Inflectional Changes of Double Marked Form: Evidence from a Corpus Study of English Verbal System

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Abstract

It is assumed languages of human beings are directed by rules; however, these rules have certain exceptions in the form of irregularities. A double-marked form in which the regular rule is added to an irregular form has been attested in languages of human beings and is considered as a type of irregularization in the morphological processing. It has been claimed that there is a correlation between this type of irregularization process and high word frequencies. The real rate and nature of these double-marked forms have rarely been documented. On the basis of data from the new linguistic corpus (WebCorp) which allows us to make refined searches given its wider range of searching possibilities, this paper investigates whether there is a correlation between these irregularization processes in the English verbal system and word frequency with the aim of addressing the research questions: Is there a relationship between irregularization with the type of double-marked forms and word frequency in current English? If so, are irregular verbs with high frequency irregularized more often than the ones with low frequency? To do so, word frequencies of 488 irregular verbs in the past and perfect were collected from the selected corpus. Then, word frequencies of their corresponding double-marked forms in both forms were collected from the same corpus. Descriptive and statistical analyses were conducted to test the importance of the difference in the results. The results of the data in this study suggested that there is a correlation between high word frequency and these irregularization processes. By considering the current irregularization processes in English verbal system, this study makes an attempt to provide an introductory source of analytical research of how linguistic information is mentally processed and represented by the human language faculty.

Keywords: irregularity, irregularization processing, word frequency.

1. Introduction:

General theoretical background

The acquisition of the inflectional expressions can be illustrated from two different approaches: single-mechanism (Chomsky & Halle, 1968; Halle & Mohanan, 1985; Rumelhart & McClelland, 1986; MacWhinney & Leinbach, 1991; Albright & Hayes, 2003 among others) approaches and dual-mechanism approaches (Chialant & Caramazza, 1995; Schreuder & Baayen, 1995; Clahsen, 1999; Pinker, 1999 among others). Single-mechanism approaches can be either rule-based single-mechanism models (all inflected words are generated by rules) or associative single-mechanism models (all inflected words are stored and processed within a single associative system using distributed representations). Dual-mechanism approaches, combining the core features of the two previous models, claim that irregular words are processed through stored full-form representations in the mental lexicon, while regular ones are computed by rules (Xu & Pinker, 1995; Pinker, 1999).

Through the acquisition of inflectional forms, certain inflectional markers can be more productive than others. Evidence for productivity comes from inflectional errors of overgeneralization, which display an illicit combination of stem and affix like *go-*goed* and *draw-*drawed.* Dual route approaches justify these errors as an overregularization of the regular rule to irregular verb stems whose past form has failed to be retrieved from associative memory. The regular rule will be applied as a default, in case there is no sufficient evidence of irregularity which depends on the frequency of the irregular past form in associative memory. The lower frequency irregular forms are, the weaker memory traces will have and consequently will be more likely to be lost, letting the use of the default rule to surface in their place. Otherwise, the higher frequency these irregular forms are, the stronger memory traces they will have, thus the less opportunities for the uses of regularization instances will be. The tendency of reducing morphological markedness is generally accepted (Pinker, 1999; Lieberman et al., 2007; Michel et al., 2011 among others). In the course of English history, a lot of irregular verbs have been undergoing regularization e.g. *chide-chid-chid, gripe-grope-gripen* and *wrothe-writhen-writhed are changed into chide-chided-chided, gripe-griped-griped* and *writhe-writhed-writhed* respectively (Pinker, 1999: 69). The associative single-mechanism models, in contrast, describe these morphological processes by appealing mainly to type frequency. This means that the regular rule is over-applied because it is by far the most common way of building the past tense (Bybee, 1995).

Another morphological processing is called irregularization. The two common types of this irregularization processing are irregular replaced by other irregulars and double-marked forms. The first type is the process of replacing irregular forms by other irregular forms e.g., *cling-clang-clung, slink-slank-slunk, think-thank-thunk* along the lines of *ring-rang-rung*. Historically, several regular verbs have become irregular in English e.g. *cost-cost-cost, sneak-snuck-snuck, hang-hung-hung, dig-dug-dug, light-lit-lit, catch-caught-caught, kneel-knelt-knelt, make-made-made and wear-wore-worn, ring-rang-rung* (Nübling, 2000; Peters, 2009; Fertig, 2013). The second type of irregularization processes is the focus of this study that is called double-markeds form (DMFs henceforth) in which the regular suffix –ed is added to the past forms (e.g. *sang-sanged*) or to the perfect forms (e.g. *sung-sunged*) of irregulars. DMFs are commonly (but not always) irregular forms, e.g. *growned* and *meanted* versus *jumpeded* (Fertig, 2013). It is generally argued that these irregularization processes are rarely studied systematically. In the same respect, Fertig (2013: 92) asserts that 'Regularization may be more common historically than irregularization, but irregularizations occur much more often than many linguists seem to realize'.

Definitely, it appears to be the case that the correlation between low word frequency and regularization processing (Pinker, 1999; Lieberman et al., 2007; Michel et al., 2011 among others). Nevertheless, Fertig (1998a, 2013) asserts that there is a correlation between high word frequency and irregularization processing. He argues that words with high word frequencies are more prone to change because of their analogically innovated variant forms that occur frequently and have an opportunity to insert themselves in lexical memory.

Fertig (2013: 37) claims that a double-marked form can be considered as 'the output of a particular rule which is reanalyzed as an input candidate for the same rule'. He offers a conceivable scenario on how most likely innovators' minds work when first producing these forms. So he claims that the innovators of such forms have not recognized yet that the forms they are hearing were previously marked for the grammatical category in question. For example, they may hear the form *kye, feet* or *childer* in circumstances where the plural meaning is not clear. Hence, in the absence of recognizable formal clues showing that these forms are plurals, those innovators may consider them as singulars and accordingly form plurals using the regular pattern. In the same vein, Pinker (1999) argues that many rural and foreign speakers currently believe *children* is singular and thus add a third suffix 'yielding the triply plural *childrens'*. Moreover, he states that:

> Nonstandard dialects are filled with double plurals such as oxens, dices, lices, and feets, and that is how we got the strangest plural in Standard English, children. Once it was childer, with the old plural suffix -er also seen in the German equivalent kinder. But people stopped hearing it as a

plural, and when they had to refer to more than one child, they added a second plural marker, -en. (Pinker, 1999: 191)

By increasing our knowledge of the multilingual mind mainly in the internet space as an increasingly multilingual domain, we may cast light on our understanding of the architecture of language in the human mind. The current study will attempt to make a humble contribution to the knowledge of how human mind works by investigating irgularization processing in the multilingual environment. To this end, a corpus study based on data from the internet will be conducted to explore whether irregularization processes with the use of DMFs take place in Contemporary English and whether there is a relationship between this irregularization processing and high word frequency. More details will be mentioned in the methodology of this study.

2. Method

In this section, the methodology used to explore English irregularization processes with the type of DMFs will be illustrated.

By running a corpus study, the purpose of this study is to explore whether there is a relationship between irregularization in the shape of DMFs and word frequency with the aim of addressing the following questions:

- *Are there instances of DMFs in current English?*
- *If so, are irregular verbs (IVs henceforth) with high frequency irregularized more often than IVs with low frequency in the past and perfect forms?*

Previously, Fertig (2013) predicts that there is indeed a correlation of high word frequency with the irregularization: IVs with high frequency are irregularized more often than IVs with low frequency.

The internet environment is selected for this study as it is expected that the speed of linguistic developments can be faster than ever before (Crystal, 2004). Accordingly, I assume that verbal_developments of irregularization may take place more quickly than usual in the multilingual environment; predominantly in the internet space. To avoid the dirt of internet with numerous erroneous forms (Kilgarriff & Grefenstette, 2003: 342), the WebCorp Linguist's Search Engine (WebCorp LSE) based at Birmingham City University from is chosen as the data source of the current study. In the WebCorp, there is a new tailored linguistic search engine that is crawling and processing the World Wide Web (WWW) to build 10-billion-word text corpora (Kehoe & Gee 2007). More restriction for the corpus can be done with the use of certain linguistic tools such as word filter, wildcards, part-of-speech (POS) and 'junk' removal. In this corpus, it is also possible to try a search of the WWW efficiently because of the inadequacy of evidence in current corpora for rarer or fresher linguistic forms and features (Bergh et al., 1998).

To detect and compare frequency effects for IVs, a comparison between verbs with highest word frequency and lowest word frequencies (the number of occurrences of the verb in the selected corpus) was made. The reason behind selecting the highest versus lowest verbs is to test word frequency hypothesis asserting that high frequency of IVs is important for their survival, as a reflection of storage (Pinker & Prince, 1988; Pinker & Ullman, 2002; Michel et al., 2011 among others). To do so, firstly a search for verbs in the form of a simple past tense was made to reach all possible IVs in WebCorp LSE. The part-of-speech tag was used to reach all the verbs in a past simple tense with the selection of {VVD}. The form of a simple past tense was chosen for this search in order to reach all possible irregular forms, as the inflectional behaviour of irregular verbs are more distinguished in the simple past tense (*I played/ I ate)* than in the simple present tense *(I play/ I eat).* A list of 10,731,561 instances in a past tense was obtained from this search. The top 10,000 verbs in the term of word frequency were considered in which a minimal word frequency was 2. All unwanted hits were removed from the list before selecting the verb sample of the study. Then, the top 122 IVs versus the bottom 122 IVs from the filtered list were selected. For each selected verb, word frequencies in the past form (*played* and *spoke*) and the related perfect form (*played* and *spoken*) were collected from the corpus (see appendix 1 and the table 1 below). Then, word frequencies of their corresponding double-marked forms (DMFs) in both forms were gathered from the sample (See appendices 2 and 3).

Table 1: The study sample of 10,000 verbs with the top word frequencies in the WebCorp

Form	IVs with high frequency	IVs with low frequency
Past	122	122
Perfect	122	122
Total	244	244
	488	

Totals of word frequencies, mean frequencies and relative frequencies of the chosen verbs split by frequency (high versus low), form (past versus perfect) and type (correct irregular verbs versus DMFs) were calculated and displayed in tables and different types of graphs for comparative and descriptive purposes. Then, statistical models were conducted to test the significance of the difference in frequency effects for irregularization instances of IVs with low and high frequencies. Lastly, the results of this investigation were compared with the predictions of the models for morphological processing to determine which can best fit the data and hence a conclusion was drawn.

3. Results and Discussion

To examine the correlation between irregularization processes in terms of DMFs and word frequency, the first step is to explore whether current English undergoes this kind of the irregularization or not by inquiring an answer to the following question:

- *Are there instances of DMFs in current English?*

If instances of the double-marked form will be attested in current English, we accordingly aim to explore a link between of DMFs and word frequency in the selected sample. Fertig (2013: 37) previously predicts the correlation of high word frequency with the irregularization: IVs with high frequency are irregularized more often than IVs with low frequency. In this study, we will test this prediction by addressing following questions:

- *Is there a relationship between irregularization with the type of DMFs and word frequency?*
- *If so, are IVs with high frequency irrgularized more often than the ones with low frequency?*

To answer these questions, a sample of the 488 IVs in the past and perfect with their word frequencies is chosen from WebCorp (See appendix 1). Then, word frequencies of their corresponding DMFs in both forms are gathered from the sample (See appendices 2 and 3).

In the selected sample of the study, it is found that there are indeed instances of irregularization processes with the use of DMFs (See tables 2 and 3 below).

Table 2: Word frequencies of DMFs of IVs with high frequency in past and perfect forms

Verbs		Form	Word-freq.	DMFs			
				Past +ed	Word-freq.	Perfect+ed	Word-freq.
1.	get	Past	364219	gotted	1	0	0
2.	make	Past	248679	maded	7	0	0
3.	take	Past	170648	tooked	3	0	0
4.	give	Past	98449	gaved	11	0	0
5.	leave	Past	87478	lefted	4	0	0

6.	lose	Past	66879	losted	3	0	0
7.	hear	Past	43279	hearded	1	0	0
8.	fall	Past	31214	felled	2	0	0
9.	meet	Past	29457	metted	1	0	0
10.	mean	Past	28086	meanted	1	0	0
11.	break	Past	27145	broked	7	0	0
12.	pay	Past	26451	paided	2	0	0
13.	choose	Past	23605	chosed	4	0	0
14.	grow	Past	24566	0	0	growned	2
15.	speak	Past	23430	spoked	3	0	0
16.	wear	Past	12504	0	0	worned	1
17.	draw	Past	11420	0	0	drawned	1
18.	rise	Past	10075	rosed	1	0	0
19.	strike	Past	8618	strucked	2	0	0
20.	stick	Past	7681	stucked	6	0	0
21.	wake	Past	7582	woked	3	0	0
22.	stole	Past	7266	stoled	17	0	0
23.	fly	Past	6046	flewed	1	0	0
24.	lie	Past	5367	layed	168	0	0
25.	dig	Past	3715	dugged	1	0	0
26.	shake	Past	3492	shooked	1	0	0
27.	drink	Past	3103	dranked	1	0	0
28.	bear	Past	2053	0	0	borned	1
29.	freeze	Past	1562	frozed	1	0	0
30.	sneak	Past	1098	snucked	3	0	0
31.	get	Perfect	105863	gotted	5	0	0
32.	leave	Perfect	82422	lefted	2	0	0
33.	hear	Perfect	71973	hearded	1	0	0
34.	fall	Perfect	12189	felled	265	0	0
35.	meet	Perfect	19988	metted	3	0	0
36.	break	Perfect	16493	broked	2	0	0
37.	pay	Perfect	57353	paided	1	0	0
38.	choose	Perfect	16722	chosed	6	0	0
39.	grow	Perfect	19345	0	0	growned	1
40.	speak	Perfect	10132	spoked	1	0	0
41.	beat	Perfect	9086	0	0	beatened	2
42.	wear	Perfect	8151	0	0	worned	2
43.	draw	Perfect	17099	0	0	drawned	1
44.	teach	Perfect	9893	taughted	3	0	0
45.	blow	Perfect	11122	blewed	1	0	0
46.	build	Perfect	29034	builted	1	0	0
47.	stick	Perfect	22001	stucked	5	0	0
48.	wake	Perfect	927	woked	2	0	0
49.	sing	Perfect	2252	0	0	sunged	1
50.	lie	Perfect	180	layed	180	0	0

51.	tear	Perfect	5335	0	0	torned	1
52.	bear	Perfect	31089	0	0	borned	6
Total			**1,943,816**		**733**		**19**

Table 3: Word frequencies of DMFs of IVs with low frequency in past and perfect forms

Verbs		**Form**	**Word-freq.**	**DMFs**			
				Past +ed	**Word-freq.**	**Perfect+ed**	**Word-freq.**
1	forbid	Past	159	0	0	forbiddened	1
2	befall	Past	128	befelled	1	0	0
3	slink	Past	57	0	0	slunked	1
4	smell	Past	12	smelted	1	0	0
5	stink	Perfect	259	stanked	2	0	0
6	spoil	Perfect	375	spoilted	1	0	0
7	bite	Perfect	1265	bitted	3	0	0
8	smite	Perfect	1019	smoted	8	0	0
9	smell	Perfect	260	smelted	2	0	0
Total			**3,534**		**19**		**2**

Out of 488 IVs, 61 DMFs are attested in the sample. From tables 2 and 3 above, we see that 52 different DMFs of IVs with high frequency in past and perfect forms are found, while there are only 9 different DMFs of IVs with low frequency in past and perfect form. In both forms, the number of word frequencies of DFMs with the '*past +-ed'* type (28 instances in the past form and 20 instances in the perfect form) is greater than the one with the '*perfect +-ed'* type (only 6 instances in the past form and 7 instances in the perfect form), as shown in the following table.

Table 4: 61 DMFs split by form and frequency in the sample

DFMs		**High frequency**	**Low frequency**	**Total**
past	past + -ed	26	2	28
	perfect + -ed	4	2	6
perfect	past + -ed	15	5	20
	perfect + -ed	7	0	7
Total		**52**	**9**	**61**

In figure 1, a pie chart represents percentages of the four types of DMFs in the sample. In the past form, the slice of DFMs with the '*past +-ed'* type presents higher rate compared to the one with the '*perfect +-ed'* type (50% versus 29% respectively). Yet, in the perfect form, the percentage of DFMs with the '*past +-ed'* type is lower compared to the ones with the '*perfect +-ed'* type (8% versus 13% respectively).

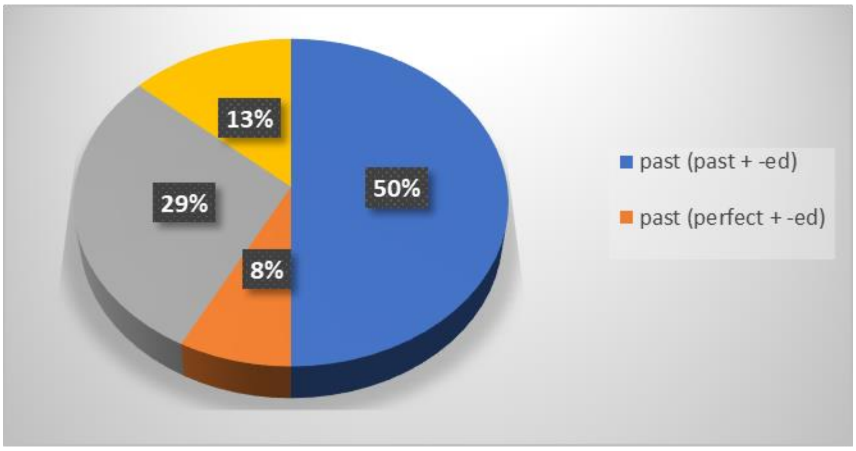

Figure 1: Percentages of the four types of DMFs in the sample

To draw comparisons, table 5 displays word frequencies of IVs and DMFs gathered from the sample.

Table 5: Word frequencies of IVs and DMFs split by form and frequency

Type / Form		**High frequency**	**Low frequency**	**Total**
IVs		6,737,521	51121	6,788,642
DFMs		752	21	773
IVs/ past		4,299,434	14213	4,313,647
DFMs/past	past + -ed	255	2	264
	perfect + -ed	5	2	
IVs/perfect		2,438,087	36908	2,474,995
DFMs/perfect	past + -ed	478	17	509
	perfect + -ed	14	0	

As shown in table 5, of the total word frequency of IVs in our sample (6,788,642), word frequency of the irregularization with the use of DFMs is 773. Word frequency of DFMs with high frequency (752) is obviously greater than the one with low frequency (21). Similarly, in both forms, word frequencies of DFMs with high frequency (past: 260 and perfect: 492) are higher than the ones with low frequency (past: 4 and perfect: 17). The differences in the frequency distributions of DFMs with high and low frequency may suggest a relationship between the irregularization and word frequency.

In order to have better understanding of this irregularization process, table 6 informs us about the central tendency of the data distribution by computing mean frequency.

Table 6: Mean frequencies of IVs and DMFs split by form and frequency

Type / Form		**High frequency**	**Low frequency**	**Total**
IVs		27,613	210	13,911
DFMs		14	2	13
IVs/ past		35,241	116.5	17,679
DFMs/past	past + -ed	10	1	11
	perfect + -ed	1	1	2
IVs/perfect		19,984	303	10,143
DFMs/perfect	past + -ed	32	3	35
	perfect + -ed	2	0	2

As can be seen in table 6, mean frequency of DFMs with high frequency (14) is greater than the one with low frequency (2). In specific, mean frequencies of DFMs with the '*past +-ed'* type in both forms (past: 11 and perfect: 35) are greater than the one with the '*perfect +-ed'* type (past: 2 and perfect: 2).

A statistical model is conducted to investigate the effects of form and frequency on word frequencies of the verbs in the sample. Two linear model are adopted, where word frequency is considered as a dependent numeric variable and fixed factors are the past form in the first model and the perfect form in the second one. A logarithmic transformation is applied to the data to remove most of skewness of the frequency distribution. The linear models reveal that the effects of frequency in the past form (β = -0.29, t = -4.36, p = 1.95e-05) and the perfect form (β = -0.07, t = -2.48, p = 0.014) are significant. This means that the differences between the frequency distributions of DFMs in both forms are significant. Thus, we conclude that there is a relationship between the irregularization process with the type of DFMs and word frequency. IVs with high frequency show more tendency towards this irregularization process than IVs with low frequency in the sample. This result is compatible with the claim of Fertig (2013) in which the correlation between high word frequency and the irregularization is confirmed.

4. Conclusion

The main concern of the present corpus-based study is to check whether there a is correlation between the irregularization processes with the type of double-marked forms (in which the regular suffix -ed is added to the past or perfect form) and high word frequency in multilingual domain of current English. The multilingual environment in the internet is selected for this study as it is expected that the linguistic developments appear to be happening more rapidly than at any earlier time in history of linguistics.

The results of the data analysis display a relationship between high word frequency and these irregularization processes, as irregular verbs with high word frequency are more prone to be irrgularized than the ones with low frequency in both forms. Accordingly, this tells us that there is a clear trend towards irregularization processes with the use of double-marked forms in the selected sample from WebCorp LSE. These findings are consistent with the prediction of Fertig (2013) who already confirms a positive correlation between this type of irregularization and words with high frequency. Fertig interprets the linguistic behavior of these irregularization instances as feeding irregulars which are considered as stems into the regular process. Put differently, such irregularization processes may be a reflection of over-use of grammatical rules and this can be in favor of rule-based single-mechanism models in which all inflected words are generated by rules.

It is hoped that by doing this analysis further researchers have a good introductory source about the irregularization processes in English verbal system. These processes are analyzed from morphological point of view, further analyses can be tackled to deal with such processes with the focus on syntactic, semantic or pragmatic domains. Moreover, another area that will be possibly productive to investigate such morphological processing is the English nominal system in the same multilingual space. This is due to the fact that the distribution of the morphological features in this system has certain resemblances to the English verbal system concerning regularity and irregularity aspects.

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Appendices

Appendix 1: Word frequencies of IVs in the past and perfect forms (without suppletives) from the sample

	IV- HF			IV- LF		
	verbs	word frequency		word frequency		
		past	perfect	verbs	past	perfect
1	say	777450	51786	overpay	497	1465
2	get	364219	105863	thrust	473	893
3	make	248679	188063	uphold	467	530
4	think	196651	32005	creep	455	472
5	come	185412	77032	shine	452	260
6	take	170648	96814	speed	425	246
7	tell	128587	38612	rewrite	403	770
8	see	122744	170973	mistake	383	3914
9	find	122430	68602	overtake	377	713
10	write	121799	74318	pen	336	0
11	give	98449	115429	forecast	323	570
12	know	97106	75836	mislead	316	508
13	leave	87478	82422	string	308	672
14	put	79044	52353	fling	307	387
15	feel	75681	12925	undertake	305	788
16	win	69927	30520	cling	298	122
17	lose	66879	63377	shrink	271	810
18	hit	56947	28127	weave	262	1453
19	become	52776	44622	withhold	261	644
20	buy	51794	16025	overthrow	258	256
21	begin	47992	10100	stride	253	0
22	spend	46682	30051	remake	243	533
23	hear	43279	71973	plead	236	123
24	run	40501	31119	sweat	232	0
25	bring	40364	25991	outgrow	228	517
26	keep	39339	15866	kneel	224	44
27	set	37560	64778	withstand	198	80
28	send	37424	22082	inset	173	23
29	fall	31214	12189	foresee	172	240
30	meet	29457	19988	breed	172	735
31	read	28890	63888	stink	170	259
32	mean	28086	21320	spell	159	182
33	throw	27813	22642	forbid	159	1979
34	lead	27427	18560	podcast	159	12
35	break	27145	16493	bend	146	30
36	pay	26451	57353	offset	144	985
37	catch	24811	26625	slit	141	51
38	choose	23605	16722	recast	139	261
39	grow	24566	19345	bust	136	1
40	speak	23430	10132	babysit	128	39

41	beat	23122	9086	befall	128	102
42	let	22822	5853	strive	118	33
43	hold	22183	30376	rid	116	479
44	sit	21916	2972	repay	107	1010
45	forget	20897	15712	sling	105	175
46	cut	19169	16836	foretell	98	102
47	sell	19015	30959	tread	97	136
48	stand	16503	1343	outrun	96	44
49	shoot	13999	8638	dwell	89	47
50	drive	13967	10686	wet	87	0
51	wear	12504	8151	spoil	85	375
52	eat	11673	6604	lean	84	29
53	draw	11420	17099	behold	84	28
54	teach	11039	9893	override	82	112
55	bet	10931	307	retell	80	149
56	blow	10226	11122	outshoot	80	59
57	rise	10075	2788	spill	79	172
58	strike	8618	5538	overrun	79	758
59	build	8004	29034	bite	78	1265
60	shut	7815	6568	partake	77	78
61	stick	7681	22001	cleave	76	1
62	wake	7582	927	retake	76	25
63	stole	7266	7592	oversleep	72	20
64	cost	7259	2269	undercut	71	111
65	quit	6725	1397	underwrite	66	168
66	understand	7142	6253	ken	61	111
67	hang	6213	3116	waylay	58	106
68	fly	6046	2074	mishear	57	109
69	fight	5747	3409	slink	57	25
70	sing	5460	2252	rewind	56	11
71	lie	5367	180	overspend	56	196
72	lay	5174	10303	overshoot	56	36
73	sleep	4896	4	wring	50	90
74	cast	4757	6060	inbreed	48	83
75	seek	3878	3003	smite	46	1019
76	wind	3781	461	rethink	44	68
77	dig	3715	17	beget	41	149
78	light	3665	3087	underthrow	35	4
79	shake	3492	1646	abide	33	21
80	hurt	3443	21903	outshine	33	42
81	split	3405	3855	knit	31	3180
82	spread	3380	4026	unsay	31	137
83	ride	3184	863	bespeak	26	1
84	drink	3103	1	unwind	23	84
85	tear	2774	5335	redraw	23	0

86	upset	2722	12730	unbind	22	30
87	ring	2279	1013	forsake	22	380
88	shed	2199	2345	unstick	21	78
89	shit	2150	1618	burnt	20	1204
90	deal	2110	5885	cowrite	19	6
91	sweep	2081	3103	shoe	18	45
92	bear	2053	31089	miscast	14	166
93	hide	1717	6245	recut	13	10
94	swing	1675	674	unmake	12	31
95	slide	1569	175	smell	12	260
96	freeze	1562	3139	foreknow	11	5
97	swear	1533	2196	typeset	11	39
98	overcome	1514	1756	inlay	11	30
99	arise	1507	384	intercut	11	47
100	feed	1470	5994	betake	11	3
101	learn	1306	1415	heave	10	9
102	withdraw	1296	1651	typecast	9	131
103	rebuild	1269	8	rerun	9	0
104	spin	1240	1258	overfeed	9	31
105	sink	1212	1258	uppercut	9	3
106	flee	1104	337	thrive	7	0
107	sneak	1098	383	overwrite	7	121
108	lend	1043	686	wed	7	653
109	spit	1026	321	sting	7	746
110	awake	897	217	chide	6	6
111	bid	861	166	overblow	5	4
112	dream	840	35	gird	5	7
113	broadcast	759	2519	overdraw	4	240
114	burst	740	0	handwrite	4	0
115	oversee	699	538	unfreeze	4	46
116	swim	677	52	bestride	4	0
117	weep	634	0	bless	3	52
118	spring	603	1130	bereave	3	0
119	bleed	591	6	overhang	3	7
120	grind	579	589	stave	2	1
121	leap	544	3	strip	2	0
122	forgive	506	2649	clap	2	0
	Total	**4299434**	**2438087**		**14213**	**36908**
		6737521			**51121**	
		6788642				

Appendix 2: Word frequencies of DMFs with high frequency in past and perfect from the sample

	Verbs	**Form**	**Word freq.**	**DMFs**			
				Past+ -ed	**Word freq.**	**Perfect+ -ed**	**Word freq.**

1.	say	Past	777450	-	0	-	0
2.	get	Past	364219	gotted	1	-	0
3.	make	Past	248679	maded	7	-	0
4.	think	Past	196651	-	0	-	0
5.	come	Past	185412	-	0	-	0
6.	take	Past	170648	tooked	3	-	0
7.	tell	Past	128587	-	0	-	0
8.	see	Past	122744	-	0	-	0
9.	find	Past	122430	-	0	-	0
10.	write	Past	121799	-	0	-	0
11.	give	Past	98449	gaved	11	-	0
12.	know	Past	97106	-	0	-	0
13.	leave	Past	87478	lefted	4	-	0
14.	put	Past	79044	-	0	-	0
15.	feel	Past	75681	-	0	-	0
16.	win	Past	69927	-	0	-	0
17.	lose	Past	66879	losted	3	-	0
18.	hit	Past	56947	-	0	-	0
19.	become	Past	52776	-	0	-	0
20.	buy	Past	51794	-	0	-	0
21.	begin	Past	47992	-	0	-	0
22.	spend	Past	46682	-	0	-	0
23.	hear	Past	43279	hearded	1	-	0
24.	run	Past	40501	-	0	-	0
25.	bring	Past	40364	-	0	-	0
26.	keep	Past	39339	-	0	-	0
27.	set	Past	37560	-	0	-	0
28.	send	Past	37424	-	0	-	0
29.	fall	Past	31214	felled	2	-	0
30.	meet	Past	29457	metted	1	-	0
31.	read	Past	28890	-	0	-	0
32.	mean	Past	28086	meanted	1	-	0
33.	throw	Past	27813	-	0	-	0
34.	lead	Past	27427	-	0	-	0
35.	break	Past	27145	broked	7	-	0
36.	pay	Past	26451	paided	2	-	0
37.	catch	Past	24811	-	0	-	0
38.	choose	Past	23605	chosed	4	-	0
39.	grow	Past	24566	-	0	growned	2
40.	speak	Past	23430	spoked	3	-	0
41.	beat	Past	23122	-	0	-	0
42.	let	Past	22822	-	0	-	0

43.	hold	Past	22183	-	0	-	0
44.	sit	Past	21916	-	0	-	0
45.	forget	Past	20897	-	0	-	0
46.	cut	Past	19169	-	0	-	0
47.	sell	Past	19015	-	0	-	0
48.	stand	Past	16503	-	0	-	0
49.	shoot	Past	13999	-	0	-	0
50.	drive	Past	13967	-	0	-	0
51.	wear	Past	12504	-	0	worned	1
52.	eat	Past	11673	-	0	-	0
53.	draw	Past	11420	-	0	drawned	1
54.	teach	Past	11039	-	0	-	0
55.	bet	Past	10931	-	0	-	0
56.	blow	Past	10226	-	0	-	0
57.	rise	Past	10075	rosed	1	-	0
58.	strike	Past	8618	strucked	2	-	0
59.	build	Past	8004	-	0	-	0
60.	shut	Past	7815	-	0	-	0
61.	stick	Past	7681	stucked	6	-	0
62.	wake	Past	7582	woked	3	-	0
63.	stole	Past	7266	stoled	17	-	0
64.	cost	Past	7259	-	0	-	0
65.	quit	Past	6725	-	0	-	0
66.	understand	Past	7142	-	0	-	0
67.	hang	Past	6213	-	0	-	0
68.	fly	Past	6046	flewed	1	-	0
69.	fight	Past	5747	-	0	-	0
70.	sing	Past	5460	-	0	-	0
71.	lie	Past	5367	layed	168	-	0
72.	lay	Past	5174	-	0	-	0
73.	sleep	Past	4896	-	0	-	0
74.	cast	Past	4757	-	0	-	0
75.	seek	Past	3878	-	0	-	0
76.	wind	Past	3781	-	0	-	0
77.	dig	Past	3715	dugged	1	-	0
78.	light	Past	3665	-	0	-	0
79.	shake	Past	3492	shooked	1	-	0
80.	hurt	Past	3443	-	0	-	0
81.	split	Past	3405	-	0	-	0
82.	spread	Past	3380	-	0	-	0
83.	ride	Past	3184	-	0	-	0
84.	drink	Past	3103	dranked	1	-	0

85.	tear	Past	2774	-	0	-	0
86.	upset	Past	2722	-	0	-	0
87.	ring	Past	2279	-	0	-	0
88.	shed	Past	2199	-	0	-	0
89.	shit	Past	2150	-	0	-	0
90.	deal	Past	2110	-	0	-	0
91.	sweep	Past	2081	-	0	-	0
92.	bear	Past	2053	-	0	borned	1
93.	hide	Past	1717	-	0	-	0
94.	swing	Past	1675	-	0	-	0
95.	slide	Past	1569	-	0	-	0
96.	freeze	Past	1562	frozed	1	-	0
97.	swear	Past	1533	-	0	-	0
98.	overcome	Past	1514	-	0	-	0
99.	arise	Past	1507	-	0	-	0
100.	feed	Past	1470	-	0	-	0
101.	learn	Past	1306	-	0	-	0
102.	withdraw	Past	1296	-	0	-	0
103.	rebuild	Past	1269	-	0	-	0
104.	spin	Past	1240	-	0	-	0
105.	sink	Past	1212	-	0	-	0
106.	flee	Past	1104	-	0	-	0
107.	sneak	Past	1098	snucked	3	-	0
108.	lend	Past	1043	-	0	-	0
109.	spit	Past	1026	-	0	-	0
110.	awake	Past	897	-	0	-	0
111.	bid	Past	861	-	0	-	0
112.	dream	Past	840	-	0	-	0
113.	broadcast	Past	759	-	0	-	0
114.	burst	Past	740	-	0	-	0
115.	oversee	Past	699	-	0	-	0
116.	swim	Past	677	-	0	-	0
117.	weep	Past	634	-	0	-	0
118.	spring	Past	603	-	0	-	0
119.	bleed	Past	591	-	0	-	0
120.	grind	Past	579	-	0	-	0
121.	leap	Past	544	-	0	-	0
122.	forgive	Past	506	-	0	-	0
123.	say	Perfect	51786	-	0	-	0
124.	get	Perfect	105863	gotted	5	-	0
125.	make	Perfect	188063	-	0	-	0
126.	think	Perfect	32005	-	0	-	0

127.	come	Perfect	77032	-	0	-	0
128.	take	Perfect	96814	-	0	-	0
129.	tell	Perfect	38612	-	0	-	0
130.	see	Perfect	170973	-	0	-	0
131.	find	Perfect	68602	-	0	-	0
132.	write	Perfect	74318	-	0	-	0
133.	give	Perfect	115429	-	0	-	0
134.	know	Perfect	75836	-	0	-	0
135.	leave	Perfect	82422	lefted	2	-	0
136.	put	Perfect	52353	-	0	-	0
137.	feel	Perfect	12925	-	0	-	0
138.	win	Perfect	30520	-	0	-	0
139.	lose	Perfect	63377	-	0	-	0
140.	hit	Perfect	28127	-	0	-	0
141.	become	Perfect	44622	-	0	-	0
142.	buy	Perfect	16025	-	0	-	0
143.	begin	Perfect	10100	-	0	-	0
144.	spend	Perfect	30051	-	0	-	0
145.	hear	Perfect	71973	hearded	1	-	0
146.	run	Perfect	31119	-	0	-	0
147.	bring	Perfect	25991	-	0	-	0
148.	keep	Perfect	15866	-	0	-	0
149.	set	Perfect	64778	-	0	-	0
150.	send	Perfect	22082	-	0	-	0
151.	fall	Perfect	12189	felled	265	-	0
152.	meet	Perfect	19988	metted	3	-	0
153.	read	Perfect	63888	-	0	-	0
154.	mean	Perfect	21320	-	0	-	0
155.	throw	Perfect	22642	-	0	-	0
156.	lead	Perfect	18560	-	0	-	0
157.	break	Perfect	16493	broked	2	-	0
158.	pay	Perfect	57353	paided	1	-	0
159.	catch	Perfect	26625	-	0	-	0
160.	choose	Perfect	16722	chosed	6	-	0
161.	grow	Perfect	19345	-	0	growned	1
162.	speak	Perfect	10132	spoked	1	-	0
163.	beat	Perfect	9086	-	0	beatened	2
164.	let	Perfect	5853	-	0	-	0
165.	hold	Perfect	30376	-	0	-	0
166.	sit	Perfect	2972	-	0	-	0
167.	forget	Perfect	15712	-	0	-	0
168.	cut	Perfect	16836	-	0	-	0

169.	sell	Perfect	30959	-	0	-	0
170.	stand	Perfect	1343	-	0	-	0
171.	shoot	Perfect	8638	-	0	-	0
172.	drive	Perfect	10686	-	0	-	0
173.	wear	Perfect	8151	-	0	worned	2
174.	eat	Perfect	6604	-	0	-	0
175.	draw	Perfect	17099	-	0	drawned	1
176.	teach	Perfect	9893	taughted	3	-	0
177.	bet	Perfect	307	-	0	-	0
178.	blow	Perfect	11122	blewed	1	-	0
179.	rise	Perfect	2788	-	0	-	0
180.	strike	Perfect	5538	-	0	-	0
181.	build	Perfect	29034	builted	1	-	0
182.	shut	Perfect	6568	-	0	-	0
183.	stick	Perfect	22001	stucked	5	-	0
184.	wake	Perfect	927	woked	2	-	0
185.	stole	Perfect	7592	-	0	-	0
186.	cost	Perfect	2269	-	0	-	0
187.	quit	Perfect	1397	-	0	-	0
188.	understand	Perfect	6253	-	0	-	0
189.	hang	Perfect	3116	-	0	-	0
190.	fly	Perfect	2074	-	0	-	0
191.	fight	Perfect	3409	-	0	-	0
192.	sing	Perfect	2252	-	0	sunged	1
193.	lie	Perfect	180	layed	180	-	0
194.	lay	Perfect	10303	-	0	-	0
195.	sleep	Perfect	4	-	0	-	0
196.	cast	Perfect	6060	-	0	-	0
197.	seek	Perfect	3003	-	0	-	0
198.	wind	Perfect	461	-	0	-	0
199.	dig	Perfect	17	-	0	-	0
200.	light	Perfect	3087	-	0	-	0
201.	shake	Perfect	1646	-	0	-	0
202.	hurt	Perfect	21903	-	0	-	0
203.	split	Perfect	3855	-	0	-	0
204.	spread	Perfect	4026	-	0	-	0
205.	ride	Perfect	863	-	0	-	0
206.	drink	Perfect	1	-	0	-	0
207.	tear	Perfect	5335	-	0	torned	1
208.	upset	Perfect	12730	-	0	-	0
209.	ring	Perfect	1013	-	0	-	0
210.	shed	Perfect	2345	-	0	-	0

211.	shit	Perfect	1618	-	0	-	0
212.	deal	Perfect	5885	-	0	-	0
213.	sweep	Perfect	3103	-	0	-	0
214.	bear	Perfect	31089	-	0	borned	6
215.	hid	Perfect	6245	-	0	-	0
216.	swing	Perfect	674	-	0	-	0
217.	slide	Perfect	175	-	0	-	0
218.	freeze	Perfect	3139	-	0	-	0
219.	swear	Perfect	2196	-	0	-	0
220.	overcome	Perfect	1756	-	0	-	0
221.	arise	Perfect	384	-	0	-	0
222.	feed	Perfect	5994	-	0	-	0
223.	learn	Perfect	1415	-	0	-	0
224.	withdraw	Perfect	1651	-	0	-	0
225.	rebuild	Perfect	8	-	0	-	0
226.	spin	Perfect	1258	-	0	-	0
227.	sink	Perfect	1258	-	0	-	0
228.	flee	Perfect	337	-	0	-	0
229.	sneak	Perfect	383	-	0	-	0
230.	lend	Perfect	686	-	0	-	0
231.	spit	Perfect	321	-	0	-	0
232.	awake	Perfect	217	-	0	-	0
233.	bid	Perfect	166	-	0	-	0
234.	dream	Perfect	35	-	0	-	0
235.	broadcast	Perfect	2519	-	0	-	0
236.	burst	Perfect	0	-	0	-	0
237.	oversee	Perfect	538	-	0	-	0
238.	swim	Perfect	52	-	0	-	0
239.	weep	Perfect	0	-	0	-	0
240.	spring	Perfect	1130	-	0	-	0
241.	bleed	Perfect	6	-	0	-	0
242.	grind	Perfect	589	-	0	-	0
243.	leap	Perfect	3	-	0	-	0
244.	forgive	Perfect	2649	-	0	-	0
	Total		6,737,521		733		19

Appendix 3: Word frequencies of DMFs with low frequency in past and perfect from the sample

	Verbs	**Form**	**Word freq.**	**DMFs**			
				Past+ -ed	**Word freq.**	**Perfect+ -ed**	**Word freq.**
1.	overpay	Past	497	-	0	-	0
2.	thrust	Past	473	-	0	-	0
3.	uphold	Past	467	-	0	-	0
4.	creep	Past	455	-	0	-	0

5.	shine	Past	452	-	0	-	0
6.	speed	Past	425	-	0	-	0
7.	rewrite	Past	403	-	0	-	0
8.	mistake	Past	383	-	0	-	0
9.	overtake	Past	377	-	0	-	0
10.	pen	Past	336	-	0	-	0
11.	forecast	Past	323	-	0	-	0
12.	mislead	Past	316	-	0	-	0
13.	string	Past	308	-	0	-	0
14.	fling	Past	307	-	0	-	0
15.	undertake	Past	305	-	0	-	0
16.	cling	Past	298	-	0	-	0
17.	shrink	Past	271	-	0	-	0
18.	weave	Past	262	-	0	-	0
19.	withhold	Past	261	-	0	-	0
20.	overthrow	Past	258	-	0	-	0
21.	stride	Past	253	-	0	-	0
22.	remake	Past	243	-	0	-	0
23.	plead	Past	236	-	0	-	0
24.	sweat	Past	232	-	0	-	0
25.	outgrow	Past	228	-	0	-	0
26.	kneel	Past	224	-	0	-	0
27.	withstand	Past	198	-	0	-	0
28.	inset	Past	173	-	0	-	0
29.	foresee	Past	172	-	0	-	0
30.	breed	Past	172	-	0	-	0
31.	stink	Past	170	-	0	-	0
32.	spell	Past	159	-	0	-	0
33.	forbid	Past	159	-	0	forbiddened	1
34.	podcast	Past	159	-	0	-	0
35.	bend	Past	146	-	0	-	0
36.	offset	Past	144	-	0	-	0
37.	slit	Past	141	-	0	-	0
38.	recast	Past	139	-	0	-	0
39.	bust	Past	136	-	0	-	0
40.	babysit	Past	128	-	0	-	0
41.	befall	Past	128	befelled	1	-	0
42.	strive	Past	118	-	0	-	0
43.	rid	Past	116	-	0	-	0
44.	repay	Past	107	-	0	-	0
45.	sling	Past	105	-	0	-	0
46.	foretell	Past	98	-	0	-	0

47.	tread	Past	97	-	0	-	0
48.	outrun	Past	96	-	0	-	0
49.	dwell	Past	89	-	0	-	0
50.	wet	Past	87	-	0	-	0
51.	spoil	Past	85	-	0	-	0
52.	lean	Past	84	-	0	-	0
53.	behold	Past	84	-	0	-	0
54.	override	Past	82	-	0	-	0
55.	retell	Past	80	-	0	-	0
56.	outshoot	Past	80	-	0	-	0
57.	spill	Past	79	-	0	-	0
58.	overrun	Past	79	-	0	-	0
59.	bite	Past	78	-	0	-	0
60.	partake	Past	77	-	0	-	0
61.	cleave	Past	76	-	0	-	0
62.	retake	Past	76	-	0	-	0
63.	oversleep	Past	72	-	0	-	0
64.	undercut	Past	71	-	0	-	0
65.	underwrite	Past	66	-	0	-	0
66.	ken	Past	61	-	0	-	0
67.	waylay	Past	58	-	0	-	0
68.	mishear	Past	57	-	0	-	0
69.	slink	Past	57	-	0	slunked	1
70.	rewind	Past	56	-	0	-	0
71.	overspend	Past	56	-	0	-	0
72.	overshoot	Past	56	-	0	-	0
73.	wring	Past	50	-	0	-	0
74.	inbreed	Past	48	-	0	-	0
75.	smite	Past	46	-	0	-	0
76.	rethink	Past	44	-	0	-	0
77.	beget	Past	41	-	0	-	0
78.	underthrow	Past	35	-	0	-	0
79.	abide	Past	33	-	0	-	0
80.	outshine	Past	33	-	0	-	0
81.	knit	Past	31	-	0	-	0
82.	unsay	Past	31	-	0	-	0
83.	bespeak	Past	26	-	0	-	0
84.	unwind	Past	23	-	0	-	0
85.	redraw	Past	23	-	0	-	0
86.	unbind	Past	22	-	0	-	0
87.	forsake	Past	22	-	0	-	0
88.	unstick	Past	21	-	0	-	0
89.	burnt	Past	20	-	0	-	0

90.	cowrite	Past	19	-	0	-	0
91.	shoe	Past	18	-	0	-	0
92.	miscast	Past	14	-	0	-	0
93.	recut	Past	13	-	0	-	0
94.	unmake	Past	12	-	0	-	0
95.	smell	Past	12	smelted	1	-	0
96.	foreknow	Past	11	-	0	-	0
97.	typeset	Past	11	-	0	-	0
98.	inlay	Past	11	-	0	-	0
99.	intercut	Past	11	-	0	-	0
100.	betake	Past	11	-	0	-	0
101.	heave	Past	10	-	0	-	0
102.	typecast	Past	9	-	0	-	0
103.	rerun	Past	9	-	0	-	0
104.	overfeed	Past	9	-	0	-	0
105.	uppercut	Past	9	-	0	-	0
106.	thrive	Past	7	-	0	-	0
107.	overwrite	Past	7	-	0	-	0
108.	wed	Past	7	-	0	-	0
109.	sting	Past	7	-	0	-	0
110.	chide	Past	6	-	0	-	0
111.	overblow	Past	5	-	0	-	0
112.	gird	Past	5	-	0	-	0
113.	overdraw	Past	4	-	0	-	0
114.	handwrite	Past	4	-	0	-	0
115.	unfreeze	Past	4	-	0	-	0
116.	bestride	Past	4	-	0	-	0
117.	bless	Past	3	-	0	-	0
118.	bereave	Past	3	-	0	-	0
119.	overhang	Past	3	-	0	-	0
120.	stave	Past	2	-	0	-	0
121.	strip	Past	2	-	0	-	0
122.	clap	Past	2	-	0	-	0
123.	overpay	Perfect	1465	-	0	-	0
124.	thrust	Perfect	893	-	0	-	0
125.	uphold	Perfect	530	-	0	-	0
126.	creep	Perfect	472	-	0	-	0
127.	shine	Perfect	260	-	0	-	0
128.	speed	Perfect	246	-	0	-	0
129.	rewrite	Perfect	770	-	0	-	0
130.	mistake	Perfect	3914	-	0	-	0
131.	overtake	Perfect	713	-	0	-	0

132.	pen	Perfect	0	-	0	-	0
133.	forecast	Perfect	570	-	0	-	0
134.	mislead	Perfect	508	-	0	-	0
135.	string	Perfect	672	-	0	-	0
136.	fling	Perfect	387	-	0	-	0
137.	undertake	Perfect	788	-	0	-	0
138.	cling	Perfect	122	-	0	-	0
139.	shrink	Perfect	810	-	0	-	0
140.	weave	Perfect	1453	-	0	-	0
141.	withhold	Perfect	644	-	0	-	0
142.	overthrow	Perfect	256	-	0	-	0
143.	stride	Perfect	0	-	0	-	0
144.	remake	Perfect	533	-	0	-	0
145.	plead	Perfect	123	-	0	-	0
146.	sweat	Perfect	0	-	0	-	0
147.	outgrow	Perfect	517	-	0	-	0
148.	kneel	Perfect	44	-	0	-	0
149.	withstand	Perfect	80	-	0	-	0
150.	inset	Perfect	23	-	0	-	0
151.	foresee	Perfect	240	-	0	-	0
152.	breed	Perfect	735	-	0	-	0
153.	stink	Perfect	259	stanked	2	-	0
154.	spell	Perfect	182	-	0	-	0
155.	forbid	Perfect	1979	-	0	-	0
156.	podcast	Perfect	12	-	0	-	0
157.	Bend	Perfect	30	-	0	-	0
158.	offset	Perfect	985	-	0	-	0
159.	Slit	Perfect	51	-	0	-	0
160.	recast	Perfect	261	-	0	-	0
161.	Bust	Perfect	1	-	0	-	0
162.	babysit	Perfect	39	-	0	-	0
163.	befall	Perfect	102	-	0	-	0
164.	strive	Perfect	33	-	0	-	0
165.	Rid	Perfect	479	-	0	-	0
166.	repay	Perfect	1010	-	0	-	0
167.	Sling	Perfect	175	-	0	-	0
168.	foretell	Perfect	102	-	0	-	0
169.	Tread	Perfect	136	-	0	-	0
170.	outrun	Perfect	44	-	0	-	0
171.	dwell	Perfect	47	-	0	-	0
172.	Wet	Perfect	0	-	0	-	0
173.	Spoil	Perfect	375	spoilted	1	-	0

174.	Lean	Perfect	29	-	0	-	0
175.	behold	Perfect	28	-	0	-	0
176.	override	Perfect	112	-	0	-	0
177.	Retell	Perfect	149	-	0	-	0
178.	outshoot	Perfect	59	-	0	-	0
179.	Spill	Perfect	172	-	0	-	0
180.	overrun	Perfect	758	-	0	-	0
181.	Bite	Perfect	1265	bitted	3	-	0
182.	partake	Perfect	78	-	0	-	0
183.	cleave	Perfect	1	-	0	-	0
184.	retake	Perfect	25	-	0	-	0
185.	oversleep	Perfect	20	-	0	-	0
186.	undercut	Perfect	111	-	0	-	0
187.	underwrite	Perfect	168	-	0	-	0
188.	Ken	Perfect	111	-	0	-	0
189.	waylay	Perfect	106	-	0	-	0
190.	mishear	Perfect	109	-	0	-	0
191.	Slink	Perfect	25	-	0	-	0
192.	rewind	Perfect	11	-	0	-	0
193.	overspend	Perfect	196	-	0	-	0
194.	overshoot	Perfect	36	-	0	-	0
195.	wring	Perfect	90	-	0	-	0
196.	inbreed	Perfect	83	-	0	-	0
197.	Smite	Perfect	1019	smoted	8	-	0
198.	rethink	Perfect	68	-	0	-	0
199.	beget	Perfect	149	-	0	-	0
200.	underthrow	Perfect	4	-	0	-	0
201.	abide	Perfect	21	-	0	-	0
202.	outshine	Perfect	42	-	0	-	0
203.	Knit	Perfect	3180	-	0	-	0
204.	unsay	Perfect	137	-	0	-	0
205.	bespeak	Perfect	1	-	0	-	0
206.	unwind	Perfect	84	-	0	-	0
207.	redraw	Perfect	0	-	0	-	0
208.	unbind	Perfect	30	-	0	-	0
209.	forsake	Perfect	380	-	0	-	0
210.	unstick	Perfect	78	-	0	-	0
211.	Burn	Perfect	1204	-	0	-	0
212.	cowrite	Perfect	6	-	0	-	0
213.	Shoe	Perfect	45	-	0	-	0
214.	miscast	Perfect	166	-	0	-	0
215.	Recut	Perfect	10	-	0	-	0

216.	unmake	Perfect	31	-	0	-	0
217.	smell	Perfect	260	smelted	2	-	0
218.	foreknow	Perfect	5	-	0	-	0
219.	typeset	Perfect	39	-	0	-	0
220.	Inlay	Perfect	30	-	0	-	0
221.	intercut	Perfect	47	-	0	-	0
222.	betake	Perfect	3	-	0	-	0
223.	heave	Perfect	9	-	0	-	0
224.	typecast	Perfect	131	-	0	-	0
225.	Rerun	Perfect	0	-	0	-	0
226.	overfeed	Perfect	31	-	0	-	0
227.	uppercut	Perfect	3	-	0	-	0
228.	thrive	Perfect	0	-	0	-	0
229.	overwrite	Perfect	121	-	0	-	0
230.	Wed	Perfect	653	-	0	-	0
231.	Sting	Perfect	746	-	0	-	0
232.	chide	Perfect	6	-	0	-	0
233.	overblow	Perfect	4	-	0	-	0
234.	gird	Perfect	7	-	0	-	0
235.	overdraw	Perfect	240	-	0	-	0
236.	handwrite	Perfect	0	-	0	-	0
237.	unfreeze	Perfect	46	-	0	-	0
238.	bestride	Perfect	0	-	0	-	0
239.	bless	Perfect	52	-	0	-	0
240.	bereave	Perfect	0	-	0	-	0
241.	overhang	Perfect	7	-	0	-	0
242.	stave	Perfect	1	stoved	1	-	0
243.	strip	Perfect	0	-	0	-	0
244.	clap	Perfect	0	-	0	-	0
	Total		51121		19		2

تغير حالة الفعل الواقع تحت تاثير التغيير المزدوج للمقاطع: دراسة لمحتوى لغوي مخزون في شبكة الانترنت حول نظام تشكيل حالات الافعال الشاذة في اللغة الانجليزية

باسمة عثمان محمود

كلية اللغات- قسم اللغة النجليزية / جامعة صلاح الدين-اربيل

ملخص

بالرغم من وجود وجود فرضيات تشير الى ان اللغات الانسانية محددة بقواعد (اشكال نمطية)، غالبا م نجد اسثناءات لهذه القواعد (اشكال شاذة). في هذا الاتجاه، خضعت الاشكال الشاذة ذات التكوين المزدوج (اشكال شاذة تم اخضاها لقواعد) للدراسة والبحث وقد تم اعتبارها كشكل جديد من الاشكال الشاذة. يدعي فيرنغ (2013) بان هنالك علاقة متبادلة بين هذا التشكيل الشاذ للافعال وبين كثرة استخدامها. مع ذلك فمن النادر وجود اعمال بحثية توثق هذه العلاقة.في هذه الورقة البحثية، استخدمنا موقع الكتروني لغوي في شبكة الانترنت يدعى (WebCorp)، يحتوي على ادوات تسهل البحث واحصاء الكلمات، لغرض الاجابة عن سؤال البحث: هل توجد علاقة متبادلة بين عملية تشكيل الافعال الشاذة ذات التكوين المزدوج وبين كثرة تردد هذه الافعال في اللغة الانكليزية المعاصرة؟وان كانت هناك علاقة، هل ان الافعال الاكثرتكراراً اكثر عرضة للتغير الشاذ المزدوج من الافعال الاقل تكرارا؟ من اجل الاجابة عن هذه الاسئلة، تم جمع وتحليل 488 فعل شاذ في حالة الزمن الماضي والماضي التام. بعد ذلك، تم احصاء عدد الافعال التي تم تشكيها بشكل مزودج بكل من صيغتي الفعل الماضي والفعل الماضي التام. وباستخدام التحليل الوصفي والاحصائي تم فحص مؤشرات اهمية النتائج المستحصلة من التحليل.من نتائج البحث، تبين ان هنالك علاقة بين كثرة تردد الافعال وبين عملية التشكيل الشاذ المزدوج للافعال. واشارة الى التشكيل الشاذ للافعال في اللغة الانكليزية، حاولت هذه الدراسة المساهمة في تقديم مصدر للبحث التحليلي عن كيفية التشكيل الذهني والتعبير عن المعلومات الخاصة باللغة من قبل المناطق المختصة باللغة في عقل الانسان.

گۆڕانكارييە گەردانييەكانی فۆڕمە جوت نيشانكراوەكان: بە ئاماژەكردن بە توێژينەوەی كۆرپەسی سيستەمی كار لە زمانی ئينگليزيد

باسمة عثمان محمود

كوليزي بە روە ردە / بە يش ئنكليزى / زانكوى سهلاحەددين-هەولێر

پوختە

وا گريمانە دەكرێ كە كۆمەڵێك ياسا هەن زمانەكانی مرۆڤ ئاڕاستە دەكەن، بەڵام چەند ڕيزپەڕييەك لەمر ياسايانەدا بەديدەكرێ لە فۆڕمی هەندێك دياردەی زمانی كە ياسابەند نين. هەندێك تاقيكردنەوە لە زمانەكانی مرۆڤدا لەسەر فۆڕمە جوت نيشانەكراوەكان تاقيكراونەتەوە كە تياياندا ياسايەك بۆ فۆڕمێكی نارێك زياد دەكرێ، ئەمەش وەك جۆرێك لە بە ياسابەند نەكردن ڕەچاو دەكرێ لە پرۆسە مۆرفۆلۆجييەكاندا. فێرتيگ (2013) پێيوايە كە پەيوەندييەك هەيە لەنێوان ئەمر جۆرە پرۆسە بە ناياسا بەنكردنە و ئەو وشانەی فريكوێنسی بەرزيان هەيە. ئەمر توێژينەوەيە لەوە دەكۆڵێتەوە كە ئايا لە سيستەمی كاری زمانی ئينگليزيدا پەيوەندی هەيە لەنێوان ئەمر پرۆسەی بە ياسا بەندنەكردنە و فريكوێنسی وشەدا. پرسيارەكانی ئەمر. توێژينەوەيە بريتين لەوەی ئايا پەيوەندی هەيە لەنێوان فۆڕمە جوت نيشانەكراوە ناياسابەندەكان و فريكوێنسی وشە لە ئێستای زمانی ئينگليزيدا؟ ئەگەر هەيە ئايا ئەو كارانەی ياسابەند نين و فريكوێنسی بەرزيان هەيە زياتر بەر ئەمر پرۆسەی بە ياسا بەندنەكردنە دەكەون بە بەراورد بەو كارانەی كە فريكوێنسی نزميان هەيە؟ ئەمر توێژينەوەيە گريمانەی بونی ئەمر جۆرە پەيوەندييە دەكا و لە خستنەڕوی جياوازييەكانياندا پشت بە شيكردنەوەی وەسفی و ئاماری دەبەستێت. توێژينەوەكە ئەوە دەخاتە ڕو كە چۆن زانياری زمانی بەشێوەيەكی هۆشەكی پرۆسەدەكرێ و لەڕێگەی توانستی زمانييەوە دەنوێنرێت.