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Competing Constructions for German Measure Noun Phrases: from Usage Data to Experiment

Abstract: In this paper, a case alternation in German measure noun phrases is examined from the perspective of cognitively oriented corpus linguistics. In certain pseudo-partitive constructions, the embedded kind-denoting noun either agrees in its case with the measure head noun (*eine Tasse guter Kaffee* ‘a cup of good coffee’) or it stands in the genitive (*eine Tasse guten Kaffees*). My analysis is formulated in terms of Prototype Theory. I assume that the choice of alternants is influenced by non-alternating neighbouring constructions representing the prototypes more directly. I argue that the frequencies with which individual lemmas occur in these prototypical non-alternating constructions partially predict which alternant is chosen and that the genitive alternant is prototypical of strongly grammaticalised measure nouns. I present a large-scale corpus study using the DECOW corpus to support this theory. In the statistical analysis, I compare Maximum Likelihood estimators to Bayesian estimators (recently proposed for similar studies), showing that results *predictably* do not differ. Finally, two experiments (forced choice and self-paced reading) are reported. The usage-based findings show a clear correlation with the behaviour of cognitive agents in both experiments. The present study therefore contributes to the well-established field of research into alternations using corpus and experimental methods.

Keywords: corpus methods and experimental methods, alternations, hierarchical models, pseudo-partitives, German

1 Cognitively oriented corpus linguistics

This paper deals with a morpho-syntactic alternation between two constructions that occurs only in a very specific type of measure noun phrase in German. By *alternation* I refer to a situation where two or more forms or constructions are available with no clear difference in acceptability, function, or meaning. The study of alternations has a long history in cognitively oriented corpus linguistics.

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tics (Bresnan et al., 2007; Bresnan & Hay, 2008; Bresnan & Ford, 2010; Divjak & Arppe, 2013; Gries, 2015a; Nessel & Janda, 2010, to name just a few publications). This area of research is based on the assumption that language is a probabilistic phenomenon (Bresnan, 2007) where alternants are chosen neither deterministically nor fully at random. Instead, multifactorial models are constructed which incorporate influencing factors from diverse levels, including contextual factors. The estimation of the model coefficients quantifies the influence that the factors have on the probability that either alternant is chosen.

For such probabilistic generalisations estimated on corpus data, there has always been an interest in correlating the findings with results from experimental work (for example, Arppe & Järviö, 2007; Bresnan et al., 2007; Bresnan & Ford, 2010; Divjak & Gries, 2008; Divjak et al., 2016; Ford & Bresnan, 2013). This is often called a *validation* of the corpus-derived findings, but Divjak (2016, 303) rightly criticises this choice of words “because it creates the impression that behavioral experimental data is inherently more valuable than textual data,” citing Tummers et al. (2005), who state that a corpus is “a sample of spontaneous language use that is (generally) realized by native speakers.” However, as Dąbrowska (2016, 486–487) convincingly argues, this does not imply that we can in some way “deduce mental representations from patterns of use,” i. e., from corpus data.¹ It would be highly surprising if this were possible and the same holds for experimental methods. Nobody assumes that we can inductively infer mental representations from experiments, which – as opposed to corpus studies – even allow for direct access to the cognitive agent and offer much better possibilities to control experimental conditions and nuisance variables. Rather, under the standard approach, a theory of cognitive representation is pre-specified. Then, predictions are derived from this theory *before* the experiment or the corpus study is conducted to *test* the theory. Technical problems of statistical inference aside, a successful experiment corroborates the theory, and a failed experiment weakens the theory. The simplest assumption would be that the same approach is adequate for corpus studies.

The present study is conducted within the general paradigm of cognitive corpus linguistics and includes a comparison of the corpus findings with results from two experiments. As a theoretical framework, I assume a model of similarity-based classification in the form of Prototype Theory. Prototype Theory has been used in alternation research in cognitively oriented corpus linguistics (see Divjak & Arppe, 2013, Gries, 2003). It is assumed that the variables an-

¹ In its colloquial meaning, the verb *deduce* seems appropriate here. However, in terms of the scientific method, we are most likely talking about *induction* rather than *deduction*.

notated in a corpus study on an alternation phenomenon define prototypes for the alternants. The similarity of a given feature vector (in a concrete sentence where one of the alternants is used) influences to a large extent which alternant is chosen by speakers. This entails that a variant of Prototype Theory with features is assumed (Rosch, 1978), instead of the monolithic prototypes of earlier versions. Prototype Theory is well suited for modeling constructional choices but it is just one of several similarity-based theories of classification, the most prominent other framework being Exemplar Theory (Medin & Schaffer, 1978; Hintzman, 1986; see Storms et al., 2000 for a comparison of the theories in experimental settings). Prototype Theory and Exemplar Theory model essentially the same types of effects and differ mainly in whether they assume higher-level abstractions as part of the cognitive representation (Prototype Theory) or try to do without them (Exemplar Theory). I am sceptical that corpus analysis alone could ever decide which theory is more suitable, given that substantial doubt has been voiced whether even experimental methods are ultimately able to do so (Barsalou, 1990).² Prototype Theory (with feature abstractions) is preferred here simply because it fits the established alternation modeling paradigm, which relies on features being weighted in statistical models. In Section 2.2, a prototype-theoretical parlance is therefore adopted.

In the remainder of the paper, I introduce the alternation phenomenon (Section 2.1) and suggest a theory-driven set of factors influencing the alternation (Section 2.2). Then the corpus study is presented, including an appropriate statistical analysis (Section 3). Two experiments that correlate results from the corpus study with experimental results are then reported (Section 4) before I sum up the paper in Section 5.

2 Case assignment in German measure NPs

2.1 Two stable cases and a case alternation

In this section, I introduce and illustrate the relevant alternating constructions. I describe the narrowly defined syntactic configuration in which the alternation occurs and I motivate the focus on *only* this narrow range rather than, for example, the whole range of nominal constructions expressing quantities.

² In Divjak & Arppe (2013), it was shown using corpus data how both models form a converging picture.

I use the term *measure noun phrase* (MNP) to refer a noun phrase (NP) in which a kind-denoting (count or mass) noun depends on another noun that specifies a quantity of the objects or the substance denoted by the kind-denoting noun. I call the kind-denoting noun the *kind noun* and the quantity-denoting noun the *measure noun*. For illustration purposes, in the English *a glass of good wine*, *glass* is the measure noun and *wine* is the kind noun. Measure nouns can be all sorts of nouns which denote a quantity (such as *litre* or *amount*) but also those denoting containers, collections, etc. (such as *glass* or *bucket*). Like Brems (2003, 284), I consider nouns as measure nouns “which, strictly speaking, do not designate a ‘measure’, but display a more nebulous potential for quantification” (also Koptjevskaja-Tamm, 2001, 530, and Rutkowski, 2007, 338).

In the case at hand, three different syntactic configurations need to be distinguished with regard to case assignment inside German MNPs. If the kind noun forms an NP with a determiner, the construction resembles (and is usually called) a *pseudo-partitive* (on partitives and pseudo-partitives see, e. g., Barker, 1998; Selkirk, 1977; Stickney, 2007; Vos, 1999; for a recent application of the terminology to German, see Gerstenberger, 2015).³ Here, the kind noun is in the genitive, and I refer to the construction in (1) as the *Pseudo-partitive Genitive Construction* (PGC).

- (1) Wir trinken [[ein Glas]_{Acc} [dieses Weins]_{Gen}]_{Acc}.
 we drink a glass this wine
 We drink a glass of this wine.

If the kind noun is bare – i. e., if it comes neither with a determiner nor a modifying adjective – it has to agree in case with the measure noun as in (2a), and the genitive as seen in the PGC is not acceptable, see (2b).

- (2) a. Wir trinken [[ein Glas]_{Acc} [Wein]_{Acc}]_{Acc}.
 we drink a glass wine
 We drink a glass of wine.
 b. *Wir trinken [[ein Glas]_{Acc} [Weins]_{Gen}]_{Acc}.

3 If the kind noun is definite, the construction instantiates a true partitive. Whereas partitives are constructions denoting a proper part-of relation as in *a sip of the wine*, pseudo-partitives – albeit syntactically similar and diachronically related to partitives in many languages – merely denote quantities and contain indefinite kind nouns as in *a sip of wine*. In the literature on German, some authors incorrectly call the pseudo-partitive a *partitive* (Hentschel, 1993) while some realise the difference and at least mention it (Eschenbach, 1994; Gallmann & Lindauer, 1994; Löbel, 1989; Zimmer, 2015).

kind NP is:	bare noun NP [...N _{meas} [N _{kind}]]	NP with adjective [...N _{meas} [AP N _{kind}]]	NP with determiner [...N _{meas} [D N _{kind}]]
narrow apposition	NAC _{bare} (2a) <i>Glas Wein</i>	NAC _{adj} (3b) <i>Glas guten Wein</i>	—
pseudo-partitive genitive	—	PGC _{adj} (3a) <i>Glas guten Weins</i>	PGC _{det} (1) <i>Glas dieses Weins</i>

Table 1: Distribution of the NAC and PGC constructions in different NP structures with examples and references to full example sentences

This construction is usually classified as a *Narrow Apposition Construction* (Löbel, 1986), henceforth NAC.⁴ Notice that the unavailability of the genitive on the kind noun can be seen as following from a rather quirky constraint that genitive NPs in German require the presence of some strongly case-marked element (determiner or adjective) in addition to the head noun in order to be acceptable (Gallmann & Lindauer, 1994; Schachtl, 1989; see also Eisenberg, 2013, 160).

The alternation can be observed *only when the kind noun occurs with an attributive adjective but without a determiner*, as in (3), where both the PGC in (3a) and the NAC in (3b) are equally acceptable. They are by-and-large functionally and semantically equivalent. However, Section 2.2 is devoted to developing hypotheses about subtle differences between them.⁵

- (3) a. Wir trinken [[ein Glas]_{Acc} [guten Weins]_{Gen}]_{Acc}.
 we drink a glass good wine
 We drink a glass of good wine.
- b. Wir trinken [[ein Glas]_{Acc} [guten Wein]_{Acc}]_{Acc}.

The distribution of the case patterns in the NAC (case identity between the measure noun and the kind noun) and in the PGC (genitive on the kind noun,

⁴ The construction as in (2a) is also referred to as the *Direct Partitive Construction* for other Germanic languages in which the PGC with the synthetic genitive is not available. This nomenclature makes sense in contrast to the *Indirect Partitive Construction* with prepositional linkers translating to *of* – i.e., analytic genitives – in such languages, see Hankamer & Mikkelsen (2008) for Danish. For German, this terminology is not distinctive enough, which is why I use the terms NAC and PGC.

⁵ Some descriptive and normative grammars take stronger positions with regard to the acceptability of the two options. See Hentschel (1993) and Zimmer (2015) for analyses of the sometimes absurd stances taken in grammars of German. As the usage and experimental data presented below (especially Section 4.1) should render it clear, there might be preferences, but we cannot assume either construction to be unacceptable.

regardless of the case of the measure noun) depending on the structure of the kind NP is summarised in Table 1. I call the narrow apposition construction with a bare kind noun the NAC_{bare} and the partitive genitive with a determiner in the kind NP the PGC_{det} . For the alternants with an adjective but no determiner in the kind noun phrase I use the terms NAC_{adj} and PGC_{adj} . In principle, this paper is about the middle column of Table 1, i. e., the syntactic configuration in which two different case patterns are acceptable. However, in Section 2.2, the outer columns (NAC_{bare} and PGC_{det}) will still play a major role when the factors controlling the alternation are named.

I now turn to some more subtle issues related to the measure noun case alternation, namely:

- i. alleged alternatives to the NAC_{adj} and the PGC_{adj} ,
- ii. similar constructions with plural/collective kind nouns,
- iii. grammaticalised non-inflected measure nouns, and
- iv. alternative constructions for expressing quantities.

First of all, (i) refers to claims found in some grammars that a generic nominative, accusative, and even dative on the kind noun are used instead of the genitive (PGC_{adj}) or case agreement (NAC_{adj}). Overviews can be found in Hentschel (1993) and Zimmer (2015). Sentence (4) shows a putative generic nominative on the kind noun inside an accusative MNP.

(4) * Wir trinken [[eine Tasse]_{Acc} [heißer Kaffee]_{Nom}]_{Acc}.

It was shown empirically in Hentschel (1993) that such sentences are de facto not acceptable. Also, in my corpus sample, they simply did not occur. Even if they are accepted by some speakers, their extremely low frequency makes it virtually impossible to study them using corpus linguistic methods (Section 3) and I consequently ignore them.

Turning to (ii), readers might have noticed that so far only MNPs denoting quantities of substances (mass kind nouns such as *ein Glas roter Wein/roten Weines* ‘a glass of red wine’) have been discussed. If the kind noun is a plural count noun as in *ein Sack kleine Äpfel* (NAC_{adj}) or *ein Sack kleiner Äpfel* (PGC_{adj}) ‘a bag of small apples’, a similar alternation between PGC and NAC can be observed. In line with experimental results reported in Zimmer (2015, 15–16), I found that the PGC is so dominant with plural kind nouns (794 of 861 cases, or over 92%, cf. Section 3) that the alternation cannot be analysed in the same way as in the singular. While this will play a role in the interpretation of the corpus findings, MNPs with plural kind nouns will not be included in the corpus study and the experiments reported in Sections 3 and 4.

As for (iii), some measure nouns have been grammaticalised in a way that they always appear in their non-inflected form. They are typical measure nouns like *Gramm* ‘gram’, *Pfund* ‘pound’ or *Prozent* ‘percent’, which have no normal plural forms at all.⁶ I treat these cases like other measure nouns because they enter into both the NAC_{adj} as in (5a) and the PGC_{adj} as in (5b). In Section 2.2, however, degrees of grammaticalisation as a factor influencing the alternation will be discussed prominently.

- (5) a. zwei Gramm brauner Zucker
 b. zwei Gramm braunen Zuckers
 two gram brown sugar
 two grams of brown sugar

Finally, (iv) suggests that there are alternative ways of expressing similar quantificational meanings. In the variationist tradition, which is strongly influenced by Labovian sociolinguistics, the *principle of accountability* would dictate that proper studies should examine a variationist *variable*, i. e., all different *ways of saying the same thing* (Labov, 1966, Labov, 1969, for an overview see Tagliamonte, 2012). In the case at hand, the variable might be something like *measuring quantities of substances and collections*. I argue that it is fully justified to focus narrowly on NAC_{adj} and PGC_{adj} with their well-defined morpho-syntactic properties, mostly because the alternative constructions are not used in the same range of contexts. Two major alternatives might be considered. First of all, the analytic (pseudo-)partitive with *von* ‘of’ is only available as an alternative to the PGC if the kind noun phrase contains a (definite or indefinite) determiner as in (6).

- (6) a. ein Glas von dem roten Wein
 a glass of the red wine
 a glass of the red wine
 b. *ein Glas von rotem Wein
 a glass of red wine
 a glass of red wine

This means that the *von* (pseudo-)partitive does not compete with the NAC_{adj} and the PGC_{adj} . In fact, there is not a single context in which they can be interchanged.

⁶ Plurals like *Pfunde* and *Prozente* have special meanings and have very restricted uses, mostly in idiomatic expressions and prefabs such as *Pfunde verlieren* ‘lose pounds.’ They cannot be used in normal MNPs.

Second, constructions with *voll (von)/voller* ‘full (of)’ and *mit* ‘with’ are available, see (7).

- (7) a. ein Glas voll von rotem Wein
 a glass full of red wine
 a glass full of red wine
- b. ein Glas voll/voller rotem/roter Wein
 a glass full-of red wine
 a glass full of red wine
- c. ein Glas mit rotem Wein
 a glass with red wine
 a glass with red wine in it/a glass filled with red wine

These construction have very idiosyncratic properties. The construction with *voller* is discussed in Zeldes (to appear) and the construction with *mit* is discussed in Bhatt (1990). They are not semantically equivalent to the NAC and the PGC and they are only available for a small subset of measure nouns. All of these constructions are used only with measure nouns denoting containers, where the whole NP always refers to the container and never to the quantity contained in it. They are consequently incompatible with measure nouns denoting natural portions such as *Schluck* ‘gulp’ or *Haufen* ‘heap’ and strongly grammaticalised nouns such as *Gramm* ‘gram’. This disqualifies them as alternatives to the NAC_{adj} or PGC_{adj} in most contexts and they are thus decidedly *not* more ways of saying the same thing. It is therefore reasonable to focus on the two well-defined alternants.

This concludes the descriptive overview of the phenomenon. I have demonstrated that there is an alternation between two measure noun constructions in a narrow syntactic configuration (kind NP with an adjective but without a determiner), and that the two constructions differ in the case of the kind noun (case agreement with the measure noun or genitive). I turn to more theory-oriented discussion in the next section.

2.2 Factors controlling the alternation

This section briefly reviews existing analyses of the PGC_{adj} vs. NAC_{adj} alternation and related issues. I also develop my own analysis and the appropriate hypotheses for the empirical studies presented in Sections 3 and 4. I discuss four main aspects: first, the different syntactic structures of the alternants NAC_{adj} and PGC_{adj} in relation to their syntactic prototypes NAC_{bare} and PGC_{det} ; second, degrees of grammaticalisation of the measure noun associated with the two

prototypes; third, a semantic prototypicality effect of the degrees of grammaticalisation (a preference to occur with cardinals); fourth, preferences in different registers.

First, my analysis is based on the idea that in the relevant syntactic structure $[N_1 [A N_2]_{NP_2}]_{NP_1}$ (as instantiated in the NAC_{adj} and the PGC_{adj}), the adjective is morpho-syntactically ambiguous between a determiner and a modifying adjective. To show this, the strong/weak inflection patterns of adjectives needs to be taken into account. In NPs with a strongly inflected determiner, attributive adjectives inflect according to the massively syncretic *weak* pattern. If there is no determiner (as is the case in the alternating constructions), attributive adjectives inflect like determiners themselves. This is called the *strong* inflectional pattern. For example, in the dative (governed here by the preposition *mit*), the strong suffix *-em* is on the determiner in (8a) and the adjective bears the weak suffix *-en*. In (8b), the strong suffix *-em* appears on the adjective because there is no determiner.

- (8) a. mit ein-**em** stark-**en** Kaffee
 with a strong coffee
- b. mit stark-**em** Kaffee
 with strong coffee

Thus, the adjectives in the NAC_{adj} and the PGC_{adj} have properties of adjectives as well as determiners. On the one hand, they are lexical adjectives and function as attributive modifiers. On the other hand, they are inflected like determiners, and they are the leftmost element in the NP, which is typical of determiners. This unusual double nature of adjectives in NPs without determiners leads to a plausible probabilistic interpretation of the pattern shown in Table 1. Whenever speakers classify the adjective in the kind noun phrase more as a determiner, they have to use the PGC_{adj} because, if there is a determiner, the PGC is the only option. When they classify the adjective more as an adjective, the kind NP has no determiner, and they have to use the NAC_{adj} .⁷

This morpho-syntactic ambiguity means that the NAC_{adj} is in fact a NAC_{bare} in disguise, and the PGC_{adj} is a PGC_{det} in disguise. This should ideally be reflected in the following basic selection effect: It is known from frameworks like Collostructional Analysis (Gries & Stefanowitsch, 2004) that lemmas are attracted with different strengths by constructions. If the NAC_{adj} is

⁷ While the generative analysis presented in Bhatt (1990) cannot properly deal with probabilistic effects, Bhatt comes close to this interpretation by analysing the kind NP in the PGC as a DP and in the NAC as an NP.

highly similar to the NAC_{bare} and the PGC_{adj} is highly similar to the PGC_{det} , the probability with which individual noun lemmas appear in the alternating constructions should be predictable at least in part from the relative frequency with which the same lemmas are used in the non-alternating constructions. Nouns which occur proportionally more often in the PGC_{det} should favour the PGC_{adj} , and nouns which occur proportionally more often in the NAC_{bare} should favour the NAC_{adj} . This basic attraction effect will be used in the corpus study Section 3.

In a probabilistic framework like Prototype Theory, the crucial question (beyond simple lemma preference effects) is, however, what controls speakers' decisions to use either alternant. In the remainder of this section, I argue that the NAC and the PGC are prototypes associated with different degrees of the grammaticalisation of the measure noun and related morpho-syntactic properties, as well as register effects. The degree of similarity of a given instance to either of the two prototypes makes speakers chose the NAC_{adj} or the PGC_{adj} .

Second, therefore, I focus on grammaticalisation. It is often assumed that pseudo-partitives arise as a form of grammaticalised partitives (e.g., Koptjevskaja-Tamm, 2001, 536–539 for Finnish and Estonian, Koptjevskaja-Tamm, 2001, 559 for European languages in general). The grammaticalisation paths uncovered by Koptjevskaja-Tamm (2001, esp. 526–530) are relevant for the case at hand. The grammaticalisation path can start out (in some languages) with constructions involving two referential nouns (not necessarily forming a single and contiguous NP) and a *separative* meaning as in (*cut*) *two slices from the cake* (Koptjevskaja-Tamm, 2001, 535). The *part-of* meaning of true partitives as in *a slice of the cake* represents the first stage of a development wherein the measure noun can already lose some semantic content, when for example words like *bite* are no longer necessarily interpreted as a piece literally bitten out of something. The pseudo-partitive stage finally instantiates a *quantity-of* relation, potentially even leading to fully grammaticalised quantifiers such as *a lot*. In German, the PGC is clearly the older construction (Zimmer, 2015). It still has the potential to form a true partitive (if the kind noun is definite). Conversely, the NAC lacks this ability to form true partitives, and it thus forms the more prototypical environment for expressing measurement (as opposed to partitivity). Hence, we can expect the NAC_{adj} to be a prototypical hosting construction for more strongly grammaticalised measure nouns. For example, highly grammaticalised non-referential nouns like *Gramm* 'gram' and *Meter* 'metre' should occur proportionally more often in the NAC_{adj} than in the PGC_{adj} .

Third, as described above, the grammaticalisation path leads from NPs denoting individuated objects standing in a *part-of* relation to a construction with a more diffuse *quantity-of* relation. Both types of relations can be numerically

quantified – inasmuch as a precise number of *parts* or a numerically exact *quantity* can be specified. However, it is much more prototypical of quantities to be specified with numerical precision. This is most obviously so with the highly grammaticalised physical measure nouns like *centilitre* which are very prototypically used with exact numeral instead of unspecific quantifiers, although both options are available (*three centilitres* vs. *several centilitres*). Since the NAC_{adj} is more closely associated with the *quantity-of* relation, cardinals as attributes of the measure noun are expected to have a higher proportional frequency in the NAC_{adj} . For illustration, (9) shows the expected alternants under this hypothesis.

- (9) a. [[Drei Centiliter] $_{\text{Nom}}$ [heißer Rum] $_{\text{Nom}}$] $_{\text{Nom}}$ sind genug.
 three centilitres hot rum are enough
 Three centilitres of hot rum is enough.
- b. [[Einige Centiliter] $_{\text{Nom}}$ [heißen Rums] $_{\text{Gen}}$] $_{\text{Nom}}$ sind genug.
 some centilitres hot rum are enough
 A few centilitres of hot rum is enough.

In (9a), the measure noun is modified by a cardinal *drei* ‘three’, and hence the NAC_{adj} is preferred. In (9b), the measure noun is modified by a non-cardinal determiner *einige* ‘some’, and the PGC_{adj} is preferred. Especially with abstract physical measure nouns (like *centilitre*), exact numerical quantification is invited. By hypothesis, however, this goes beyond a selection effect tied to measure lemmas and cardinal quantifiers are expected to co-occur relatively more often with the NAC_{adj} . The statistical model presented in Section 3 will be specified in a way that it can detect such a preference.

Fourth and finally, it was found that the PGC_{adj} is more typical of higher registers or even exclusive to written language (see Hentschel, 1993, 320–323). This is not surprising, given that the genitive – an intrinsic part of the PGC – is generally underrepresented in colloquial vernacular variants of German as a result of a diachronic process wherein many (but by no means all) uses of the genitive are replaced by other cases or periphrastic constructions (Fleischer & Schallert, 2011). Under an integral view of prototypes, which incorporate effects related to larger contexts and registers, such preferences can be part of what defines the construction prototypes. In the corpus study in Section 3, register effects will therefore be modelled – even if only using two very simple proxy variables.

To summarise the discussion and core hypotheses, I assume that the alternation is controlled by the similarity of the chosen lemmas (including the degree of grammaticalisation of measure nouns), certain morpho-syntactic choices, as well

as the larger utterance context to two prototypes instantiated more straightforwardly by the two non-alternating cases of NAC and PGC. Concretely:

- i. The relative frequencies with which measure noun lemmas and kind noun lemmas appear in the prototypical (non-alternating) PGC_{det} and NAC_{bare} are predictive of the probability with which the alternating PGC_{adj} and the NAC_{adj} are chosen.
- ii. (Classes of) more strongly grammaticalised measure nouns favour the NAC_{adj} .
- iii. Measure nouns modified by cardinals favour the NAC_{adj} .
- iv. The PGC_{adj} is associated with higher registers.

In the next section, I report the corpus study that was designed to test these hypotheses on usage data. The resulting models will then be compared to experimental methods in Section 4.

3 Corpus study

3.1 Corpus choice and sampling

For the present study, I used the German *Corpus from the Web* (COW) in its 2014 version DECOW14A (Schäfer & Bildhauer, 2012, and Schäfer, 2015, as well as Biemann et al., 2013, and Schäfer & Bildhauer, 2013, for overviews of web corpora in general and the methodology of their construction), which contains almost 21 billion tokens.⁸ I chose this corpus for two main reasons.⁹ First, the external validity of any study is increased through a higher heterogeneity of the sample (Maxwell & Delaney, 2004, 30), and the DECOW corpus has clearly a much more heterogeneous composition compared to the only other very large

⁸ The COW corpora (Dutch, English, French, German, Spanish, Swedish) are made available for free at <https://www.webcorpora.org>. At the time of this writing, a newer 2016 version DECOW16 has already been released.

⁹ The use of web data for linguistic research does require explicit and careful justification. Due to the noisy nature and unknown composition of the web, only carefully designed and established web corpora like the COW corpora or the SketchEngine corpora (Kilgariff et al., 2014) should be used. Clearly, using search engine results is “bad science” for many reasons, most prominently total irreproducibility of results, as Kilgariff (2006) pointed out more than ten years ago. Careless use of search engine results is still found, however, see for example De Clerck & Brems (2016, 171–175).

corpus of German, the DeReKo (Kupietz et al., 2010) of the Institute for the German Language (IDS), which contains almost exclusively newspaper texts.¹⁰ Second, it was already mentioned that normative grammars often adopt clear positions regarding the grammaticality of either the NAC_{adj} or the PGC_{adj} . Thus, newspaper text or any other text that conforms strongly to normative grammars might not represent the alternation phenomenon fully (and without bias) because authors and proofreaders who must adhere to normative guidelines might favour one alternative or the other explicitly. Web corpora, on the other hand, contain at least some amount of non-standard language from forums and similar sources. For these or similar reasons, COW corpora have been used in a number of peer-reviewed publications, for example Goethem & Hiligsmann (2014), Goethem & Hüning (2015), Müller (2014), Schäfer (2016 aop), Schäfer & Sayatz (2014), Schäfer & Sayatz (2016), and Zimmer (2015). Therefore, DECOW is the obvious choice for this study.

I now turn to the sampling procedure applied to obtain concordances for manual annotation and statistical analysis. Among the factors potentially influencing the alternation (see Section 2) were lemma-specific preference effects. Therefore, it was highly desirable to obtain a sample in which most of the highly frequent actually-occurring combinations of kind nouns and measure nouns were represented. I applied a three-stage process in order to obtain such a sample, which consisted of the following steps:

- i. generating a list of the one hundred most frequent mass nouns,
- ii. deriving a list of all measure nouns with which the mass nouns co-occur in the NAC_{bare} , and
- iii. sampling the target constructions by querying each combination of mass noun and measure noun found in step (ii).

In step (i), I exported a list of all nouns in the DECOW14A01 sub-corpus sorted by their token frequency and manually went through it from the most frequent noun downwards, selecting the first one hundred mass nouns that occurred in the list.¹¹ Abstract nouns which partially behave like mass nouns (like *Spaß* ‘fun’ or *Gefahr* ‘danger’) were excluded because they are usually not quantified in the same way as concrete mass nouns. The hundredth selected mass noun

10 It was shown in Bildhauer & Schäfer (2016) that, for example, the spread of topics is much smaller in DeReKo compared to DECOW.

11 DECOW14A01 is the first slice (roughly a twentieth) of the complete DECOW14A corpus. It contains just over one billion tokens.

was *Schmuck* ‘jewellery’, which is the 3,054th most frequent noun in the original frequency list.

This resulting list of mass nouns was used in step (ii) to derive a list of measure nouns co-occurring with the mass nouns. In order to generate this list, I utilised the fact that a direct sequence of two nouns almost always instantiates the bare-noun NAC if the second noun is a mass noun. Hence, I searched for all sequences N_1N_2 where N_2 was one of the mass noun lemmas extracted in step (i). Then, the resulting 100 lists of noun-noun combinations were each sorted by frequency in descending order and sieved manually to remove erroneous hits. From each of the 100 lists, I also removed noun-noun combinations that had a frequency below 2, except if the individual list would have otherwise been shorter than 20 noun-noun combinations. The result was a list of the most frequent 2,365 individual combinations of a measure noun and a mass noun.

In step (iii), each of these 2,365 noun–noun combinations was queried in the target constructions (PGC_{adj} and NAC_{adj}) individually in each of the first ten slices of DECOW (roughly 10 billion tokens). In order to reduce the sample size for the manual annotation process, the final concordance was sampled from the results of these 2,365 queries. Since the mass nouns in the sample were distributed according to the usual power law, I used all hits for nouns with a frequency up to 100 and a sample of 100 of all those with higher frequency. The final sample contained 6,843 sentences, which was reduced to 5,063 in the manual annotation process due to removal of noisy material, erroneous hits and uninformative cases where the measure noun was in the genitive, in which case the NAC_{adj} cannot be distinguished from the PGC_{adj} . Given the careful sampling procedure described in this section, we can be highly sure that it contains all relevant and reasonably frequent noun–noun combinations in the target constructions.¹²

Finally, two auxiliary samples were also drawn. As mentioned in Section 2.2, the distribution of the measure noun and kind noun lemmas in the NAC_{bare} and the PGC_{det} with a determiner will be modelled as factors influencing the alternation. Therefore, all noun-noun pairs from the process described above were also queried in the two non-alternating constructions, resulting in 17,252 hits for the PGC_{det} and 315,635 hits for the NAC_{bare} .

¹² In a similar fashion, the 100 most frequent measure nouns occurring with plural kind nouns were listed and queried, resulting in a sample of 871 sentences. As stated in Section 2, the NAC_{adj} is virtually never used with plural kind nouns, and this sample was not used except for quantifying the frequency of occurrence of the constructions (67 times NAC_{adj} and 794 times PGC_{adj}). However, the sample is distributed in the data package accompanying this paper.

Unit of reference	Variable	Type	Levels (for factors only)
Document	Badness	numeric	
	Genitives	numeric	
Sentence	Cardinal	factor	Yes, No
	Construction (response)	factor	NACa, PGCa
	Measurecase	factor	Nom, Acc, Dat
Kind lemma	Kindattraction	numeric	
	Kindfreq	numeric	
Measure lemma	Measureattraction	numeric	
	Measureclass	factor	Physical, Container, Amount, Portion, Rest
	Measurefreq	numeric	

Table 2: Annotated variables for the main sample

3.2 Variables and annotation

The full set of manually annotated variables for the main sample is given in Table 2, and I briefly discuss it now.¹³ Notice first that *Construction* is the response variable (or ‘dependent variable’) with the values *PGCa* and *NACa*.

The variables *Kindattraction* and *Measureattraction* encode the ratio with which a given kind noun lemma or measure noun lemma occurs in the PGC_{det} and the NAC_{bare} . They were calculated from the auxiliary samples described at the end of Section 3.1 as a log-transformed quotient. The higher the value, the more often the noun occurs in the PGC_{det} (proportionally).¹⁴ Additionally, *Kindfreq* and *Measurefreq* are the logarithm-transformed frequencies per

13 All numeric variables were also z-transformed (i. e., centered to the mean and rescaled such that they have a standard deviation of 1) to facilitate their interpretation in the regression models reported in the next section.

14 It could be argued that some more advanced measure of attraction strength should be used, as is done in Collostructional Analysis (Stefanowitsch & Gries, 2003; Gries & Stefanowitsch, 2004), see also Gries (2015b). Three main points speak against such an approach in the present case. First, the goal here is to quantify how often lemmas occur in the PGC_{det} and the NAC_{bare} , and these constructions do not compete at all but are rather mutually exclusive. Collostructional approaches are not made for such scenarios. Second, the attraction values will be used as regressors in a hierarchical logistic regression and the values resulting from collostructional analysis, i. e., logarithmised Fisher p-values, have a very unfavourable distribution in the case at hand. They cluster around 0 and they include values of $-\infty$. Third, I tried using collexeme strength as a regressor (with smoothing to remedy the mathematical problems) and the results were unsatisfactory compared to the simple quotient used here.

1,000,000 words of each lemma, extracted from the frequency lists distributed by the DECOW corpus creators on their web page. They were added to control for basic frequency effects.

In Section 2.2, it was hypothesised that classes of measure lemmas might have different preferences for the two alternants. To capture this, class information was annotated for measure lemmas. The classification was inspired by the list in Koptjevskaja-Tamm (2001, 530) but due to the low frequencies of many of the potential classes, a very coarse classification was finally used. With typical examples and their frequencies in the final sample, the classes are: *Physical* (abstract precisely measurable units such as *Liter* ‘litre’, *Meter* ‘metre’, *Gramm* ‘gram’; $f=1,968$), *Container* (*Eimer* ‘bucket’; $f=740$), *Amount* (*Menge* ‘amount’; $f=1,364$), *Portion* (natural portions like *Happen* ‘bite’ or *Krümel* ‘crumb’; $f=713$). The few lemmas that did not fit into either of these classes were labelled *Rest* ($f=278$).

The variable *Cardinal* encodes whether the measure noun is modified by a cardinal ($f=1,939$) or not ($f=3,124$). The purpose of this variable is to test whether cardinals really favour the NAC_{adj} as hypothesised in Section 2.2.

To capture the influence of register or style mentioned in Section 2.2, two proxy variables were used. At the document level, the DECOW corpus has an annotation for *Badness*. As described in Schäfer et al. (2013), *Badness* measures how well the distribution of highly frequent short words in the document matches a pre-generated language model for German. Documents with higher *Badness* usually contain more incoherent language, shorter sentences, etc. If the PGC_{adj} actually favours higher registers and styles, a high *Badness* should be correlated with fewer occurrences. Documents in DECOW14 have also been annotated with a variable called *Genitives*. The higher the values of this variable, the lower the proportion of genitives among all case-bearing forms is. A high number of genitives is indicative of higher registers. However, the use of this variable as a regressor in the present study might be considered problematic. Since the PGC_{adj} contains a genitive itself, the regressor variable *Genitive* and the document-level variable *Genitives* are not fully independent. Since instances of the PGC_{adj} make up for only a minute fraction of all genitives, I still use *Genitives* as a regressor with the appropriate caveats.

Finally, one variable was added as nuisance variable in the context of the present study. It was reported in the literature that MNPs in the dative and with a masculine or neuter kind noun favour the PGC_{adj} more than the corresponding nominative and accusative MNPs (Hentschel, 1993; Zimmer, 2015). As an example, *mit einem Stück frischen Brots* ‘with a piece of fresh bread’ (PGC_{adj}) would be preferred more strongly against *mit einem Stück frischem Brot* (NAC_{adj}). As with all the examples, native speakers of German will most

likely notice that differences are subtle. To control for this effect, the case of the measure noun was manually annotated (variable *Measurecase*).

3.3 On statistical analysis

In this section, I justify the choice of statistical models which I use in Section 3.4. Readers might think that the method used here for modeling grammatical alternations – namely (Hierarchical) Logistic Regression/Generalised Linear (Mixed) Models or GL(M)Ms – does not require much justification. After all, GLMMs have been established as the major tool in the analysis of alternation phenomena. All studies mentioned at the outset of Section 1 use some form of regression/GLMM. Over the past few years, however, modified or alternative methods have been proposed. From among these methods, I just make a few remarks on Bayesian estimation (see Gelman et al., 2014) as it was proposed in Levshina (2016) and Divjak (2016), for example. Conceptually, I see three points of discussion that should be kept apart. First, Bayesian methods are sometimes touted as superior tools for scientific inference compared to frequentist methods. Second, it has been proposed that the Bayesian interpretation of probability is more cognitively adequate for the modeling of linguistic data (Divjak, 2016, 301–302). Third and very specific to this paper, given established methods in the modeling of alternation and variation, it has to be decided whether so-called Bayesian methods lead to substantially different results.

The first and second point cannot be discussed in detail here.¹⁵ With regard to the third point, Levshina (2016, 251–252) argues for Bayesian estimation in mixed regression settings. First, she claims that “while frequentist statistics only allows one to test whether the null hypothesis can be rejected, Bayesian statistics enables one both to test the null hypothesis and to estimate the probability of specific parameter values given the data.” This does not do justice to frequentist methods in that a strong focus on the rejection of the null hypothesis is characteristic only of Fisher’s approach. In the Neyman-Pearson approach, results ideally *favour* the main hypothesis vis-à-vis the alternative hypothesis (cf. Lehmann, 1993, 2011; Perezgonzalez, 2015). Also, especially Neyman-style frequentism has well-known extensions to estimation, for example in the form of

¹⁵ However, there is a number of critical papers by statisticians (even prominent Bayesians) and philosophers of science in which the extreme credibility that has recently been assigned to (subjective and automatic) Bayesian approaches (and especially the standard inductivist interpretation of Bayesianism) is questioned (for example, Gelman & Shalizi, 2013; Mayo, 2011; Senn, 2011).

confidence intervals (see Greenland et al., 2016, esp. p. 340). She then explains that a “distinctive feature of Bayesian statistics is the use of so-called priors” and that “posterior probabilities depend on both the prior beliefs and the data, whereas the results of a frequentist model depend only on the data” (Levshina, 2016, 252). Remarkably, given this statement, she does *not* use informative priors and in her footnote 8 (Levshina, 2016, 252) admits that priors were probed using trial and error. So, the proclaimed major advantage of Bayesian modeling was apparently not taken advantage of.¹⁶ Now, Maximum Likelihood Estimation (MLE) – the traditional method which could have been used instead – is not exactly *frequentist* in the sense of Neyman-Pearson testing theory. MLE, like inductive Bayesianism, conditions on the particular data inasmuch as it searches for the most likely set of parameters given the data. What is more, Bayesian estimators are in fact based on the Likelihood and merely multiply it by the prior (Gelman et al., 2014, 6–8). If the prior is flat, results converge (see also Gelman & Hill, 2006, 347). The same is true if the sample size is large compared to the number of parameters, at least for finite-dimensional parameter models (Freedman, 1999, 1119–1120), a well-established result known as the *Bernstein-von Mises theorem*. With a modest model structure including 17 fixed effects and 2,646 data points in Levshina (2016), it is highly likely that the same results would have been obtained with Maximum Likelihood methods. In fact, she admits that changing the priors did not lead to substantially different results in her footnote 8. This is a clear sign that the prior is “swamped by the data” (Freedman, 1999, 1119).

If there had been evidence in Levshina’s study that Bayesian and MLE methods did *not* converge, it would have been an occasion to demonstrate the selective superiority of the algorithms used in Bayesian estimation. After all, there are situations where Bayesian estimators can be more robust, namely with heavily censored data, complex hierarchical models, perfect separation, etc. (see Freedman, 1999, Gelman & Hill, 2006, 345–348). I want to state clearly that these points do not in any way invalidate the results presented in Levshina (2016). However, being “Bayesian” is most likely not among its selling points. Additionally, I want to voice the concern that many practitioners are probably already struggling with getting an adequate grasp of advanced statistical methods and that it might therefore be wise to use the more conservative and better understood method if the alternative method is not absolutely required for substantive

16 In the words of Senn (2011): “You may believe you are a Bayesian but you are probably wrong.” Gelman & Hill (2006, 347–348) “view any noninformative prior distribution as inherently provisional” and give recommendations how to proceed once posteriors have been obtained from noninformative priors.

reasons. In Section 3.4, I estimate the parameters of my hierarchical model with MLE and Markov-Chain Monte Carlo (MCMC) methods (the currently most prominent estimator used in Bayesian settings) to demonstrate their expectable convergence.

3.4 A hierarchical model of the measure noun alternation

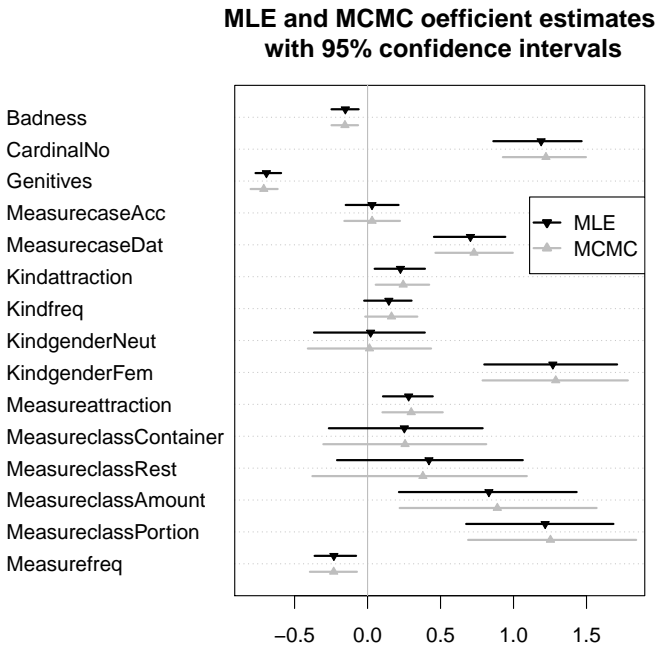


Fig. 1: Coefficients (MLE and MCMC) with 95% confidence intervals (for details see text); the intercept (*Cardinal=Yes*, *Measurecase=Nom*, *Kindgender=Masc*, *Measureclass=Physical*; 0 for all numeric z-transformed regressors) is -4.328 (MLE) and -4.441 (MCMC)

In this section, I report the results of fitting a multilevel model to the data using R (R Core Team, 2014), *lme4* (Bates et al., 2015) for Maximum Likelihood Estimation (MLE) and *rstanarm* (Gabry & Goodrich, 2016) for Bayesian

Markov-Chain Monte Carlo (MCMC) estimation (see Section 3.3). The purpose is to model the influence of the regressors specified in Table 2 on the probability that the PGC_{adj} is chosen over the NAC_{adj} . All regressors from Table 2 were included, and the measure lemma and the kind noun lemma were specified as varying-intercept random effects. The sample size was $n=5,063$ with 1,1344 cases of PGC_{adj} and 3,929 cases of NAC_{adj} . The results of the estimation are shown in Table 3 and in Figure 1. The regressors with the measure lemma as their unit of reference have no within-measure lemma variance, and the *glmer* function automatically estimates them as *group level predictors* (or *second-level effects*), cf. Gelman & Hill (2006, 265–269,302–304). The same goes for those listed with the kind lemma as their unit of reference. Given the coding of the response variable, coefficients leaning to the positive side can be interpreted as favouring the PGC_{adj} .

Standard diagnostics for MLE show that the model quality is quite good. Generalised variance inflation factors for the regressors were calculated to check for multicollinearity (Fox & Monette, 1992; Zuur et al., 2010), and none of the corrected $\text{GVIF}^{1/2\text{df}}$ was higher than 1.6. Nakagawa & Schielzeth’s pseudo-coefficient of determination is $R_m^2 = 0.409$ and $R_c^2 = 0.495$ (see Gries, 2015a for a basic introduction to these R^2 measures, or else Nakagawa & Schielzeth, 2013). The rate of correct predictions is 0.843, which means a proportional reduction of error of $\lambda = 0.297$. The lemma intercepts have standard deviations of $\sigma_{\text{Measurelemma}} = 0.448$ and $\sigma_{\text{Kindlemma}} = 0.604$.

The coefficient estimates are specified in Table 3 for each regressor (or regressor level) in the columns labelled *Coefficient*. For a robust quantification of the precision of the estimation, I ran a parametric bootstrap (using the *confint.merMod* function from *lme4*) with 1,000 replications and using the percentile method for the calculation of the intervals. The resulting 95% bootstrap confidence intervals are reported in Table 3 in the columns labelled *CI low* and *CI high* (= upper and lower 2.5th percentiles). The column *CI excludes 0* shows an asterisk for those intervals that do not include 0. Furthermore, for each regressor, a p-value was obtained by dropping the regressor from the full model, re-estimating the nested model, and comparing it to the full model. Instead of inexact Wald approximations and Likelihood Ratio Tests, I used a drop-in bootstrap replacement for the Likelihood Ratio Test from the function *PBmodcomp* from the *pbkrtest* package (Halekoh & Højsgaard, 2014). I call the corresponding value p_{PB} and it is given in the appropriately labelled columns in Table 3. Only *Kindfreq* ($p_{\text{PB}} = 0.095$) can be seen as slightly too high to be convincing (non-significant).

Finally, I show that MCMC does not necessarily lead to different results. Actually, given the low complexity of the model and the large sample size, it

Level	Regressor	PPB	Level	Coefficient		CI low		CI high		CI excludes 0	
				MLE	MCMC	MLE	MCMC	MLE	MCMC	MLE	MCMC
First	Badness	0.002		-0.152	-0.155	-0.247	-0.247	-0.061	-0.065	*	*
	Cardinal	0.001	No	1.189	1.222	0.862	0.927	1.466	1.496	*	*
	Genitives	0.001		-0.693	-0.711	-0.768	-0.801	-0.592	-0.616	*	*
	Measurecase	0.001	Acc Dat	0.030 0.705	0.031 0.729	-0.150 0.455	-0.159 0.465	0.212 0.944	0.222 0.995	*	*
Second (Kind)	Kindattraction	0.020		0.225	0.244	0.049	0.056	0.393	0.422	*	*
	Kindfreq	0.095		0.146	0.164	-0.023	-0.016	0.301	0.341		
	Kindgender	0.001	Neut Fem	0.021 1.269	0.013 1.289	-0.367 0.800	-0.409 0.788	0.392 1.709	0.435 1.783	*	*
Second (Measure)	Measureattraction	0.001		0.282	0.299	0.106	0.102	0.447	0.515	*	*
	Measureclass	0.001	Container Rest	0.252 0.421	0.257 0.379	-0.265 -0.209	-0.303 -0.378	0.788 1.063	0.813 1.091		
			Amount Portion	0.831 1.217	0.889 1.253	0.215 0.675	0.220 0.689	1.432 1.684	1.569 1.840	*	*
	Measurefreq	0.005		-0.231	-0.232	-0.363	-0.395	-0.079	-0.073	*	*

Table 3: Coefficient table comparing Maximum Likelihood Estimation (MLE, with 95% bootstrap confidence interval) and 'Bayesian' Markov-Chain Monte Carlo estimation (MCMC); the intercept (*Cardinal*=Yes, *Measurecase*=Nom, *Kindgender*=Masc, *Measureclass*=Physical; 0 for all numeric z-transformed regressors) is -3.548 (MLE) and -3.700 (MCMC)

would be surprising if they did (see Section 3.3). The model was re-estimated using the *stan_glmr* function from the *rstanarm* package, which provides an *lme4*-compatible syntax for estimating common model types with the *stan* software (Carpenter et al., 2017). The algorithm was run with 4 chains and 1,000 iterations and I used plausible default priors. Most notably, priors for coefficients were specified as $\mathcal{N}(0, 10)$ because coefficients higher than 10 or lower than -10 are extremely rare in well-specified models on appropriate data.¹⁷ The algorithm converged and for all coefficients, the \hat{R} diagnostic was exactly 1. The resulting coefficients and intervals as well as an * for “confidence interval does not contain 0” are also given in Table 3 in the columns labelled *MCMC*. Both methods lead to exactly the same results (minus negligible numerical differences) as expected given the modest complexity of the model structure and the large sample size. The signs and magnitudes of the coefficients are identical and confidence intervals have the same width and symmetry properties. Figure 1 illustrates this by also showing both estimates. Since both estimators converge, I only interpret the MLE model in the next section.

3.5 Interpretation

The results reported in Section 3.4 generally confirm the hypotheses from Section 2.2. First, the prototypicality effect related to the non-alternating PGC_{det} and NAC_{bare} can be shown (see the effect plots in Figure 2).¹⁸ The effect is as expected: if a lemma appears relatively more often in the PGC_{det} (compared to its frequency in the NAC_{bare}), the PGC_{adj} tends to be chosen over the NAC_{adj} with this specific lemma. The effect for measure nouns is stronger, and it was estimated with higher precision.

An interesting picture emerges for the lemma frequencies. A higher-than-average lemma frequency of measure nouns favours the NAC_{adj} ($\beta_{\text{Measurefreq}} = -0.231$, $p_{\text{PB}} = 0.005$), which is as expected if we assume at least a tendency for highly grammaticalised items to be more frequent. With kind nouns, higher

¹⁷ Consider that with a coefficient of 10, each increase by 1 in the regressor variable increases the odds by $\exp(10) = 22,026.47$. To reliably estimate such coefficients, extremely large samples would be required.

¹⁸ Effect plots were created using the *effects* package (Fox, 2003). They show the changes in probability for the outcome (y-axis) dependent on values of a regressor (x-axis) at typical values of all other regressors. The vertical bars (categorical variables) and grey areas (continuous variables) are asymptotic 95% confidence intervals calculated from *glm*. They are not bootstrapped.

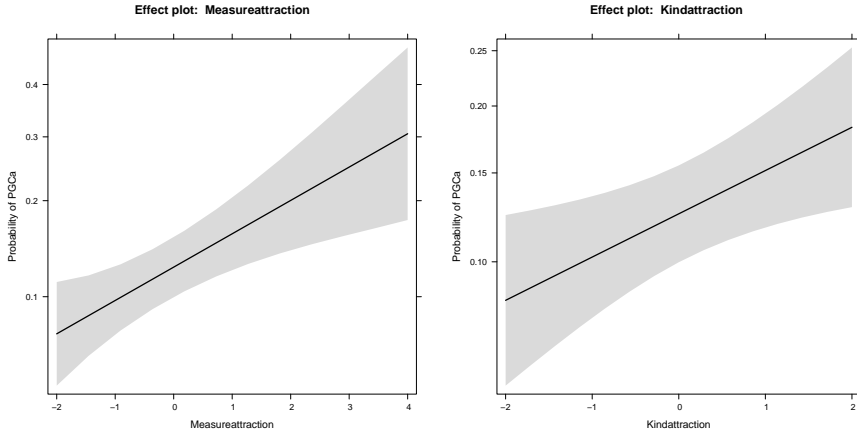


Fig. 2: Effect plots for the regressors *Measureattraction* and *Kindattraction*; y-axes are not aligned

frequency seems to favour the PGC_{adj} ($\beta_{\text{Kindfreq}} = 0.146$, $p_{\text{PB}} = 0.095$). However, there is no clear theoretical interpretation (see Section 2.2) and the estimate is imprecise (not significant at $\alpha = 0.05$, see above). The effect can therefore be ignored or treated as a nuisance variable.

In Section 2.2, it was also hypothesised that classes of measure nouns with a higher degree of grammaticalisation should favour the PGC_{adj} . The *Measureclass* second-level predictor was successfully estimated ($p_{\text{PB}} = 0.001$). Looking at the effect plot in Figure 3, it is evident that abstract non-referential physical measure nouns (such as *Gramm* ‘gram’ or *Liter* ‘litre’) with a high degree of grammaticalisation favour the NAC_{adj} . At the other end of the scale, nouns denoting natural portions like *Haufen* ‘heap’, *Bündel* ‘bundle’, *Schluck* ‘gulp’ favour the PGC_{adj} . These are referential nouns, confirming the hypothesis that it is prototypical of the PGC to contain two referential nouns, while the NAC prototypically only contains one (the kind noun).

I now turn to the predicted effect of cardinals as modifiers of the measure noun. Figure 4 shows that cardinals indeed influence the choice of the alternant ($p_{\text{PB}} = 0.001$), and that cardinals have a strong tendency to co-occur with the NAC_{adj} . This effect was predicted in Section 2.2.

The register-related proxy variables point to the expected direction. Increased *Badness* of the document favours the NAC_{adj} ($\beta_{\text{Badness}} = -0.152$, $p_{\text{PB}} = 0.002$) and so does a lower density of genitives ($\beta = -0.693$, $p_{\text{PB}} = 0.001$). While these are poor proxies to register (and partially circular in the case of *Genitives*), this result can at least encourage future work into register effects.

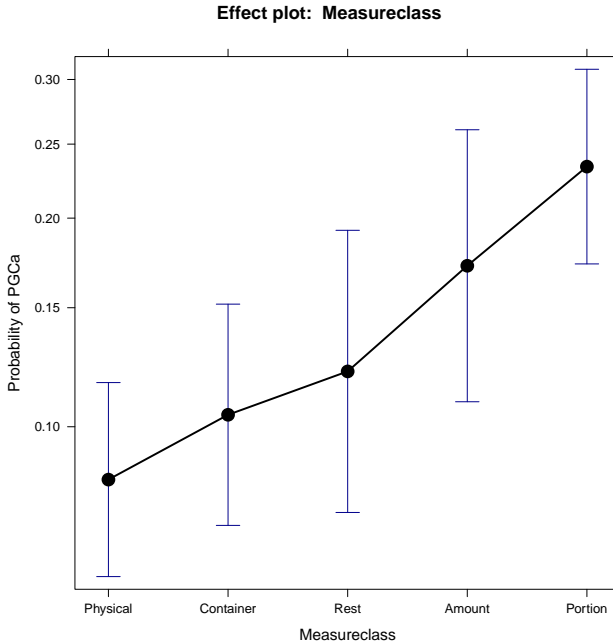


Fig. 3: Effect plot for the regressor *Measureclass*

The influence of *Measurecase* ($p_{PB} = 0.001$) is as predicted in previous analyses (see Section 2.2). A measure noun in the dative favours the PGC_{adj} with $\beta_{MeasurecaseDat} = 0.705$ (compared to the nominative, which is on the intercept). Although *Measurecase* is a nuisance variable in the context of this study, convergence with previous work strengthens its validity.

4 Correlating corpus findings with experiments

4.1 Experiment 1: forced-choice

In the two experiments reported in this section, I use probabilities for the alternating constructions calculated for attested material and I correlate these probabilities with the participants' reactions. Thus, a direct link can be established between output material found in corpora and the behaviour of linguistic agents (see also Section 1). Both experiments use sentences containing attested MNPs from the corpus sample (embedded into simplified sentences) as stimuli.

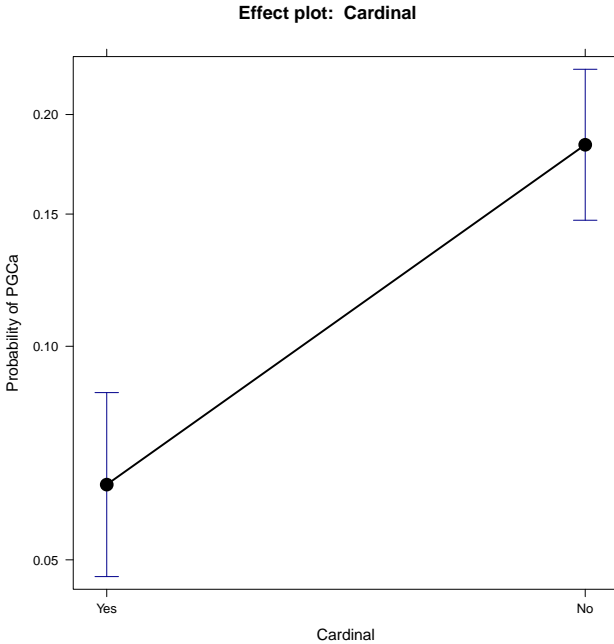


Fig. 4: Effect plot for the regressor *Cardinal*

Also, the probabilities that the corpus-based model assigns to the two alternants in these sentences are used as the main regressor in both studies.

The first experiment tests preferences for constructions explicitly. Ford & Bresnan (2013) use the *split-100* task in which participants have to distribute 100 points between the alternatives, assigning more points to more natural sounding alternative. In essence, participants distribute a probability mass between two alternants, which is intended to produce more subtle results compared to a two-alternative forced-choice task such as in Rosenbach (2013), where participants have to choose one of two alternants. The *split-100* paradigm has been criticised in Arppe & Järvikivi (2007). The criticism was reiterated in Divjak et al. (2016), where they use a forced-choice task. In Verhoeven & Temme (2017, to appear), it was shown that results from forced-choice and *split-100* experiments mostly converge (with some numeric intricacies related to the non-linear distribution of preferences for alternants). I present a forced-choice experiment in this Section and not a *split-100* experiment, mainly because in a dry run of the experiment, participants complained about the unnaturalness of distributing a probability mass across two alternants. Participants had to choose between two sentences

that differed only in that one contained the NAC_{adj} and the other contained the PGC_{adj} . The analysis compares the probabilities assigned to stimuli by the corpus-derived model with the frequency with which participants chose the alternants for the same stimuli.

There were 24 participants (native speakers of German without reading or writing disabilities) aged 19 to 30 living permanently in Berlin, who were recruited from introductory linguistics courses at Freie Universität Berlin. Although the experiment was conducted in the last four weeks of their first semester, participants had no deeper explicit knowledge of linguistics, grammar, or experimental methods. None of them had ever participated in a forced-choice experiment before. Participation was voluntary but participants received credit in partial fulfillment of course requirements.

As stimuli, attested MNPs from the corpus study were used, but the sentences were radically simplified to avoid influences from contextual nuisance factors as much as possible. The approach is also justified because according to the theoretical assessment in Section 2.2, the choice of alternants depends mostly on a very local constructional context. I sampled 16 MNPs from the concordance and made sure that the simplifications and normalisations did not affect any of the regressors used in the corpus study. In the simplified sentences, the case, number, etc. of the MNP remained the same as in the attested sentence, as did the choice of lexical material within the MNP. Eight sentences contained masculine or neuter kind nouns and the other eight contained feminine kind nouns. Furthermore, in each of the masculine/neuter and feminine groups, four sentences originally containing the NAC_{adj} and four sentences originally containing the PGC_{adj} were chosen. More precisely, the sentences were sampled as *highly prototypical examples* of PGC_{adj} (high probability assigned by GLMM) and NAC_{adj} (low probability assigned by GLMM), respectively.¹⁹ High and low probability were defined as the top and bottom 20% of all probabilities assigned by the GLMM. Lemmas and feature combinations were made unique within each group whenever possible. The design is summarised in Table 4.

The final pairs of stimuli were the sentence containing the attested and preferred alternant (according to the corpus GLMM) on the one hand and a modified version containing the dispreferred alternant on the other hand. They were presented next to each other and a 20 second time limit for each choice was set.²⁰ The position on the screen (left/right) and the order of sentences were

¹⁹ Remember from Section 3 that the model predicts the probability that the PGC_{adj} is chosen over the NAC_{adj} .

²⁰ No participant ever exceeded the time limit.

	Masculine/Neuter	Feminine
high prob. for PGC_{adj}	4 sentences	4 sentences
low prob. for PGC_{adj}	4 sentences	4 sentences

Table 4: The four groups of sentences chosen as stimuli; in each group of four sentences, combinations of important factor values were made unique whenever possible

randomised for each participant. As fillers, 23 pairs of sentences exemplifying similar but unrelated alternation phenomena from German morpho-syntax were used. Thus, participants saw 39 pairs of sentences and 78 sentences in total. They were instructed to select from each pair of sentences the one that seemed more natural to them in the sense that they would use it rather than the other one. The experiment was conducted using *PsychoPy* (Peirce, 2007).

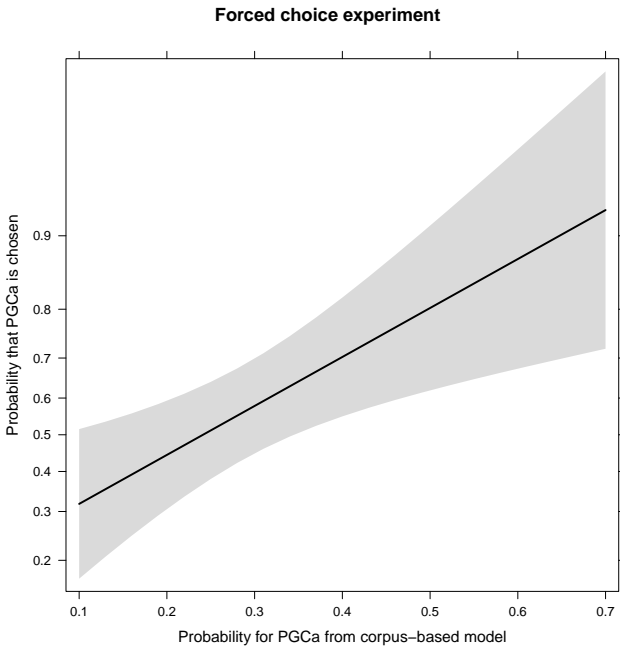


Fig. 5: Effect plot for the multilevel logistic regression in the forced-choice experiment: predictability of participants' choices using the probabilities derived from the corpus-based GLMM

Then, a multilevel logistic regression was specified with the probability of the PGC_{adj} predicted for each sentence by the corpus-based GLMM as the only fixed effect *Modelprediction*.²¹ A random intercept and slope were added for the individual sentence (item) in order to catch idiosyncrasies of single sentences. Also, a random intercept and slope for participants was added.²² Coefficients were estimated with Maximum Likelihood Estimation (*lmer* function from *lme4*). The number of observations was $n=384$.

A certain amount of the variance can be accounted for by idiosyncrasies of single sentences ($\sigma_{\text{Sentence}} = 1.785$, $\sigma_{\text{Sentence}}^{\text{Modelprediction}} = 5.996$, 16 levels).²³ Also, among participants, there are clearly different preferences ($\sigma_{\text{Participant}} = 0.781$, $\sigma_{\text{Participant}}^{\text{Modelprediction}} = 0.484$, 24 levels). On the extreme ends, one participant chose the PGC_{adj} in 13 of 16 cases and two participants only chose it in 5 of 16 cases. The regressor *Modelprediction* achieves $p_{\text{PB}} = 0.007$ (1,000 replications) and is estimated at 5.408 relative to an intercept of -1.304. The confidence interval from a parametric bootstrap (1,000 replications, percentile method) for the regressor is acceptable but slightly large with a lower bound of 1.626 and an upper bound of 8.397. The pseudo-coefficients of determination are $R_m^2 = 0.227$ and $R_c^2 = 0.561$, which means that over 22% of the variance in the data can be explained by considering only the predictions from the corpus-based GLMM. The effect display for the single fixed regressor *Modelprediction* is given in Figure 5. The result is very clear. The higher the probability of the PGC_{adj} predicted from usage data, the more often participants chose the PGC_{adj} alternant in the forced-choice task. In summary, the forced-choice experiment clearly succeeded in corroborating the results from the corpus study in as much as the preferences extracted from usage data correspond to native speakers' choices.

4.2 Experiment 2: self-paced reading

The second experiment tests preferences more implicitly. It is expected that reading less prototypical alternants (the one assigned a low probability by the

21 The document-level variables *Badness* and *Genitives* were set to 0, which is the mean for z-transformed variables.

22 The random slopes were added to comply with Barr et al. (2013, 257) who predict *catastrophically high Type I error rates* for experimental designs with within-subject manipulations if random effects structures are not kept maximal. Notice that the model reported here was estimated with conceptually identical results with regard to the predictor of interest (*Modelprediction*) if only random intercepts were used.

23 I use σ_r^f to denote the standard deviation of the random intercepts for the fixed effect f varying by random effect r .

corpus-derived model) in a given context and with given lexical material incurs a processing overhead for the reader (Kaiser, 2013). In this section, a self-paced reading experiment is therefore presented. In a very similar fashion, Divjak et al. (2016) apply the self-paced reading paradigm in the validation of corpus-based models. The analysis compares the corpus-derived probabilities with potential lags in reading time for sentences with the preferred and the non-preferred constructions.

Concretely, the exact same stimuli as in the forced-choice experiments were used. Each participant read both the 16 sentences with the alternant predicted by the corpus model and the 16 modified sentences with the alternant that the corpus model did not predict.²⁴ To minimise repetition effects, the stimuli for each participant were separated into two blocks of 16 targets and 33 fillers per block. In the experiment, participants first read all sentences from the first block, then all sentences from the second block. From each target sentence pair, one sentence was assigned to the first block and the other sentence to the other block. The assignment of members of the individual sentence pairs to the blocks was randomised for each participant individually, as was the order within each block. The sentences from each pair of alternants were kept as far apart as possible. The fillers also came in pairs such that the second block exclusively contained sentences to which participants had been exposed in the first block in slightly modified form. In total, each participant read 98 sentences. After each sentence, participants had to answer simple (non-metalinguistic) yes-no questions about the previous sentence as distractors. The distractor questions were different between the first and the second blocks. There were 38 participants recruited in exactly the same manner as for the experiment reported in Section 4.1. None of them had ever participated in any kind of reading experiment, and none of them took part in the first experiment. The experiment was conducted using *PsychoPy*.

The reading times were residualised per speaker based on the reading times of all words (not just the targets) by that speaker. The adjective and the kind noun (i. e., the constituents bearing the critical case markers) were used as the target region, for instance the bracketed words in the example *zwei Gläser [sprudelndes Wasser]* ‘two glasses of sparkling water’. Outliers farther than 2 interquartile ranges from the mean logarithmised residualised reading time were removed (64 data points), resulting in a total number of $n=1,152$ observations.

²⁴ Notice that lemmas and their frequencies as well as lemma classes are included as regressors in the corpus-based GLMM and there was consequently no additional controlling of lemma frequencies, etc.

Regressor	Coefficient	CI low	CI high	CI excludes 0
ConstructionPGCa	0.054	0.012	0.095	*
Modelprediction	-0.006	-0.113	0.110	
Position	-0.005	-0.005	0.004	
ConstructionPGCa:Modelprediction	-0.125	-0.234	-0.023	*

Table 5: Fixed effect coefficient table for the LMM used to analyse the self-paced reading experiment; the intercept is 0.829

An LMM was specified with the logarithmised residual reading times as the response variable.

The probabilities derived from the corpus GLMM (*Modelprediction*) were added as the main regressor of interest. It should be remembered that the corpus GLMM predicts the probability of the PGC_{adj} . As a consequence, the higher the GLMM prediction is, the more prototypical the sentence is for containing the PGC_{adj} . It is therefore expected that reading times are higher when the value of *Modelprediction* is higher but the sentence contains the NAC_{adj} . However, when the sentence contains the PGC_{adj} , reading times should be lower when *Modelprediction* is higher. To account for this, an interaction between *Modelprediction* and *Construction* (levels *PGCa* and *NACa*) was added to the model.

Furthermore, the position (1–98) of the sentence in the individual experiment (*Position*) was included as a fixed effect to control for the usual increase in reading speed during an experiment run. Random intercepts were specified for *Participant* and *Item* (the 16 sentence pairs are one *Item* each).²⁵

Table 5 shows the coefficient estimates with a 95% parametric bootstrap confidence interval (1,000 replications, percentile method). The standard deviation of the participant intercepts is $\sigma_{Participant} = 0.079$ and of the item intercepts $\sigma_{Item} = 0.037$. Comparing the full model to a model without the main regressor *Modelprediction* (and consequently also without the interaction with *Construction*) in a PB test gives $p_{PB} = 0.036$. The pseudo-coefficients of determination are $R_m^2 = 0.237$ and $R_c^2 = 0.346$.

The overall model quality is high and the effect plot for the main effect is shown in Figure 6. The estimate for the sentences with NAC_{adj} is obviously imprecise and no differences in reading times are observed. There is a clearer effect in the sentences with PGC_{adj} , which is also confirmed by the

²⁵ I tried random slopes in order to keep the random effect structure maximal (Barr et al., 2013) but it was impossible to get the algorithm to converge due to the added complexity of the interaction.

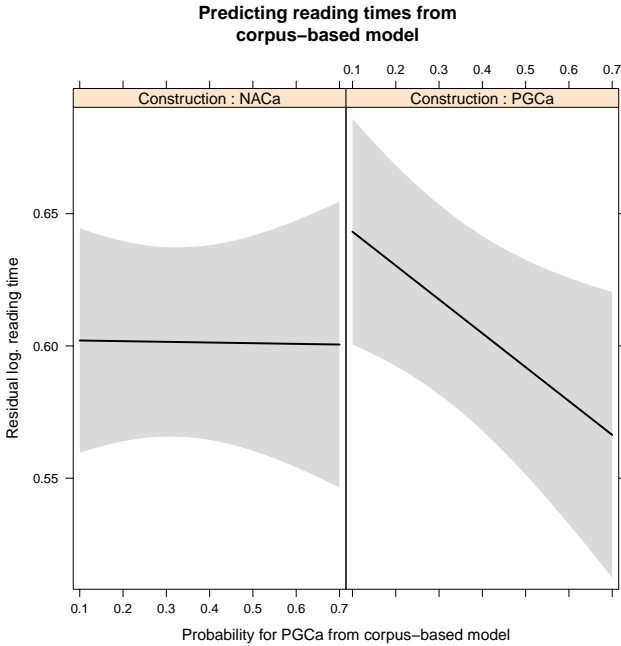


Fig. 6: Effect plot for the LMM in the self-paced reading experiment: modeling participants' residualised log reading times on the probabilities given by the corpus-based GLMM

significant results from the bootstrapped confidence intervals (see Table 5) and from the PB test reported above. The PGC_{adj} brings about an increased reading time ($\beta_{ConstructionPGCa} = 0.054$), which is plausible because it is the much rarer construction (see Section 3). However, if it occurs in a prototypical context and with prototypical lexical material, reading times drop ($\beta_{ConstructionPGCa:Modelprediction} = -0.125$). This can be seen in the downward slope in the right panel of Figure 6. This fits into the general picture inasmuch as the construction with the lower frequency might be developing towards a more sharply defined prototype.²⁶ Conversely, the NAC_{adj} (like the NAC in general) might be the highly frequent default which does not incur a reading time penalty, even if it is not the optimal choice in the given context and with the given lexical material.

²⁶ In this context, it should be remembered from Section 3.1 that even the PGC_{det} is much rarer than the NAC_{bare} (17,252 vs. 315,635 occurrences in the auxiliary corpus samples).

This concludes the report of the two experiments. In the final section, I take stock and summarise the contribution of the present study to the research on alternations in cognitive linguistics.

5 Conclusions

This paper stands in a now ten year-old tradition of research on grammatical alternations using corpus and experimental data. In my view, the main tenets of this line of research are: (i) Language, viewed from a cognitively realistic angle, is a probabilistic phenomenon and cannot be modelled appropriately within Aristotelian frameworks that assume discrete categories. (ii) Corpora are collections of usage events (language production) and can therefore be used to evaluate both the claim made in (i) and specific theoretical claims (in case studies) about factors influencing speakers' decisions to use specific forms or constructions. (iii) Given (ii), we expect results from corpus analyses and from appropriate experiments to yield similar results, not necessarily as a form of validation of the corpus-based findings, but as converging evidence. I consider these three points to be of utmost importance because they clearly set this brand of cognitive linguistics apart from *both* Aristotelian frameworks of the generative flavour *and* introspective, non-empirical, and anti-quantitative versions of cognitive linguistics (see Dąbrowska, 2016 for a pithy philippic against such approaches).

The present paper adds to the evidence that all of the aforementioned three points are correct. A grammatical alternation in German measure NPs was examined using corpus data based on factors partly derived from existing accounts, formulated in terms of construction prototypes. The preferences extracted from the DECOW web corpus were confirmed in a forced-choice experiment, in which participants explicitly chose alternants in line with the corpus-derived model. In a more implicit self-paced reading experiment, it was shown that the much rarer alternant brings about a reading time penalty except in cases for which the corpus model predicts very high probability for this alternant.

Future work could extend these results and provide a general picture of the constructions expressing measurements (see Section 2.1). This would be a much more complicated task given that the choices then would no longer be binary and that the meaning of the alternative ways of expressing measurements are semantically more varied. Finally, I want to point out that German is mildly under-researched in the specific framework used here. This is quite surprising given the fact that German morpho-syntax is famous for its alternations, which

are usually called *Zweifelsfälle* ('cases of doubt') in the traditional literature (Duden, 2011; Klein, 2009). Instead of being drowned in normative, descriptive, or didactic discussions, they could serve as ideal test cases in cognitive linguistics.

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References

- Arppe, Antti & Juhani Järvi­kivi. 2007. Every method counts: Combining corpus-based and experimental evidence in the study of synonymy. *Corpus Linguistics and Linguistic Theory* 3(2). 131–159.
- Barker, Chris. 1998. Partitives, double genitives and anti-uniqueness. *Natural Language and Linguistic Theory* 16(4). 679–717.
- Barr, Dale J., Roger Levy, Christoph Scheepers & Harry J. Tily. 2013. Random effects structure for confirmatory hypothesis testing: Keep it maximal. *Journal of Memory and Language* 68(3). 255–278.
- Barsalou, Lawrence W. 1990. On the indistinguishability of exemplar memory and abstraction in category representation. In Thomas K. Srull & Robert S. Wyer (eds.), *Advances in social cognition, volume III: Content and process specificity in the effects of prior experiences*, 61–88. Hillsdale: Lawrence Erlbaum Associates.
- Bates, Douglas, Martin Mächler, Ben Bolker & Steve Walker. 2015. Fitting linear mixed-effects models using lme4. *Journal of Statistical Software* 67(1). 1–48.
- Bhatt, Christa. 1990. *Die syntaktische struktur der nominalphrase im deutschen*. Tübingen: Narr.
- Biemann, Chris, Felix Bildhauer, Stefan Evert, Dirk Goldhahn, Uwe Quasthoff, Roland Schäfer, Johannes Simon, Leonard Swiezinski & Torsten Zesch. 2013. Scalable construction of high-quality web corpora. *Journal for Language Technology and Computational Linguistics* 28(2). 23–60.
- Bildhauer, Felix & Roland Schäfer. 2016. Automatic classification by topic domain for meta data generation, web corpus evaluation, and corpus comparison. In Paul Cook, Stefan Evert, Roland Schäfer & Egon Stemle (eds.), *Proceedings of the 10th web as corpus workshop (WAC-X)*, 1–6. Association for Computational Linguistics.
- Brems, Lieselotte. 2003. Measure noun construction: An instance of semantically-driven grammaticization. *International Journal of Corpus Linguistics* 8(2). 283–312.

- Bresnan, Joan. 2007. Is syntactic knowledge probabilistic? Experiments with the English dative alternation. In Sam Featherston & Wolfgang Sternefeld (eds.), *Roots: Linguistics in search of its evidential base* (Studies in Generative Grammar), 77–96. Berlin/New York: De Gruyter Mouton.
- Bresnan, Joan, Anna Cueni, Tatiana Nikitina, & Harald Baayen. 2007. Predicting the dative alternation. In Gerlof Boume, Irene Kraemer, & Joost Zwarts (eds.), *Cognitive foundations of interpretation*, Amsterdam: Royal Netherlands Academy of Science.
- Bresnan, Joan & Marilyn Ford. 2010. Predicting syntax: Processing dative constructions in American and Australian varieties of English. *Language* 86(1). 168–213.
- Bresnan, Joan & Jennifer Hay. 2008. Gradient grammar: An effect of animacy on the syntax of ‘give’ in New Zealand and American English. *Lingua* 118. 245–259.
- Carpenter, Bob, Andrew Gelman, Matthew Hoffman, Daniel Lee, Ben Goodrich, Michael Betancourt, Marcus Brubaker, Jiqiang Guo, Peter Li & Allen Riddell. 2017. Stan: A probabilistic programming language. *Journal of Statistical Software* 76(1). 1–32.
- Dąbrowska, Ewa. 2016. Cognitive linguistics’ seven deadly sins. *Cognitive Linguistics* 27(4). 479–491.
- De Clerck, Bernard & Lieselotte Brems. 2016. Size nouns matter: A closer look at mass(es) of and extended uses of SNs. *Language Sciences* 53. 160–176.
- Divjak, Dagmar. 2016. Four challenges for usage-based linguistics. In Jocelyne Daems, Eline Zenner, Kris Heylen, Dirk Speelman & Hubert Cuyckens (eds.), *Change of paradigms – new paradoxes – recontextualizing language and linguistics*, 297–309. Berlin/Boston: De Gruyter Mouton.
- Divjak, Dagmar & Antti Arppe. 2013. Extracting prototypes from exemplars what can corpus data tell us about concept representation? *Cognitive Linguistics* 24(2). 221–274.
- Divjak, Dagmar, Antti Arppe & R. Harald Baayen. 2016. Does language-as-used fit a self-paced reading paradigm? In Tanja Anstatt, Anja Gattnar & Christina Clasmeier (eds.), *Slavic languages in psycholinguistics*, 52–82. Tübingen: Narr Francke Attempto.
- Divjak, Dagmar & Stefan Th. Gries. 2008. Clusters in the mind? Converging evidence from near-synonymy in Russian. *The Mental Lexicon* 3(2). 188–213.
- Duden. 2011. *Richtiges und gutes Deutsch - Das Wörterbuch der sprachlichen Zweifelsfälle*. Mannheim/Zürich: Dudenverlag 7th edn.
- Eisenberg, Peter. 2013. *Grundriss der deutschen Grammatik: Der Satz*. Stuttgart: Metzler 4th edn.
- Eschenbach, Carola. 1994. Maßangaben im Kontext - Variationen der quantitativen Spezifikation. In Sascha W. Felix, Christopher Habel & gert Rickeit (eds.), *Kognitive Linguistik – Repräsentationen und Prozesse*, 207–228. Opladen: Westdeutscher Verlag.
- Fleischer, Jürg & Oliver Schallert. 2011. *Historische Syntax des Deutschen : eine Einführung*. Tübingen: Narr.
- Ford, Marilyn & Joan Bresnan. 2013. Using convergent evidence from psycholinguistics and usage. In Manfred Krug & Julia Schlüter (eds.), *Research methods in language variation and change*, 295–312. Cambridge, MA: Cambridge University Press.
- Fox, John. 2003. Effect displays in R for Generalised Linear Models. *Journal of Statistical Software* 8(15). 1–27.
- Fox, John & Georges Monette. 1992. Generalized collinearity diagnostics. *Journal of the American Statistics Association* 87. 178–183.

- Freedman, David. 1999. On the Bernstein-von Mises theorem with infinite-dimensional parameters. *The Annals of Statistics* 27(4). 1119–1140.
- Gabry, Jonah & Ben Goodrich. 2016. *rstanarm: Bayesian applied regression modeling via stan*. R package version 2.12.1.
- Gallmann, Peter & Thomas Lindauer. 1994. Funktionale Kategorien in Nominalphrasen. *Beiträge zur Geschichte der deutschen Sprache* 116.
- Gelman, Andrew, John B. Carlin, Hal S. Stern, David B. Dunson, Aki Vehtari & Donald B. Rubin. 2014. *Bayesian data analysis*. Boca Raton: Chapman & Hall 3rd edn.
- Gelman, Andrew & Jennifer Hill. 2006. *Data analysis using regression and multilevel/hierarchical models*. Cambridge: Cambridge University Press.
- Gelman, Andrew & Cosma Rohilla Shalizi. 2013. Philosophy and the practice of Bayesian statistics. *British Journal of Mathematical and Statistical Psychology* 66. 8–38.
- Gerstenberger, Laura. 2015. Number marking in German measure phrases and the structure of pseudo-partitives. *Journal of Comparative Germanic Linguistics* 18. 93–138.
- Goethem, Kristel Van & Philippe Hilgsmann. 2014. When two paths converge: Debonding and clipping of Dutch 'reuze'. *Journal of Germanic Linguistics* 26(1). 31–64.
- Goethem, Kristel Van & Matthias Hüning. 2015. From noun to evaluative adjective: Conversion or debonding? Dutch top and its equivalents in German. *Journal of Germanic Linguistics* 27(4). 365–408.
- Greenland, Sander, Stephen J. Senn, Kenneth J. Rothman, John B. Carlin, Charles Poole, Steven N. Goodman & Douglas G. Altman. 2016. Statistical tests, P values, confidence intervals, and power: a guide to misinterpretations. *European Journal of Epidemiology* 31. 337–350.
- Gries, Stefan Th. 2003. Towards a corpus-based identification of prototypical instances of constructions. *Annual Review of Cognitive Linguistics* 1. 1–27.
- Gries, Stefan Th. 2015a. The most underused statistical method in corpus linguistics: Multi-level (and mixed-effects) models. *Corpora* 10(1). 95–126.
- Gries, Stefan Th. 2015b. The role of quantitative methods in cognitive linguistics: corpus and experimental data on (relative) frequency and contingency of words and constructions. In Jocelyne Daems, Eline Zenner, Kris Heylen, Dirk Speelman & Hubert Cuyckens (eds.), *Change of paradigms - new paradoxes: recontextualizing language and linguistics*, 311–325. Berlin/New York: De Gruyter Mouton.
- Gries, Stefan Th. & Anatol Stefanowitsch. 2004. Co-varying collexemes in the into-causative. In Michel Achard & Suzanne Kemmer (eds.), *Language, culture, and mind*, 225–236. Stanford, CA: CSLI.
- Halekoh, Ulrich & Søren Højsgaard. 2014. A Kenward-Roger approximation and parametric bootstrap methods for tests in linear mixed models – the R package pbkrtest. *Journal of Statistical Software* 59(9). 1–30.
- Hankamer, Jorge & Line Mikkelsen. 2008. Definiteness marking and the structure of Danish pseudopartitives. *Journal of Linguistics* 44(2). 317–346.
- Hentschel, Elke. 1993. Flexionsverfall im Deutschen? Die Kasusmarkierung bei partitiven Genitiv-Attributen. *Zeitschrift für Germanistische Linguistik* 21(3). 320–333.
- Hintzman, Douglas L. 1986. Schema abstraction in a multiple-trace memory model. *Psychological Review* 93(4). 411–428.
- Kaiser, Elsi. 2013. Experimental paradigms in psycholinguistics. In Robert J. Podesva & Devyani Sharma (eds.), *Research methods in linguistics*, 135–168. Cambridge University Press.

- Kilgarriff, Adam. 2006. Googleology is bad science. *Computational Linguistics* 33(1). 147–151.
- Kilgarriff, Adam, Vít Baisa, Jan Bušta, Miloš Jakubíček, Vojtěch Kovář, Jan Michelfeit, Pavel Rychlý & Vít Suchomel. 2014. The Sketch Engine: ten years on. *Lexicography* 1–30.
- Klein, Wolf-Peter. 2009. Auf der Kippe? Zweifelsfälle als Herausforderung(en) für Sprachwissenschaft und Sprachnormierung. In Marek Konopka & Bruno Strecker (eds.), *Deutsche Grammatik – Regeln, Normen, Sprachgebrauch*, Berlin: De Gruyter.
- Koptjevskaja-Tamm, Maria. 2001. “A piece of the cake” and “a cup of tea”: partitive and pseudo-partitive nominal constructions in the Circum-Baltic languages. In Östen Dahl & Maria Koptjevskaja-Tamm (eds.), *The Circum-Baltic languages: Typology and contact*, vol. 2, 523–568. Amsterdam and Philadelphia: John Benjamins.
- Kupietz, Marc, Cyril Belica, Holger Keibel & Andreas Witt. 2010. The German reference corpus DeReKo: A primordial sample for linguistic research. In Nicoletta Calzolari, Khalid Choukri, Bente Maegaard, Joseph Mariani, Jan Odijk, Stelios Piperidis, Mike Rosner & Daniel Tapias (eds.), *Proceedings of the seventh international conference on language resources and evaluation (LREC '10)*, 1848–1854. Valletta, Malta: European Language Resources Association (ELRA).
- Labov, William. 1966. *The social stratification of English in New York City*. Washington, DC: Center for Applied Linguistics.
- Labov, William. 1969. Contraction, deletion, and inherent variability of the english copula. *Language* 45(4). 715–762.
- Lehmann, Erich L. 1993. The Fisher, Neyman-Pearson theories of testing hypotheses: one theory or two? *Journal of the American Statistics Association* 88. 1242–1249.
- Lehmann, Erich L. 2011. *Fisher, neyman, and the creation of classical statistics*. New York, NY: Springer.
- Levshina, Natalia. 2016. When variables align: A Bayesian multinomial mixed-effects model of English permissive constructions. *Cognitive Linguistics* 27(2). 235–268.
- Löbel, Elisabeth. 1986. Apposition in der Quantifizierung. In Armin Burkhardt & Karl-Hermann Körner (eds.), *Pragmantax. Akten des 20. Linguistischen Kolloquiums Braunschweig 1985*, .
- Löbel, Elisabeth. 1989. Q as a functional category. In Christa Bhatt, Elisabeth Löbel & Claudia Schmidt (eds.), *Syntactic phrase structure phenomena*, 133–158. Amsterdam, Philadelphia: Benjamins.
- Maxwell, Scott E. & Harold D. Delaney. 2004. *Designing experiments and analyzing data: A model comparison perspective*. Mahwa, New Jersey, London: Taylor & Francis.
- Mayo, Deborah G. 2011. How can we cultivate Senn’s ability? *Rationality, Markets, and Morals* 3. 14–18.
- Medin, Douglas L. & Marguerite M. Schaffer. 1978. Context theory of classification learning. *Psychological Review* 85(3). 207–238.
- Müller, Sonja. 2014. Zur Anordnung der Modalpartikeln “ja” und “doch”: (In)stabile Kontexte und (non)kanonische Assertionen. *Linguistische Berichte* 238. 165–208.
- Nakagawa, Shinichi & Holger Schielzeth. 2013. A general and simple method for obtaining R^2 from generalized linear mixed-effects models. *Methods in Ecology and Evolution* 4(2). 133–142.
- Nesset, Tore & Laura A. Janda. 2010. Paradigm structure: Evidence from russian suffix shift. *Cognitive Linguistics* 21(4). 699–725.

- Peirce, Jonathan W. 2007. Psychopy – Psychophysics software in Python. *Journal of Neuroscience Methods* 162(1–2). 8–13.
- Perezgonzalez, Jose D. 2015. Fisher, Neyman-Pearson or NHST? A tutorial for teaching-data testing. *Frontiers in Psychology* 6(223). 1–11.
- R Core Team. 2014. *R: A language and environment for statistical computing*. R Foundation for Statistical Computing Vienna, Austria. <http://www.R-project.org/>.
- Rosch, Eleanor. 1978. Principles of categorization. In Eleanor Rosch & Barbara B. Lloyd (eds.), *Cognition and categorization*, 27–48. Hillsdale: Lawrence Erlbaum Associates.
- Rosenbach, Anette. 2013. Combining elicitation data with corpus data. In Manfred Krug & Julia Schlüter (eds.), *Research methods in language variation and change*, 278–294. Cambridge, MA: Cambridge University Press.
- Rutkowski, Paweł. 2007. The syntactic structure of grammaticalized partitives (pseudo-partitives). In Tatjana Scheffler, Joshua Tauberer, Aviad Eilam, & Laia Mayol (eds.), *Proceedings of the 30th annual penn linguistics colloquium*, vol. 1 (University of Pennsylvania Working Papers in Linguistics 13), 337–350. Philadelphia: Pennsylvania Graduate Linguistics Society.
- Schachtl, Stefanie. 1989. Morphological case and abstract case: Evidence from the German genitive construction. In Christa Bhatt, Elisabeth Löbel & Claudia Schmidt (eds.), *Syntactic phrase structure phenomena*, 99–112. Amsterdam, Philadelphia: Benjamins.
- Schäfer, Roland. 2015. Processing and querying large web corpora with the COW14 architecture. In Piotr Bański, Hanno Biber, Evelyn Breiteneder, Marc Kupietz, Harald Lungen & Andreas Witt (eds.), *Proceedings of Challenges in the Management of Large Corpora 3 (CMLC-3)*, UCREL Lancaster: IDS.
- Schäfer, Roland. 2016 aop. Prototype-driven alternations: The case of German weak nouns. *Corpus Linguistics and Linguistic Theory* ahead of print.
- Schäfer, Roland, Adrien Barbaresi & Felix Bildhauer. 2013. The good, the bad, and the hazy: Design decisions in web corpus construction. In Stefan Evert, Egon Stemle & Paul Rayson (eds.), *Proceedings of the 8th web as corpus workshop (wac-8)*, 7–15. Lancaster: SIGWAC.
- Schäfer, Roland & Felix Bildhauer. 2012. Building large corpora from the web using a new efficient tool chain. In Nicoletta Calzolari (Conference Chair), Khalid Choukri, Thierry Declerck, Mehmet Uğur Doğan, Bente Maegaard, Joseph Mariani, Asuncion Moreno, Jan Odijk & Stelios Piperidis (eds.), *Proceedings of the eight international conference on language resources and evaluation (LREC'12)*, 486–493. Istanbul, Turkey: European Language Resources Association (ELRA).
- Schäfer, Roland & Felix Bildhauer. 2013. *Web corpus construction* (Synthesis Lectures on Human Language Technologies). San Francisco: Morgan and Claypool.
- Schäfer, Roland & Ulrike Sayatz. 2014. Die Kurzformen des Indefinitartikels im Deutschen. *Zeitschrift für Sprachwissenschaft* 33(3). 215–250.
- Schäfer, Roland & Ulrike Sayatz. 2016. Punctuation and syntactic structure in “obwohl” and “weil” clauses in nonstandard written German. *Written Language and Literacy* 19(2). 215–248.
- Selkirk, Elisabeth O. 1977. Some remarks on noun phrase structure. In Peter W. Culicover, Thomas Wasow & Adrian Akmajian (eds.), *Formal syntax: Papers from the MSSB-UC Irvine conference on the formal syntax of natural language*, Newport Beach, California, 285–316. New York: Academic Press.

- Senn, Stepen J. 2011. You may believe you are a Bayesian but you are probably wrong. *Rationality, Markets, and Morals* 2. 48–66.
- Stefanowitsch, Anatol & Stefan Th. Gries. 2003. Collostructions: Investigating the interaction between words and constructions. *International Journal of Corpus Linguistics* 8(2). 209–243.
- Stickney, Helen. 2007. From pseudopartitive to partitive. In Alyona Belikova, Luisa Meroni & Umeda Mari (eds.), *Proceedings of the 2nd conference on generative approaches to language acquisition North America (GALANA)*, 406–415. Somerville.
- Storms, Gert, Paul De Boeck & Wim Ruts. 2000. Prototype and exemplar-based information in natural language categories. *Journal of Memory and Language* 42. 51–73.
- Tagliamonte, Sali A. 2012. *Variationist sociolinguistics: Change, observation, interpretation*. Malden/Oxford: Wiley-Blackwell.
- Tummers, José, Kris Heylen & Dirk Geeraerts. 2005. Usage-based approaches in cognitive linguistics: A technical state of the art. *Corpus Linguistics and Linguistic Theory* 1(2). 225–261.
- Verhoeven, Elisabeth & Anne Temme. 2017, to appear. Word order acceptability and word order choice. In Sam Featherston, Robin Hörnig, Reinhild Steinberg, Birgit Umbreit & Jennifer Wallis (eds.), *Linguistic Evidence 2016 Online Proceedings*, Tübingen: Universität Tübingen.
- Vos, Riet. 1999. *A grammar of partitive constructions* (Tilburg dissertation in language studies). Tilburg: Tilburg University.
- Zeldes, Amir. to appear. The case for caseless prepositional constructions with “voller” in German. In Hans C. Boas & Alexander Ziem (eds.), *Constructional approaches to argument structure in German* (Trends in Linguistics: Studies and Monographs), Berlin: De Gruyter.
- Zimmer, Christian. 2015. Bei einem Glas guten Wein(es): Der Abbau des partitiven Genitivs und seine Reflexe im Gegenwartsdeutschen. *Beiträge zur Geschichte der deutschen Sprache und Literatur* 137(1). 1–41.
- Zuur, Alain F., Elena N. Ieno & Chris S. Elphick. 2010. A protocol for data exploration to avoid common statistical problems. *Methods in Ecology and Evolution* 1(1). 3–14.