good	520	legal	1368
dumb	190	idiotic	137	lunatic	38	great	432	best	1357
racist	179	racist	135	true	38	stupid	414	cool	1280
nice	147	bizarre	88	dangerous	35	evil	373	crazy	1241
popular	105	silly	88	dumb	33	seditious	335	solid	1011
silly	96	paranoid	83	good	30	insane	299	bad	939
huge	71	dumbass	82	retarded	20	dumb	266	favorite	713
interesting	70	fake	60	ignorant	19	true	223	original	674
grand	66	popular	59	dead	17	racist	197	stupid	656
idiotic	60	favorite	52	silly	17	ridiculous	177	dumb	589
paranoid	60	good	51	mad	16	paranoid	163	better	517
bizarre	59	dumbest	48	avid	15	favorite	161	weird	510
dumbest	58	moronic	47	moronic	15	fake	157	unified	447
dangerous	57	interesting	45	prominent	12	greatest	131	ridiculous	357

Table 4: Comparison of the 20 most frequent terms occuring before the five target expressions.

5.4.3 Statistical tests

The hypothesis testing boils down to a simple analysis of variance (ANOVA; also see Chapter 7). ANOVA has two basic assumptions: it assumes that the data follows a normal distribution and that the group variances are homogeneous. Based on the descriptive statistics calculated above, we expect that both assumptions are violated. We also performed an Anderson-Darling test as well as Levene's test. The Anderson-Darling test is a goodness-of-fit test which is typically used to determine whether the data follows a normal distribution, especially if the data contains a high number of observations. The Levene's test checks for the homogeneity of variances (homoscedasticity). Both tests are significant on 0.001-alpha level. Since both assumptions for the ANOVA are violated, we should instead opt for a non-parametric alternative. In this case, we will use Wilcoxon rank sum tests (using Bonferroni correction; also see Chapter 2).

Hypothesis 1 states that 'conspiracy theory' has significantly lower sentiment values than 'theory'. To test this, we need to subset the data and specify a one-sided two-sample Wilcoxon test as follows:

```
h1_data <- filter(corpus, target_phrase %in% c("conspiracy theory", "theory"))
h1_data$target_phrase <- as.factor(h1_data$target_phrase)
> levels(h1_data$target_phrase)

[1] "conspiracy theory" "theory"

> wilcox.test(sentiment ~ target_phrase, data = h1_data, alternative = "less")

        Wilcoxon rank sum test with continuity correction

data:  sentiment by target_phrase
W = 66408276, p-value < 2.2e-16
alternative hypothesis: true location shift is less than 0
```

On l.212, we subset the data including only ‘conspiracy theory’ and ‘theory’, assigning the subset to <h1_-data>. The group variable, <h1_data$target_phrase>, then gets coerced to a factor (l.213), with the group levels ordered as specified on l.214. The Wilcoxon test is calculated on l.215, where we specify the formula ($y \sim x$), the data (<h1_data>), and the alternative hypothesis, i.e. that the mean for ‘conspiracy theory’ is less than the mean for ‘theory’. The alternative hypothesis follows the order of the factor levels, which is why it is important to check whether the order is correct (l.213–14). The output of the test shows that the null hypothesis has to be rejected on 0.001-alpha level (p-value $< 2.2 \cdot 10^{-16}$) in favour of the alternative hypothesis. In other words, Hypothesis 1 cannot be rejected.

Hypothesis 2 states that the terms ‘conspiracy theory’, ‘conspiracy theories’, and ‘conspiracy theorist’ each have significantly lower adjectival sentiment scores than ‘conspiracy’. Hence, we have to subset the data by dropping the data for ‘theory’ (l.220), since it is not part of the hypothesis. Hypothesis 2 is one-sided, as it states a direction for the group differences, i.e. ‘conspiracy’ has a significantly higher average adjectival sentiment score than the other terms. Thus, we will perform a one-sided pairwise Wilcoxon test, which will test that for each group pair Y–X, X is lower than Y. For this, it is important that ‘conspiracy’ is the first level (l.221–222). The test is detailed on l.223:

```
218 library(rstatix)
219 library(coin)
220 h2_data <- filter(corpus, !target_phrase == "theory")
221 h2_data$target_phrase <- as.factor(h2_data$target_phrase)
222 > levels(h2_data$target_phrase)

[1] "conspiracy"          "conspiracy theories" "conspiracy theorist" "conspiracy theory"

223 > pairwise.wilcox.test(x = h2_data$sentiment, g = h2_data$target_phrase, alternative = "less",
↪  p.adjust.method = "bonf")

        Pairwise comparisons using Wilcoxon rank sum test with continuity correction

data:  h2_data$sentiment and h2_data$target_phrase

                    conspiracy conspiracy theories conspiracy theorist
conspiracy theories <2e-16     -                   -
conspiracy theorist <2e-16     1                   -
conspiracy theory   <2e-16     1                   1

P value adjustment method: bonferroni
```

We are only interested in the leftmost column, where each row is compared to the column head (‘conspiracy’) as to whether the row has significantly lower sentiment scores than the column head. The other pairs can be ignored for our purposes. As we can see, ‘conspiracy theory’, ‘conspiracy theories’, and ‘conspiracy theorist’ each indeed have significantly lower adjectival sentiment scores than ‘conspiracy’, on 0.001-alpha level (p-value $< 2 \cdot 10^{-16}$). Thus, Hypothesis 2 cannot be rejected.

It is also advised to report the effect sizes (also see Chapter 1), i.e. the magnitude of group differences. This is, a big sample size often leads to significant group differences, all the while the effect sizes remain very small. Hence, for a comprehensive assessment of the differences, we should compute the effect sizes using the `wilcox_effectsize()`-function (from the `rstatix`-package[46] (Kassambara 2021) loaded on l.218):

```
224 > wilcox_effsize(data = h2_data, formula = sentiment ~ target_phrase, alternative = "less", p.adjust.method
↪  = "bonf")[1:3,]

# A tibble: 3 x 7
  .y.       group1     group2              effsize    n1    n2 magnitude
  <chr>     <chr>      <chr>                 <dbl> <int> <int> <ord>
1 sentiment conspiracy conspiracy theories  0.248  15032  5400 small
2 sentiment conspiracy conspiracy theorist  0.125  15032  1949 small
3 sentiment conspiracy conspiracy theory    0.0923 15032  5049 small
```

The effects are small to medium (0.092 – 0.248).

[46] The `coin`-package (Hothorn et. al. 2021) loaded on l.219 is a dependency of the `rstatix`-package and has to be loaded separately.

Hypothesis 3 states that the average adjectival sentiment scores for the terms 'conspiracy theory', 'conspiracy theories', and 'conspiracy theorist' are each significantly below the midpoint (i.e., smaller than 0); the average value for 'theory' is significantly above the midpoint. For this, we specify a one-sided test for each target phrase with the null hypothesis that the average sentiment is equal to 0:

```
wilcox.test(corpus$sentiment[corpus$target_phrase == "conspiracy theory"], alternative = "less", mu = 0)
wilcox.test(corpus$sentiment[corpus$target_phrase == "conspiracy theories"], alternative = "less", mu = 0)
wilcox.test(corpus$sentiment[corpus$target_phrase == "conspiracy theorist"], alternative = "less", mu = 0)
wilcox.test(corpus$sentiment[corpus$target_phrase == "theory"], alternative = "greater", mu = 0)
```

Every test is significant on 0.001-alpha level. Thus, Hypothesis 3 cannot be rejected.

To sum up, we cannot reject any of the three hypotheses.

5.5 Discussion

In this section, we guided you through various processes of a computational corpus analysis of the term 'conspiracy theory'. We started building our own corpus by collecting data from Reddit via the Pushshift Reddit API. After we compiled our corpus, we annotated our corpus syntactically, extracted the target features, and annotated the corpus with sentiment scores from VADER.

The statistical analysis we ran on the data delivered the expected results. 'Conspiracy theory' not only seems to be a negative evaluative term, we also cannot explain its negative evaluative function through any of its composite terms. Our conclusion cannot be rejected based on the objection that our corpus is not representative of ordinary talk or that our database is too small. Furthermore, our analysis is less susceptible to biases given the coding of adjectives, but relies on the automated annotation of a sentiment annotation algorithm.

Consequently, while our conclusion is similar to the conclusion we arrived at by the end of Section 4, we can now more confidently argue in favor of the thesis that 'conspiracy theory' is indeed an evaluative term. That said, other objections might be forthcoming that need further collection of data or at least certain adaptations in the design of our corpus analysis.

6 Conclusion

Philosophers have begun applying corpus-analytic methods on a wide range of philosophical topics. The results of those studies already had a significant impact on current debates in fields such as epistemology, philosophy of mind, and moral philosophy. At the same time, however, most philosophers so far shy away from doing corpus analysis themselves. Arguably, the two main reasons for this are simply unawareness of how easy it is to access large corpora, as well as a perceived difficulty in developing corpus-based hypotheses. In this paper we have introduced easy-access corpora, highlighted similarities in the approaches researchers have used to illuminate philosophical problems via corpus-analytic tools, and ran various corpus analyses for the term 'conspiracy theory' on pre-built corpora as well as our own corpus, which we compiled from reddit comments. We hope many philosophers will follow in making the most of the existing tools as well as contributing to the development of this exciting field. There is no better time to start your own corpus study.

7 Appendix

This appendix lists the correct answers to the exercises from Section 2. Please note that COCA is a dynamic corpus and is expanded on a regular basis. Thus, the results you get might diverge from the results at the time this chapter was written (Summer 2022). Although the numbers might be different, the outcome should not be vastly different.

- Exercise 1: 39

- Exercise 2: The most frequent nouns appearing after ‘talking about’ (insert <talking about NOUN>) are ‘people’, ‘things’, and ‘sex’. The most frequent adjectives appearing before ‘thinking’ (insert <ADJ thinking>) are ‘critical’, ‘wishful’, and ‘creative’.
- Exercise 3: The chart function on COCA reveals that since the beginning of the millenia, the term ‘robot’ has been used more frequently, but has not increased much within the last 20 years. While the term ‘conservative’ has seen as steady rise in its use till the 1980s, the frequency of the term ‘liberal’ has decreased over the last 200 years.
- Exercise 4: The most common adjectival collocates of the term ‘happiness’ are ‘true’, ‘human’, ‘personal’, ‘happy’, and ‘eternal’.
- Exercise 5: One interesting qualitative difference between ‘praising’ and ‘blaming’ is that ‘praising’ seems to be more frequently used in a religious setting, whereas ‘blaming’ is primarily used in worldly settings. People seem to be saying that they are afraid of flying and heights, but not that they are frightened of flying and heights (don’t forget to put in NOUN in the collocates box).

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