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An Algorithm for Argument Extraction from Russian Treebanks

Abstract. A key feature distinguishing arguments from adjuncts is their verb-specific nature, including a verb’s ability to require specific morphosyntactic devices for argument encoding. Building on this observation, we operationalize arguments as dependents whose encoding device occurs with a given verb at a significantly higher-than-average frequency. We apply an argument extraction algorithm to a dataset of 132,221 verb dependents from Russian treebanks available in the Universal Dependencies (UD) platform. To evaluate the algorithm’s performance, we compare its results to a manually annotated subset, informed by *The Active Dictionary* and a detailed semantic understanding of argumenthood. The frequency-based algorithm achieves an acceptable precision (approx. 0.83), with particularly few false positives, making it a promising tool for cross-linguistic applications in typologically diverse languages with UD treebanks. Theoretically, we argue that a quantitative distributional approach to valency—originally proposed in Yu. D. Apresjan’s early pioneering work—broadly aligns with the in-depth semantic analyses of individual verbs and their meanings found in his later works, including *The Active Dictionary*.

Keywords: Russian, argument, treebank, frequency, case, preposition, dependency

# 1. Objectives and Approach

In his early 1965 paper, Yuri Derenikovich Apresjan proposed a hypothesis stating that “there is a regular correspondence between the syntactic properties of words and their semantic features” (Apresjan, 1965, p. 51). To the present day, this idea remains a cornerstone in the study of verbs and their valency across various approaches and perspectives (Helbig & Schenkel, 1983, pp. 61–62; Levin, 1993; Lazard, 1994, p. 133; Levin & Rappaport Hovav, 2005; Malchukov & Comrie (eds.), 2015, etc.).

Despite the apparent appeal of this claim, it immediately presents a challenge in selecting analytical tools. One extreme is to rely on the syntactic properties of verbs, such as their combinatorial potential, to infer claims about their meanings. This approach benefits from a potentially solid empirical foundation, including frequency data, but its drawback is that such inferences must be treated with caution and ideally verified through independent semantic evidence. The other extreme is to make meticulous judgments about verb meanings and trace the mechanisms by which syntactic patterns emerge from semantic nuances. The main issue with this approach is that meanings are not directly observable and inevitably remain a theoretical construct.

While numerous insightful studies fall somewhere along the spectrum between these two extremes, Apresjan’s contribution to the field is exceptional in that he made influential contributions spanning the entire range of possible approaches throughout his career. In his early work, he explored the extraction of semantic information from verbs’ distributional properties, employing a wide array of quantitative techniques (Apresjan, 1965; 1967). Over time, he shifted toward the in-depth semantic end of the continuum, placing increasing emphasis on thought experiment (“мысленный эксперимент”, see Apresjan & Páll, 1982, p. 39) and semantic decomposition (“толкование”, Apresjan, 1974; 1995). This shift was also reflected in his extensive work on dictionaries (Mel’čuk et al., 1984; Apresjan (Ed.), 2004), culminating in “The Active Dictionary”, an endeavor launched in 2014 and continuing to the present day, even after Yuri Derenikovich’s passing (Apresjan (Ed.), 2014-).

This shift likely reflects Apresjan’s growing dissatisfaction with the computational distributional approach of his early work, leading him to conclude that detailed semantic analysis is more accurate, insightful, and ultimately superior. While this may be true, lexicographic approaches to valency based on semantic decomposition have two inherent limitations. First, no dictionary can cover all verbs and their variable usage in actual texts—a limitation that has become even more apparent with the advent of large corpora. Even for well-documented languages like Russian, dictionaries inevitably have a restricted scope. Second, an approach relying on nuanced intuitions is typically feasible only for a researcher’s native language and is impractical for most of the world’s languages, especially those without strong lexicographic traditions.

Given these considerations, combining the quantitative distributional perspective with the semantics-oriented lexicographic approach remains essential for advancing the study of verb-dependent relationships. Our paper follows this approach to address the longstanding problem of distinguishing arguments from adjuncts. Specifically, we propose a co-occurrence-based quantitative technique for automatically differentiating arguments from adjuncts and apply it to Russian treebanks from the Universal Dependencies (UD) project (de Marneffe et al., 2021), aligning with Apresjan’s early methodology. We then compare the results with the treatment of argumenthood in “The Active Dictionary” (Apresjan (Ed.), 2014–), the hallmark of his later approach.

The results presented below are valuablein their own right and, hopefully, contribute to our understanding of valency from a token-based typological perspective. More importantly, however, the technique introduced here paves the way for its application to languages that lack detailed, semantically oriented accounts of their verbal lexica but have UD treebanks available. In this sense, our study serves as a preparatory step for a larger research project aimed at cross-linguistic comparison of valency class systems from a token-based perspective.

The paper is structured as follows. Section 2 examines the argument–adjunct distinction and key argumenthood criteria. Section 3 outlines our data and methodology, detailing the algorithm for distinguishing arguments from adjuncts based on cooccurrence frequencies in treebanks. Section 4 evaluates the algorithm’s performance and theoretical implications. Finally, Section 5 provides a brief summary and outlook.

# 2. The argument-adjunct distinction: state of the art

Since at least Tesnière’s “Éléments de syntaxe structurale” (1959), it has been wiely recognized that some verb dependents are more closely associated with the verb than others (Lazard, 1994; Dixon, 2009, pp. 97-128). A textbook example of this distinction appears in (1), where *ona* ‘she’ and *našim otdelom* ‘our department’ represent participants inherent to the meaning of *rukovodit’* ‘to manage’, while the adverbial phrase *s sentjabrja* ‘since September’ is not essential to the verb’s meaning.

(1) *Ona rukovodit našim otdelom s sentjabrja.*

‘She has been managing our department since September’.

While intuitively appealing, this distinction is far from unproblematic, even in terminology. The common English terms *arguments* and *adjuncts* are not universally accepted (see Frajzyngier et al., 2024 for an overview of alternatives), and mapping terms across linguistic traditions—e.g., *actants* vs. *circonstants* in French or *актанты* vs. *сирконстанты* in Russian—further complicates the picture. The real challenge, however, lies not in terminology but in finding suitable criteria for distinguish verbal dependents. The numerous formal and semantic criteria used to separate arguments from adjuncts often yield conflicting classifications. As a result, some scholars argue that a rigid two-way classification of verbal dependents is neither feasible nor necessary in typological research (Jacobs, 1994; Haspelmath, 2014, p. 9). Despite these caveats, we will use *arguments* and *adjuncts* as the standard terms. Before presenting our perspective, we briefly highlight key distinctions from the literature.

The key distinction between arguments and adjuncts, in both the Moscow Semantic School and beyond, is that arguments correspond to a predicate’s inherent participants—essential to its meaning in terms of semantic decomposition (*толкование*) (Apresjan, 1974; Boguslavskij, 1996, p. 23). Variations on this idea can be found in Van Valin (2001, p. 93) and Frajzyngier et al. (2024). A classic example is Apresjan’s decomposition of *arendovat’* (‘to rent’): “A rents C” means that in exchange for compensation D, person A acquires from person B the right to use property C for a period T” (Apresjan, 1995, Vol. 1, p. 120). While this approach often yields clear results, it is not without issues—for instance, the verb *arendovat’* involves five potential arguments, but not all are equally essential (e.g., property C must be identifiable, while compensation D may remain unspecified). Since semantic decomposition is a theoretical construct, criteria for determining a verb’s inherent elements can vary (Testelec, 2001, p. 168–178).

Approaches to argumenthood fall into two broad categories: semantic and syntactic. A common semantic strategy is to classify dependents by roles (agents, patients, experiencers, locations, etc.). While some correlations exist—agents are typically arguments, while places and causes often are not—this is not a panacea. For instance, instruments can behave as either arguments or adjuncts, forming a continuum (Koenig et al., 2008; Bohnemeyer, 2007). More nuanced distinctions have been proposed, such as Jolly’s (1993) view that adjuncts, as modifiers, are hybrids: they express semantic roles like arguments but also predicate information of their own. While such insights are valuable, they are difficult to operationalize, making them less useful for tasks like data annotation and cross-linguistic comparison.

Syntactic criteria might seem more reliable, with obligatoriness being an obvious candidate. While arguments are generally more obligatory than adjuncts, this is not a universal test, as strict syntactic obligatoriness is largely illusory (Helbig & Schenkel, 1983, pp. 35–36). Most languages allow omitting participants under certain conditions (see Ljaševskaja & Kaškin, 2015, p. 502 for Russian), and even non-obligatory prepositional phrases can function as arguments when they are used (Jolly, 1993, p. 283). Moreover, languages vary greatly in how freely they permit omission, further limiting obligatoriness as a cross-linguistic criterion.

Closely tied to argumenthood criteria is the distinction between *core* and *oblique* dependents. While no universal definition exists,[[1]](#footnote-1) “oblique” typically refers to dependents that, despite being inherent to a verb’s meaning, are syntactically similar to adjuncts—such as prepositional phrases in *graduate from Harvard* or *apologize for the mistake*. This approach is useful for language-specific analysis but poses challenges for cross-linguistic comparison due to variation in case systems, adpositional usage, and verb indexing strategies.

Thus, defining the argument–adjunct distinction through simple formal contrasts is problematic (Haspelmath, 2014). However, deeper syntactic contrasts may be more useful for cross-linguistic studies. For instance, Helbig & Schenkel (1983, p. 38) highlight how German verbs like *wohnen* ‘to live, reside’ and *sterben* ‘to die’ interact differently with locative phrases. While *Er wohnte in Dresden* ‘He lived in Dresden’ and *Er starb in Dresden* ‘He died in Dresden’ appear structurally similar, their internal organization differs, as shown in (2) and (3).

(2) *\*Er wohnte, als er in Dresden war*, lit.‘He lived when he was in Dresden’. (Helbig & Schenkel, 1983, p. 38)

(3) *Er starb, als er in Dresden war* ‘He dies when he was in Dresden’. (Helbig & Schenkel, 1983, p. 38)

Helbig & Schenkel (1983, p. 38) classify locative phrases with *wohnen* ‘to live’ as “restricted verb complements” (*enge Verbergänzung*) and with *sterben* ‘to die’ as “free verb complements” (*freie Verbergänzung*), aligning with the argument–adjunct distinction. While insightful, such language-specific syntactic tests are unlikely to be universally applicable (Haspelmath 2014).

Apart from morphosyntactic differences, arguments are inherently “verb-specific and thus have to be learned together with each verb, whereas the use of adjuncts is independent of particular verbs” (Haspelmath, 2014, p. 5; see also Beavers, 2010, p. 842). A key aspect of argument verb-specificity is that verbs typically require specific coding devices, such as cases and adpositions (Testelec, 2001, p. 187; see also Jacobs, 1994 on formal specificity as a dimension of valency). This property, known as “subcategorization” (syntactic combinability), coexists with “selection” (semantic combinability). Its lexical nature is evident in (4), where each Russian verb, despite semantic similarities, follows a distinct valency pattern.

(4) a. *Petja simpatiziruet Ma*š*e*.

‘Petja likes Maša’ (the nominative + dative pattern; here and below, the coding device for the experiencer is mentioned first).

b. *Petja vosxiščaetsja Ma*š*ey*.

‘Petja admires Maša’ (the nominative + instrumental pattern).

c. *Petja vljubilsja v Mašu*.

‘Petja fell in love with Maša’ (the nominative + *v* ‘in’ accustive pattern).

d. *Petja ljubit Mašu.*

‘Petya loves Maša’ (the nominative + accusative pattern).

e. *Petja razočarovalsja v Maše.*

‘Petja is disappointed in Maša’ (the nominative + *v* ‘in’ locative pattern).

f. *Pete nadoela Maša.*

‘Petya is fed up with Maša’ (the dative + nominative pattern).

In contrast, adjuncts are typically shaped by their own meaning and lexical makeup, with the head verb playing little role. This is shown in (5), where each adjunct follows a distinct coding pattern but can combine not just with *videt’sja* ‘see each other’ but with any Russian verb compatible with temporal adverbials (*priexat’* ‘arrive’, *ženit’sja* ‘marry’, etc.).

(5) a. *My videlis’ vtorogo sentjabrja*.

‘We saw each other on September 2nd’ (the genitive pattern).

b. *My videlis’ vo vtornik.*

‘We saw each other on Tuesday’ (the *v* ‘in’ accusative pattern).

c. *My videlis’ na prošloj nedele.*

‘We saw each other last week’ (the *na* ‘on’ locative pattern).

d. *My videlis’ na Pasxu.*

‘We saw each other on Easter’ (the *na* ‘on’ accusative pattern).

e. *My videlis’ prošlym letom.*

‘We saw each other last summer’ (the instrumental pattern).

Since arguments are verb-specific, unlike adjuncts, their documentation and analysis have largely been a lexicographic task, as seen in numerous dictionaries by Apresjan and colleagues (Apresjan & Páll, 1982; Mel’čuk et al., 1984; Apresjan (Ed.), 2004; Apresjan (Ed.), 2014–). While theoretical linguistics sometimes offers gradual approaches to argumenthood with various criteria, lexicographers take a practical stance: dictionaries list verbs with a discrete set of dependents and their encoding patterns. This also applies to lexical databases like FrameNet and its derivatives, which focus on arguments rather than adjuncts. A case in point is FrameBank, based on Russian data (Ljaševskaja & Kaškin, 2015, p. 502).

Most approaches view the link between verbs and specific coding devices, such as cases and adpositions, as a **typical property** of arguments rather than their defining feature. While dictionaries, which lack frequency data and do not capture usage variability, may not emphasize this link, it plays a key role in automatically identifying arguments based on their co-occurrence with verbs in corpora—a process known as “subcategorization frame acquisition” (Korhonen et al., 2000). In the next section, we propose such a technique building our analysis on the Russian data.

# 3. Data and methods

## 3.1. Data extraction and preannotation

The data for this study come from Universal Dependencies (UD), a collection of treebanks covering about 150 languages (Nivre et al., 2020; Zeman et al., 2023). Here, we focus on Russian treebanks, though the methodology applies to any UD treebank. All the spreadsheets mentioned in Section 3 are available as Supplementary Materials at [LINK REMOVED FOR THE SAKE OF ANONYMIZATION].

UD treebanks have several properties that make them well-suited for quantitative valency studies. First, they are based on naturalistic texts (fiction, blogs, news, etc.). Second, the Russian UD treebanks are large: as of October 2024, they contain 1,896,343 tokens across 116,324 sentences. Third, unlike most corpora, UD treebanks provide deep morphological and syntactic annotation, consistently applied across diverse languages, facilitating token-based typological analysis. Specifically, UD annotation includes lemmatization, allowing automatic tracing of usage patterns across morphological forms and syntactic contexts. Finally, as their name suggests, UD treebanks explicitly mark dependency relations, categorized into a concise set of universal types (e.g., “nominal subject”, “indirect object”, “adverbial modifier”).

UD treebanks also have inherent limitations. The most significant, though irrelevant to this study, may affect its planned typological extension: UD is heavily biased toward “major” languages, limiting typological diversity. “Minor” languages are underrepresented, and existing corpora vary in size, content, and quality.

Additionally, UD annotation presents technical challenges for studying verbal arguments. The framework treats function words like adpositions and auxiliaries as dependents of their associated content words (de Marneffe et al., 2021, p. 269), diverging from standard dependency grammar. For instance, in *give the toys to the children*, *give* takes *toys* as a direct object (“obj”) and *children* as an oblique object (“obl”), with *to* analyzed as a dependent of *children* under a “case” relation. This approach enhances cross-linguistic comparability between case-rich languages and those relying on adpositions. However, it complicates the automatic extraction of argument-encoding devices associated with specific verbs, as discussed below.

As a first step, we extracted all dependents tagged as direct objects (“obj”), indirect objects (“iobj”), or oblique objects (“obl”) of finite verbs in the Russian UD treebanks. For this, we used a Python script developed by REMOVED FOR THE SAKE OF ANONYMIZATION. The script generates a spreadsheet where each row represents a nominal or pronominal dependent annotated for 27 parameters. The key parameters for this analysis are:[[2]](#footnote-2)

- “entry no”: unique identifier for the target dependent.

- “corpus” and “id”: tags uniquely identifying the sentence containing the target dependent.

- “sentence”: the full sentence with the target dependent and head verb.

- “verb lemma”: infinitive form of the head verb.

- “object form”: inflected form of the dependent.

- “object dependency relation”: UD treebank tag for the dependent (“obj”, “iobj”, “expl”, or “obl”).

- “object case”: case marking of the dependent (e.g., “Acc”, “Dat”, “Gen”).

- “adposition lemma”: any adposition identified as a dependent of the target dependent.

Table 1 presents the annotation of a single raw entry from our spreadsheet as an example (displayed as a column rather than a row for technical reasons).

Table 1. Sample spreadsheet entry (8 selected parameters)

|  |  |
| --- | --- |
| entry no | 23959 |
| corpus | ru\_syntagrus-ud-dev.conllu |
| id | 2020\_Corpus2\_0Khochu\_byt\_negrom.xml\_304 |
| sentence | Я смотрю на круглое личико , и мне кажется , что это – она. |
| verb lemma | смотреть |
| object dependency relation | obl |
| object form | личико |
| object case | Acc |
| adposition lemma | на |

Our initial spreadsheet contains 132,221 entries, meaning roughly every 14th word in the corpus is a non-subject dependent of a finite verb, either an argument or an adjunct. Next, we annotated the encoding devices associated with these dependents. By default, this was a combination of case form and adposition (if present), e.g., “naACC” for the entry in Table 1. However, due to UD annotation errors—such as misdisambiguation of homonymous case forms or incorrect lemmatization of prepositions—parts of the process were manual. Ultimately, we identified 92 distinct encoding devices, twice the number found in Apresjan (1965, p. 46), largely due to the presence of rare adpositions in UD treebanks.

At this stage, we removed entries where the encoding device could not be identified (e.g., indeclinable elements), marking them with <NA> tags. We also excluded nominals that were not dependents at the verb phrase level, such as the expletive eto ‘this’ in sentences like *No eto my opjat’ sil’no zabegaem* ‘But here we’re getting ahead of ourselves again.’ After filtering out these entries, the dataset was reduced to 122,551 entries.

Table 2 presents partial annotations, including the “encoding device”, for three entries from the sentence *Posle etogo ljudi rasskazyvali zalu o rezul’tatax* ‘After that, people told the audience about the results.’

Table 2. Partial annotations of three sample entries, including “encoding device” tags

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| entry no | verb lemma | object depen-dency relation | object form | object case | adposition lemma | encoding device |
| 2386 | *рассказывать* | obl | этого | Gen | после | posleGEN |
| 2387 | *рассказывать* | iobj | залу | Dat |  | DAT |
| 2388 | *рассказывать* | obl | результатах | Loc | о | oLOC |

As noted earlier, UD explicitly rejects the argument-adjunct distinction, opting instead for the core-oblique distinction. The UD documentation justifies this choice: “… the argument/adjunct distinction is subtle, unclear, and frequently argued over … the best practical solution is to eliminate it … The core-oblique distinction is … both more relevant and easier to apply cross-linguistically than the argument-adjunct distinction” (<https://universaldependencies.org/u/overview/syntax.html>; retrieved March 1, 2025). In UD, this distinction is based on the morphosyntactic encoding of dependents (de Marneffe, 2021, p. 268), partially overlapping with parameters like morphological case and disregarding whether a dependent is obligatorily selected by a specific verb.

While reluctance to provide discrete argument vs. adjunct annotation is understandable, distinguishing “obj”, “iobj”, and “obl” dependents is not entirely satisfactory either. The UD documentation offers only vague definitions, such as “iobj” as a “nominal core argument of a verb that is not its subject or (direct) object” or “obl” as “a nominal functioning as a non-core (oblique) modifier of a predicate” (de Marneffe, 2021, p. 266). Beyond their vagueness, these categories are inconsistently applied. The “obj” tag typically marks accusative prepositionless objects, yet 2,850 of 37,691 “obj” entries involve diverse encoding strategies with unclear rationale. Often, these cases involve verbs sometimes classified as transitive due to features like passive formation (Kamynina, 1999, p. 146; but see Fowler, 1996 for a different approach). However, annotation remains inconsistent—e.g., the instrumental *rukami* ‘(with) arms’ as a dependent of *maxat’* ‘to wave’ is appears variably as “obj”, “iobj” and “obl”.

The “obj” vs. “obl” distinction is more meaningful for accusative prepositionless dependents: “obj” mainly marks clear direct objects, while “obl” and “obl:tmod” typically indicate adverbial time or frequency modifiers, such as *vsju nedelju* ‘the whole week’ or *každuju minutu* ‘every minute.’ Though not entirely consistent, this distinction helps differentiate direct objects from adverbials, a contrast not captured by other parameters.

## 3.2. Argumenthood annotation algorithm

In the previous section, we showed that UD-internal tags do not distinguish arguments from adjuncts. This challenge forms the basis of our analysis, which aims to develop an algorithm for automatic argumenthood annotation.

The core principle of our algorithm, introduced in Section 2, is that argument-encoding devices—such as cases and prepositions in Russian—are verb-specific and quantitatively distinct from adjuncts, whose distribution is governed by semantic compatibility and internal structure. Based on this, argumenthood can be operationalized as follows: a dependent is interpreted as an argument if the relative frequency of its encoding device with a given verb exceeds a certain baseline. This approach treats argumenthood as a gradable phenomenon but can be converted into a discrete distinction by setting a cut-off point for the frequency difference.

This approach closely resembles Apresjan’s concept of “government strength” (“сила управления”), defined as “the proportion of cases in which a given verb occurs with a specific (prepositional-)case form out of the total occurrences of the verb” (Apresjan, 1965, pp. 51–52), where adjuncts are dependents with very low government strength. Comparing observed frequency to a baseline is a standard method in subcategorization frame acquisition (Korhonen et al., 2000). The main challenge is determining this baseline. A simple approach sets a fixed threshold (e.g., >20% of a verb’s occurrences), while we use a more refined method, comparing observed frequency to expected frequency, which is calculated under the assumption that the encoding device occurs equally often with all verbs in the corpus.

This concept was implemented in R (R Core Team, 2021) using the readxl (Wickham & Bryan, 2023) and writexl (Ooms, 2024) packages. The procedure was as follows: Based on the raw dataset from Section 3.1, we created a spreadsheet (*valency\_frames*) where each row represents a finite verb token in the treebank, and columns correspond to the 92 attested encoding devices (e.g., “ACC”, “INS”, “naACC”). Cells contain “0” or “1” depending on whether the verb token has a dependent in the specified (prepositional-)case form. For example, the first three entries in Table 2 are merged into one row with “1” in the columns for “posleGEN”, “DAT”, and “oLOC”. The *valency\_frames* spreadsheet includes 87,979 entries, matching the number of verb tokens in the raw data. It was also used to calculate verb lemma prevalence; for instance, *rasskazyvat’* ‘tell (IPFV)’, shown in Table 2, appears 153 times in the dataset.

Next, we created a summary spreadsheet (*verbs\_and\_encoding\_devices*) grouping cooccurrences with encoding devices by verb lemmas. The 7,539 rows represent distinct verb lemmas, while the 92 columns indicate the prevalence of encoding devices cooccurring with each verb. For example, for *rasskazyvat’* ‘tell (IPFV)’, which appears 153 times in the data, 76 instances involve a dependent encoded by *o* ‘about’ + locative, 58 by the dative case, and only 2 by *posle* ‘after’ + genitive (as seen in Table 2), along with additional dependent types.

The figures in this spreadsheet represent observed frequencies. Expected frequencies were calculated by determining the overall relative prevalence of each encoding device across all verb tokens in the corpus and multiplying it by the total number of tokens for each verb lemma. For example, dependents in the prepositionless dative case appear in 7,929 out of 87,979 clauses, yielding a ratio of 0.09. Under the null hypothesis that *rasskazyvat’* ‘tell (IPFV)’ selects the dative case at the same rate as other verbs, we would expect about 13.8 occurrences (= 153 × 7,929 / 87,979). The observed count (58) far exceeds this, indicating a stronger-than-average preference for the dative case with *rasskazyvat’*.

As the final stage in the analysis, we needed a procedure to infer argumenthood status from the differences between observed and expected frequencies. We used a two-step algorithm:

- If the expected frequency of a verb-encoding combination was ≥5, we applied the χ²-test. The combination was classified as an argument relation if the observed frequency exceeded the expected frequency and the p-value was <0.05.

- Otherwise, we used Fisher’s exact test with the same p-value threshold (<0.05) and an additional condition that the observed count exceeded 2.

This procedure is largely similar to two subcategorization frame acquisition methods discussed by Korhonen et al. (2000). The key difference is the use of Fisher’s exact test to address issues with low-frequency items, which make the χ²-test unreliable (Korhonen et al., 2000, p. 205). The additional requirement that the observed frequency exceed 2 helps prevent premature argumenthood classification for rare combinations.

Using this procedure, we assigned a binary argument vs. non-argument status to each verb-encoding combination, following the standard discrete approach to argumenthood (Levin & Rappaport Hovav, 2005). For example, *rasskazyvat’* ‘tell (IPFV)’ was classified as selecting arguments marked by the dative case, *o* ‘about’ + locative, and *pro* ‘about’ + accusative.

The binary argumenthood judgments are summarized in a spreadsheet (*argumenthood\_df*), where “1” denotes arguments and “0” adjuncts. However, this format is not very clear visually. Instead of presenting it directly, Table 3 combines data from two spreadsheets: it shows observed frequencies of verb-encoding combinations from *verbs\_and\_encoding\_devices*, with boldface indicating “1”s from *argumenthood\_df*, marking algorithmically identified arguments.

Table 3. Selected verb – encoding device combinations frequencies and their argumenthood

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  |  | INS | ACC | DAT | vLOC | sGEN | nadINS | dljaGEN |
| *представлять* | ‘represent’ | 33 | **244** | 28 | 22 | 1 | 0 | **14** |
| *иметь* | ‘have’ | 7 | **794** | 1 | 102 | 10 | 1 | **24** |
| *посоветовать* | ‘advise’ | 0 | **22** | **15** | 1 | 0 | 0 | 1 |
| *называть* | ‘call’ | **109** | **273** | 0 | 33 | 2 | 0 | 0 |
| *подвергнуться* | ‘undergo’ | 0 | 1 | **21** | 3 | 1 | 0 | 0 |
| *вынудить* | ‘force’ | 0 | **13** | 0 | 1 | 1 | 0 | 0 |
| *закончить* | ‘finish’ | 5 | **50** | 0 | 14 | 0 | 1 | 0 |
| *работать* | ‘work’ | 38 | 19 | 0 | **193** | **22** | **38** | 5 |
| *становиться* | ‘become’ | **256** | 2 | 1 | 34 | 5 | 0 | **20** |

The spreadsheet *argumenthood\_df*, which annotates each verb-encoding combination based on the quantitative argumenthood test, is valuable in its own right and can serve as a reference for future analyses.

However, at this stage, we encountered a systematic complication, exemplified by the verb *rasskazyvat’* ‘tell’ discussed above. Intuitively, this verb is transitive, with accusative objects like *istorii* ‘stories’ functioning as clear arguments. Indeed, *rasskazyvat’* appears with an accusative object 28 times in our data. Yet, under our algorithm, accusative dependents of *rasskazyvat’* did not meet the quantitative argumenthood criteria: their frequency was not significantly higher than expected, reflecting the verb’s diverse valency patterns (see Table 2). This negative result is purely mathematical—since transitive verbs are common, the expected cooccurrence rate with an accusative object is high, complicating algorithmic identification (Korhonen et al., 2000, p. 204).

This issue is even more pronounced in languages with many labile verbs, where overt direct objects appear less frequently than in strictly transitive verbs. To address this, we made an exception when integrating algorithmic argumenthood judgments into our raw data: every accusative object was classified as an argument (but see Section 4.3 for an additional correction). This decision reflects the special status of the basic transitive pattern in most languages, encompassing a broad range of verbs centered on action (Lazard, 1994, pp. 134–135). Many linguists argue that case assignment in canonical transitives is structural rather than lexical (Yip et al., 1987, p. 222; see also de Marneffe et al., 2021, p. 267).

In any event, our binary annotation remained fully automatic and content-agnostic—aside from accusative dependents, which were assigned “1” by default, all other combinations were tagged “1” or “0” based on the frequency-based algorithmic test.

The resulting spreadsheet (*data*) integrates UD treebank annotations, Python-generated annotations, semi-manual encoding device annotations, and algorithmic binary argumenthood classifications. In Section 4, we evaluate the quality of our argumenthood classification.

## 3.3. Incorporating lexicographic annotations

To assess the algorithm’s performance (Section 3.2), we compared its results with annotations based on a qualitative item-by-item analysis of raw entries, distinguishing arguments from adjuncts. For this, we relied on two dictionaries: Rozental’s *Upravlenie v russkom jazyke* (*Government in the Russian Language*) (Rozental’, 1986) and *The Active Dictionary*, initiated by Yu.D. Apresjan (Apresjan (Ed.), 2014–).[[3]](#footnote-3) These sources differ in scope, target audience, and approach to argumenthood.

Rozental’s dictionary is a practical, prescriptive reference that lacks detailed analysis of argumenthood. It focuses on verbs with variable or problematic valency, omitting frequent, prototypically transitive verbs like *ubivat’* ‘kill’ while including more complex derivatives like *ubivat’sja* ‘grieve, mourn bitterly.’ For covered verbs, it provides typical valency patterns, often with brief explanations of relevant meanings.

In contrast, *The Active Dictionary* is a comprehensive academic work that reflects Apresjan and colleagues’ views on argumenthood, semantic decomposition, and combinatorial potential. Each entry provides detailed information on meaning, syntax, and usage, including a standardized representation of government (*управление*).

The dictionary-based annotations relied on whether the dictionaries listed the relevant encoding devices for the specific meaning of the given verb. Since this process was manual and required semantic analysis, it was time-consuming and impractical for the entire dataset. Ultimately, we obtained annotations for the first 5,423 entries, ordered alphabetically by verb lemma.

The annotations distinguish between “1” (the usage pattern is listed in the verb’s government pattern and considered an argument), “0” (not listed and not an argument), and <NA> (verb not included in the dictionary). Additional tags, detailed in the Supplementary Materials, appear in separate columns. The most important is “s” (for *semantic argument*), used when a syntactic dependent fulfills a semantic valency in the verb’s decomposition but the specific form is not listed in its government pattern. An example is entry 65030, shown in (6).

(6) *Kasparov uložilsja v dva s nebol'šim časa: on energično xodil, daže počti begal ot stola* ***k stolu****, rezko perestavljaja figury.*

‘Kasparov managed to finish in just over two hours: he moved energetically, almost running from table to table, swiftly rearranging the pieces.’

*The Active Dictionary* states that in this meaning, *begat’* has three semantic arguments, one of which expresses variable motion directions. We infer that *k stolu* ‘to the table’ functions as an argument in Apresjan’s framework (hence the main tag “1”). However, the exact syntactic form (*k* ‘to, toward’ + dative) is not specified in the verb’s government pattern (*модель управления*), warranting the additional tag “s.”

Manual dictionary-based argumenthood annotations are included in the final spreadsheet (*data\_with\_dictionary\_annotations*).

# 4. Results

In this section, we compare our argument-extracting algorithm’s performance with a manually annotated data subset based on dictionaries. Our goals are twofold: first, to identify weaknesses in the algorithm to better understand its limitations and potential improvements; second, to highlight quantitative insights that may be overlooked in lexicography, which typically ignores text frequencies. That said, we do not seek to replace the standard, semantically grounded concept of argumenthood with a simplistic, black-box algorithm. Rather, we aim to compare both perspectives for their mutual benefit.

## 4.1. Rozental’s dictionary

Before evaluating our algorithm, we quantitatively compare two lexicographic approaches to argumenthood—those of Rozental’s dictionary (Rozental’, 1986) and *The Active Dictionary* (Apresjan (Ed.), 2014–)—as shown in Table 4. The counts reflect manual annotations of a subset of UD entries, as discussed in Section 3.3. Verbs absent from the dictionaries resulted in <NA>s.[[4]](#footnote-4)

Table 4. Argumenthood: Rozental’s dictionary vs. *The Active Dictionary*

|  |  |  |  |
| --- | --- | --- | --- |
|  |  | *The Active Dictionary* |  |
|  |  | yes | no | <NA> | total |
| Rozental’s dictionary | yes | **984** | 47 | 65 | 1,096 |
| no | 696 | **510** | 37 | 1,243 |
| <NA> | 2,267 | 646 | 171 | 3,084 |
|  | total | 3,947 | 1,203 | 273 | 5,423 |

As Table 4 shows, *The Active Dictionary* covers 95% (5,150 of 5,423) of the manually annotated dataset, far surpassing Rozental’s 43%. Overall, the two sources align, with matching annotations (boldfaced in the table) more common than discrepancies. However, Apresjan’s approach is more inclusive, as seen in the imbalance between the two disagreement scenarios (696 vs. 47). This difference underscores the lack of a principled consensus on argumenthood in naturalistic data rather than preselected examples. In Rozental’s approach, fewer than half of (pro)nominal dependents in the text are arguments, compared to about 77% in Apresjan’s. This discrepancy should be taken into account when evaluating our algorithm’s performance. Table 5 cross-tabulates our algorithmized annotations with those based on Rozental’s dictionary.

Table 5. Argumenthood: Rozental’s dictionary vs. frequency-based algorithm

|  |  |  |  |
| --- | --- | --- | --- |
|  |  | frequency-based algorithm |  |
|  |  | yes | no | total |
| Rozental’s dictionary | yes | 1,007 | 89 | 1,096 |
| no | 682 | 561 | 1,243 |
| <NA> | 2,193 | 891 | 3,084 |
|  | total | 3,882 | 1,541 | 5,423 |

As noted earlier, more than half of UD entries contain verbs missing from Rozental’s dictionary, making algorithmic approaches inherently superior for corpus analysis—even aside from the time-consuming nature of dictionary-based annotations. More importantly, the two approaches handle arguments asymmetrically: nearly all dependents listed in Rozental’s government patterns (92%, see Table 4, first row) are also classified as arguments by our algorithm. However, the reverse does not hold—Rozental’s non-arguments are more often identified as arguments than as adjuncts by our algorithm. This again underscores the restricted and conservative nature of Rozental’s approach to argumenthood. Manual inspection shows that these additional arguments identified by the algorithm typically do meet standard semantics-based criteria, as seen in (7) and (8).

(7) *Ja ničem ne bolel*.

‘I wasn’t sick with anything.’

(8) *Vot etim parnjam ja verju*!

‘These guys I do trust!’

We conclude that our algorithm is better suited for detecting argumenthood in corpora than Rozental’s dictionary. This is not a critique of Rozental’—his dictionary was intended for contexts unrelated to automatic annotation. The rest of the paper compares our results with *The Active Dictionary*, which has a broader scope and a strong theoretical foundation.

## 4.2. Apresjan’s dictionary: an overview

Table 6 summarizes our algorithm’s performance relative to *The Active Dictionary*, as Table 5 did for Rozental’s dictionary.

Table 6. Argumenthood: *The Active Dictionary* vs. frequency-based algorithm

|  |  |  |  |
| --- | --- | --- | --- |
|  |  | frequency-based algorithm |  |
|  |  | yes | no | total |
| *The Active Dictionary* | yes | 3,409 | 538 | 3,947 |
| no | 329 | 874 | 1,203 |
| <NA> | 144 | 129 | 273 |
|  | total | 3,882 | 1,541 |  |

Based on Table 5, our algorithm performs sufficiently well if *The Active Dictionary* is taken as the gold standard. Precision for algorithmic positives is approximately 0.91, meaning that of the 3,738 entries identified as arguments, 3,409 are also classified as such in *The Active Dictionary* (excluding verbs missing from the dictionary; see Korhonen et al. (2000) for the definition of precision). Precision for negatives is lower (≈0.62), resulting in an overall precision of ≈0.83. We refer to mismatches as “false positives” (Section 4.3) and “false negatives” (Section 4.4). This standard terminology does not imply that the dictionary is always correct and the algorithm is wrong; as we show below, the two approaches sometimes capture different aspects of argumenthood.

## 4.3. False positives

As seen in Table 6, false positives are rare, accounting for 329 out of 5,423 entries. One possible source is our decision (see Section 3.2.) to classify all prepositionless accusatives as arguments, including cases like (9).

(9) *Želudok bolit ne prekraščaja pjatyj den’.*

‘The stomach has been hurting nonstop for the fifth day’.

The noun phrase *pjatyj den’* (‘(for) the fifth day’) is clearly an adjunct, traditionally analyzed as a circumstantial (*обстоятельство*) in Russian grammar. Thus, classifying all prepositionless accusatives as arguments inevitably leads to errors in such cases. The UD distinction between dependents bearing “obj” and “obl” (or occasionally “obl:tmod”) relations might seem helpful here. Table 7 cross-tabulates this distinction with the manual annotation based on *The Active Dictionary* for all prepositionless accusatives.

Table 7. Prepositionless accusative dependents: UD-internal annotations vs. *The Active Dictionary*

|  |  |  |  |
| --- | --- | --- | --- |
|  |  | UD-internal annotations |  |
|  |  | “obj” | “obl” | “obl:tmod” | total |
| *The Active dictionary* | yes | 1,068 | 53 | 6 | 1,127 |
| no | 6 | 19 | 7 | 32 |
| <NA> | 73 | 0 | 1 | 74 |
|  | total | 1,147 | 72 | 14 | 1,233 |

As seen in Table 7, the “obl” and especially “obl:tmod” tags are slightly more common among adjuncts than arguments based on *The Active Dictionary*. To refine our algorithm, we adjusted the final annotation (the “argumenthood\_corrected” column in our dataset) to rely on UD-inherent tags for accusative dependents: “obj” was classified as an argument, while all others were adjuncts. This adjustment may aid future analyses of languages where direct object-like dependents convey adverbial relations but had little impact on our algorithm’s accuracy for Russian. In any case, Russian accusative dependents contribute minimally to false positives. Since we applied a special rule for prepositionless accusatives, we exclude them from further discussion of our algorithm’s performance, focusing on the remaining 4,190 entries.

A substantial share of false positives arises from polysemous encoding devices, as illustrated by examples (10) and (11).

(10) *S ego pomošč’ju možno uznat’, čto* ***varitsja******v staleplavil’noy peči****.*

‘With its help, one can find out what is **being** **brewed in the steelmaking furnace**.’

(11) ***V drevnem Kitae******varilos’*** *pivo iz prorosšego risa.*

‘**In ancient China**, beer **was** **brewed** from sprouted rice.’

Our algorithm detected a statistical association between *varit’sja* (‘be brewed’) and the encoding device *v* (‘in’) with the locative case. In (10), this correctly classifies the boldfaced phrase as an argument, aligning with *The Active Dictionary*. However, the algorithm generalizes this pattern to all occurrences of the same encoding device with *varit’sja*, leading to an error in (11), where the phrase denotes general localization rather than the vessel or container meaning inherent in the verb’s semantics.

While cases like (11) are clear annotation errors, the algorithm sometimes captures patterns overlooked even in *The Active Dictionary*’s detailed analysis. One such case is shown in (12).

(12) ***Dlya pozitivista******est’*** *tol’ko fakty i različnye sposoby ix vzaimouvjazki*.

‘**For a positivist, there are** only facts and various ways to connect them’.

The algorithm classified *dlja* (‘for’) phrases as arguments of *byt’* (‘to be’) based on their frequent cooccurrence, though *The Active Dictionary* does not list this among the verb’s many meanings and government patterns. While the boldfaced phrase in (12) is not a typical argument, it is not a standard adjunct either. Adjuncts typically narrow a clause’s truth-conditional reference—for instance, *She baked a cake for him* necessarily entails *She baked a cake*. In (12), however, there is no such entailment that only facts exist and can be connected in various ways. Instead, the *dlja*-phrase effectively introduces a new meaning of *byt’* akin to ‘seem’ or ‘be considered,’ where it functions as an argument.

Another case where the algorithm offers semantic insights is shown in (13).

(13) *No kogda oni gus’kom* ***breli po lesnoy tropinke*** *... on uzhe tverdo znal, čto ničego ne budet*.

‘But when they **trudged** in single file **along the forest path** ... he already knew for sure that nothing would happen’.

**Based on frequent cooccurrence, the algorithm classified** po **(‘along, by’) phrases and instrumental-case dependents as arguments of** bresti **(‘to trudge’). While** The Active Dictionary **does not include such phrases in the verb’s government pattern, their frequent corpus occurrence aligns with its semantic decomposition: ‘A person (A1) slowly moves toward place (A2) from place (A3), struggling to lift their feet due to weakness, fatigue, or difficult conditions—water, deep snow, or mud’ (Apresjan (Ed.), 2014, p. 351). Though the path is not treated as a variable like A1, A2, or A3, which defines arguments, its typical properties are explicitly mentioned, making it more integral to the verb’s meaning than a standard adjunct.**

## 4.4. False negatives

False negatives occur when the algorithm fails to classify a verb’s dependent as an argument, despite the dictionary recognizing it as such. In our manually annotated dataset, they are more frequent (538 entries) than false positives (329 entries). Two main scenarios account for false negatives.

The first scenario involves rare verbs. The algorithm requires statistically significant differences and sets an absolute threshold of at least three occurrences for a verb-plus-encoding-device combination. Verbs appearing only once or twice cannot yield arguments under these conditions, as illustrated by (14).

(14) *Novikov uže ballotirovalsja v mery*.

‘Novikov has already run for mayor’.

In (14), ballotirovat’sja (‘to run for office’) appears with v (‘in’) and the rare “2nd accusative”, a form used for animate nouns patterned after inanimate ones. This encoding device, specific to verbs denoting a change in social status, clearly marks arguments. However, with only one occurrence of ballotirovat’sja in our dataset, the algorithm could not extract its argument-encoding pattern.[[5]](#footnote-5)

Thus, data scarcity is the primary cause of false negatives—an issue with no perfect solution. While our algorithm currently produces binary annotations (argument vs. adjunct), a more realistic approach might be to filter out low-frequency verbs and assign <NA>s in unclear cases instead of (potentially false) negatives.

The second major source of false negatives occurs with highly frequent, syntactically versatile verbs (see Tao et al., 2024 on the correlation between verb frequency and valency diversity). Verbs like *vernut’* (‘return’), *bit’* (‘beat’), and *vesti* (‘lead’) appear in numerous valency patterns, some of which are relatively infrequent. As a result, the algorithm fails to identify certain argument structures. This issue was already noted in Apresjan (1965), where polysemy was disregarded when extracting semantic information from frequency distributions.

Apart from the two main causes of false negatives, we also expected them to arise with verbs exhibiting “flexible” government patterns compatible with the same meaning. As noted in Apresjan and Páll (1982), many Russian verbs do not require a fixed preposition but can combine with various preposition-case pairs expressing a shared semantic role. For instance, *vernut’sja* (‘return’) can take different prepositions depending on the noun rather than the verb, e.g., *vernut’sja iz otpuska* (‘return from vacation’), *ot druga* (‘from a friend’s place’), *s koncerta* (‘from a concert’). In Apresjan and Páll’s framework, such flexible patterns are categorized as P1 (source), P2 (goal), P3 (static location), and P4 (path). Similar observations appear in Helbig & Schenkel (1983, p. 43), Ljaševskaja & Kaškin (2015, p. 482), and The Active Dictionary (Apresjan (Ed.), 2014–).

We accounted for flexible government patterns in our manual annotations based on *The Active Dictionary* (see Section 3.3), marking verbs with such patterns with an additional “s” tag. This distinction is illustrated in (15), which follows a rigid government pattern, and (16), which exhibits a flexible one—despite both involving the same preposition-case combination.

(15) *Ušakov* ***vglyadyvalsya v temnotu*** *trezvymi glazami*.

‘Ushakov peered into the darkness with sober eyes’.

(16) *Timorcy prinosjat v žertvu byka – zakalyvayut i s pesnyami* ***brosajut v more****.*

‘The Timorese sacrifice a bull—slaughter it and throw it into the sea with songs’.

Since our argument-extracting algorithm relies on the frequency of specific encoding devices rather than their groups, verbs with flexible government patterns were expected to exhibit more diffuse distributional profiles, reducing the algorithm’s efficiency. Table 8 presents the data used to test this hypothesis.

Table 8. Frequency-based argument-extraction algorithm: rigid vs. flexible government patterns

|  |  |  |
| --- | --- | --- |
|  | frequency-based algorithm |  |
|  | yes | no | total |
| rigid | 837 | 221 | 1,058 |
| flexible | 1,445 | 317 | 1,762 |
|  | 2,282 | 538 | 2,820 |

The data in Table 8 show that false negatives occur at similar rates for rigid (21%) and flexible (18%) patterns. This suggests that, despite their theoretical compatibility with various encoding devices, verbs with flexible government patterns tend to favor specific ones in actual usage, making their distributional behavior resemble that of verbs with rigid patterns.

# 5. Summary and outlook

The argument–adjunct distinction is complex, spanning formal and semantic dimensions that create interrelated but not identical contrasts. This complexity is evident in the evolution of Yu. D. Apresjan’s views on argumenthood, from his early quantitative distributional approach to the in-depth semantic analyses of his later work.

This paper seeks to reconcile different approaches to argumenthood using Russian data. We propose an algorithm for extracting arguments from UD treebanks and evaluate its performance against semantically nuanced lexicographic sources, primarily *The Active Dictionary* (Apresjan (Ed.), 2014–). The key idea is that verb arguments typically require specific encoding forms, such as prepositions and cases in Russian, leading to frequency peaks in the distribution of encoding devices across verb lemmas. In contrast, adjuncts are not lexically determined and show flatter distributions. Based on this principle, the algorithm identifies verb–encoding device combinations that occur significantly more often than expected under a flat zero hypothesis.

Evaluated against *The Active Dictionary*, the algorithm performed well, achieving an overall precision of about 0.83. False positives were particularly rare, indicating that dependents identified as arguments by the algorithm generally align with those recognized in semantic-based lexicography. The asymmetry between infrequent false positives and more common false negatives likely reflects an inherent distinction between semantic valency and formal government: while formal government presupposes semantic valency, the reverse is not necessarily true (Helbig & Schenkel, 1983, p. 44).

The low rate of false positives is promising for the practical goals of this study. This paper is part of a broader effort to analyze argumenthood and valency cross-linguistically in typologically diverse languages. For Russian, such analysis—though time-consuming—can, in principle, rely on semantic pattern analysis, given the availability of high-quality lexicographic resources. However, for most languages, such resources are lacking and unlikely to emerge soon. In this context, an algorithm that reliably extracts arguments from UD treebanks, even if incomplete, provides a valuable starting point for a quantitative, token-based study of valency patterns.

Beyond its practical applications, the frequency-based argument extraction algorithm also yields insights into the theoretical understanding of argumenthood. (i) Verbs can exhibit cooccurrence frequency peaks with dependents not traditionally considered full-fledged arguments, yet their presence can alter verb meaning and affect argument structure (e.g., *byt’ dlja* + Genitive, ‘be for someone’; see Section 4.3). (ii) While canonical arguments correspond to variables in a verb’s semantic decomposition, frequency peaks also occur with dependents that represent key semantic components, revealing complex links between syntactic and semantic structure (e.g., *bresti* ‘to trudge’; see Section 4.3). (iii) A quantitative, token-based perspective suggests that distinctions between rigid government patterns, which require a specific encoding form, and more flexible patterns, where verbs allow multiple competing encoding devices with similar spatial meanings, may not be entirely clear-cut (see Section 4.4).

# References

Apresjan, Yu. D. (1965). Opyt opisanija značenij glagolov po ix sintaksičeskim priznakam (tipam upravlenija). *Voprosy yazykoznanija, 5*, 51–66.

Apresjan, Yu. D. (1967). *Eksperimental’noe issledovanie semantiki russkogo glagola*. Moscow: Nauka.

Apresjan, Yu. D., & Páll, E. (1982). *Russkij glagol — vengerskij glagol. Upravlenie i sočetaemost’* (Vols. 1–2). Budapest: Tankönyvkiadó.

Apresjan, Yu. D. (1974). *Leksičeskaja semantika: Sinonimičeskie sredstva jazyka*. Moscow: Nauka.

Apresjan, Yu. D. (1995). *Izbrannye trudy* (Vols. 1–2). Moscow: Jazyki russkoj kul’tury.

Apresjan, Y. D. (Ed.). (2004). *Novyj ob”jasnitel’nyj slovar’ sinonimov russkogo yazyka* (2nd ed.). Moscow: Jazyki russkoj kul’tury.

Apresjan, Yu. D. (Ed.). (2014–). *Aktivnyj slovar’ russkogo jazyka* (Vol. 1, 2014; Vol. 2, 2014; Vol. 3, 2017; Vol. 4, Part 1, 2023; Vol. 4, Part 2, 2024). Moscow: Jazyki slavjanskoj kul’tury.

Barðdal, J. (2011). Lexical vs. structural case: A false dichotomy. Morphology, 21, 619–654. <https://doi.org/10.1007/s11525-010-9174-1>

Beavers, J. (2010). The structure of lexical meaning: Why semantics really matters. Language, 86(4), 821–864.

Boguslavskij, I. M. (1996). Sfera dejstvija leksičeskix edinic. Moscow: Jazyki russkoj kul’tury.

Bohnemeyer, J. (2007). Morpholexical transparency and the argument structure of verbs of cutting and breaking. Cognitive Linguistics, 18(2), 153–177.

de Marneffe, M.-C., Manning, C. D., Nivre, J., & Zeman, D. (2021). Universal Dependencies. Computational Linguistics, 47(2), 255–308.

Dixon, R. M. W. (2009). Basic linguistic theory. Volume 1: Methodology. Oxford: Oxford University Press.

Dryer, M. S. (with Gensler, O. D.). (2013). Order of object, oblique, and verb. In M. S. Dryer & M. Haspelmath (Eds.), WALS Online (v2020.4) [Data set]. Zenodo. <https://doi.org/10.5281/zenodo.13950591> (Available online at <http://wals.info/chapter/84>, accessed on 2025-02-25.)

Fowler, G. (1996). Oblique passivization in Russian. The Slavic and East European Journal, 40(3), 519–545.

Frajzyngier, Z., Gurian, N., & Karpenko, S. (2024). Minimal participant structure and the emergence of the argument/adjunct distinction. Studies in Language, 48(1), 181–227. <https://doi.org/10.1075/sl.22029.fra> (Published online: August 24, 2023).

Haspelmath, M. (2014). Arguments and adjuncts as language-particular syntactic categories and as comparative concepts. Linguistic Discovery, 12(2), 3–11.

Helbig, G., & Schenkel, W. (1983). Wörterbuch zur Valenz und Distribution deutscher Verben. Tübingen: Max Niemeyer.

Jacobs, J. (1994). Kontra Valenz. Trier: Wissenschaftlicher Verlag Trier.

Jolly, J. A. (1993). Preposition assignment in English. In R. D. Van Valin Jr. (Ed.), Advances in Role and Reference Grammar (pp. 275–310). Amsterdam: Benjamins.

Kamynina, A. A. (1999). Sovremennyj russkij jazyk. Morfologija. Moscow: Moscow State University.

Koenig, J.-P., Mauner, G., Bienvenue, B., & Conklin, K. (2008). What with? The anatomy of a role. Journal of Semantics, 25(2), 175–220.

Korhonen, A., Gorrell, G., & McCarthy, D. (2000). Statistical filtering and subcategorization frame acquisition. In Proceedings of the Joint SIGDAT Conference on Empirical Methods in Natural Language Processing and Very Large Corpora (pp. 199–205). Hong Kong, China.

Lazard, G. (1994). L’actance. Paris: Presses Universitaire de France.

Ljaševskaja, O. N., & Kaškin, E. V. (2015). Tipy informacii o leksičeskix konstrukcijax v sisteme FrejmBank. Trudy Instituta russkogo jazyka im. V. V. Vinogradova, 6, 464–555.

Levin, B. (1993). English verb classes and alternations: A preliminary investigation. Chicago: University of Chicago Press.

Levin, B., & Rappaport Hovav, M. (2005). Argument realization. Research Surveys in Linguistics. Cambridge University Press.

Malchukov, A., & Comrie, B. (Eds.). (2015). Valency classes in the world’s languages (Vols. 1-2). Berlin, Boston: De Gruyter Mouton.

Mel’čuk, I. A., Žolkovskij, A. K., & Apresjan, Y. D. (1984). Tolkovo-kombinatornyj slovar’ sovremennogo russkogo jazyka: Opyty semantiko-sintaktičeskogo opisanija russkoj leksiki. Wien: Wiener Slavistischer Almanach.

Nivre, J., de Marneffe, M.-C., Ginter, F., Hajič, J., Manning, C. D., Pyysalo, S., Schuster, S., Tyers, F., & Zeman, D. (2020). Universal dependencies v2: An ever-growing multilingual treebank collection. In Proceedings of the 12th Language Resources and Evaluation Conference (pp. 4034–4043). Marseille: European Language Resources Association.

Ooms, J. (2024). writexl: Export data frames to Excel 'xlsx' format (R package version 1.5.1). Retrieved from [https://CRAN.R-project.org/package=writexl](https://CRAN.R-project.org/package%3Dwritexl) (accessed January 16, 2024).

Plungjan, V. A., & Raxilina, E. V. (1998). Paradoksy valentnostej. Semiotika i informatika, 36, 108–119. Moscow: Jazyki russkoj kul’tury.

R Core Team. (2021). R: A language and environment for statistical computing. Vienna: R Foundation for Statistical Computing. Retrieved from <https://www.R-project.org/> (accessed May 11, 2024).

Rozental’, D. E. (1986). Upravlenie v russkom jazyke (2nd ed.). Moscow: Kniga.

Tao, S., Donatelli, L., & Hahn, M. (2024). More frequent verbs are associated with more diverse valency frames: Efficient principles at the lexicon-grammar interface. Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), 11795–11810. August 11–16, 2024.

Testelec, J. G. (2001). Vvedenie v obščij sintaksis. Moscow: RGGU.

Tesnière, L. (1959). Éléments de syntaxe structurale. Paris: Klincksieck.

Van Valin, R. D. Jr. (1993). A synopsis of Role and Reference Grammar. In R. D. Van Valin Jr. (Ed.), Advances in Role and Reference Grammar (pp. 1–166). Amsterdam: Benjamins.

Van Valin, R. D. Jr. (2001). An introduction to syntax. Cambridge: Cambridge University Press.

Wickham, H., & Bryan, J. (2023). readxl: Read Excel files (R package version 1.4.3). Retrieved from [https://CRAN.R-project.org/package=readxl](https://CRAN.R-project.org/package%3Dreadxl) (accessed January 16, 2024).

Yip, M., Maling, J., & Jackendoff, R. (1987). Case in tiers. Language, 63(2), 217–250.

Zeman, D., et al. (2023). Universal dependencies 2.12. LINDAT/CLARIAH-CZ digital library at the Institute of Formal and Applied Linguistics (ÚFAL), Faculty of Mathematics and Physics, Charles University. Retrieved from <http://hdl.handle.net/11234/1-5150>.

1. In Role and Reference Grammar, “oblique” refers to core arguments marked by an adposition or oblique case, such as to Bill in Harry gave the key to Bill (Van Valin, 1993, pp. 40–41; Beavers, 2010). Others use “oblique” in the broader sense of adjunct or adverbial modifier (Dryer & Gensler, 2013). [↑](#footnote-ref-1)
2. Additional parameters related to word order, verb morphology, and animacy are not relevant here but are available in the Supplementary Materials and will be used in other parts of our project. [↑](#footnote-ref-2)
3. The annotations discussed in this section were manually provided by Vera Arbieva Pais, to whom we express our sincere gratitude. [↑](#footnote-ref-3)
4. Apart from directly identifying the necessary verbs in dictionaries, we sometimes inferred them from aspectual pairs or reflexive counterparts. We used <NA> only when none of these approaches yielded a satisfactory result. [↑](#footnote-ref-4)
5. The algorithm extracted this pattern only for three verbs: pojti (‘become X’ in such contexts), vyjti (‘make one’s way to X’), and vybit’sja (‘rise to be an X’). [↑](#footnote-ref-5)