Corpus-assisted Synonym Comparison between DECLARE and ANNOUNCE in English

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ABSTRACT

DECLARE and ANNOUNCE are two common verbs frequently used in English context. These pair synonyms have not only shared similarities but also differences. In order to clarify the differences and stipulate the best selection of these two words in different contexts as a rule, a corpus-assisted project is done by using the methodology of “multiple logistic regression analysis” on four distinctive predictors which determine the differences.

1. Literature Review

According to the Concise Oxford English Dictionary(Oxford 2008), definitions for each of two words are found to show their similarities and differences.

DECLARE:

1. to say something officially or publicly
2. to state something clearly and definitely
3. **declare yourself** to say clearly and openly who you are or what you intend to do
4. **declare something** to tell the tax authorities how much money you have earned
5. **declare something** to tell customs officers (= at the border of a country) that you are carrying goods on which you should pay tax
6. (in cricket) to decide to end your innings (= the period during which your team is batting) before all your players have batted

ANNOUNCE:

1. to tell people something officially, especially about a decision, plans, etc.
2. to give information about something in a public place, especially through a loudspeaker
3. to say something in a loud and/or serious way
4. **announce yourself/somebody** to tell somebody your name or somebody else’s name when you or they arrive at a place
5. **announce something** to introduce, or to give information about, a programme on the radio or television

As interpretations shown above, it is prone to find DECLARE and ANNOUNCE are interchangeable, and two example sentences can explain this interchangeability, representing say something officially or publicly, as follows:

(1) The government **announced / declared** the danger to be past.
(2) The Government **announced / declared** its fight against inflation with all its consequences for local government spending.

From Apart from shared parts, their differences are also striking. For example, ANNOUNCE sometimes mainly focuses on say decisions, plans like ANNOUNCE engagement, while war and DECARE are always the fixed combination, that is DECLARE war. In these example contexts, two words cannot replace each other.

Not few researches have taken in-depth look into these two words. Collocation of including adverb, subject, and object for each word, meaning, grammar patterns have been analyzed(Effendi, Amalia and Lalita 2020). Sentiment, as an important predictor has been discussed that DECLARE is mostly scattered in neutral and negative contexts, while ANNOUNCE in positive and neutral ones(SHEN and YANG 2019).

2. Methodology

This case study uses multiple logistic regression to form a rule of selection between two variants: DECLARE and ANNOUNCE, referring to 4 predictors: sentiment, objectivity, type and emotion.

Two programming languages are used: R and Python. R is mainly applied for multiple logistic regression such as localizing sentences containing variants, storing data into CSV files and multiple logistic regression; while Python is for text pre-processing, including XML-to-TXT transformation, random sentence selection and sentiment analysis.

3. Corpus Materials

The data is taken from BNC(British National Corpus), specifically, BNC XML Edition (2007). The XML Edition of the BNC contains 4049 texts and 96986707 words. It has two types of source texts including written texts and spoken texts. The source materials in this corpus are selected from the time period from the year of 1960 to 1993.

XML is a good tool for parsing corpus data, such as pos tagging; however, this case study does not rely on grammatical analysis or other XML-related parsing. Therefore, the XML version of BNC corpus is transformed into TXT version.

4. Variants and Predictors

When two synonyms are compared based on multiple logistic regression methodology, there must be variants(DECLARE and ANNOUNCE; DECLARE is 1, representing success level, while ANNOUNCE is 0)(Figure 1), and predictors(there are four predictors in this case study, namely sentiment, objectivity, type and emotion)(Figure 2).Three predictors are classified manually, and the classification has been checked for times according to classification rules.

variant	meaning	parameters
DECLARE	success	1
ANNOUNCE	failure	0

Figure 1 Success scale for variants

predictors	meaning	parameters
sentiment	To find out target sentences' sentiment	positive, neutral, negative
objectivity	The subject of the variants	org, pers
type	Four genres	ACPROSE, FICTION, NEWS, OTHERSP
emotion	Whether the variant windows are emphasized with special tones	violent, plain

Figure 2 Predictors' meaning

4.1 Variants

There are two variants, namely DECLARE and ANNOUNCE. DECLARE is selected as the success level.

4.2 The Predictor "sentiment"

The collocations of variants shows sentiment, specifically, positive, neutral and negative.
Example sentences can interpret such phenomenon.

(1) …John Plamenatz **announced** enthusiastically that "the voice of the people is heard everlastingly"…. (positive)
(2) …But this agency is pathologized. Psychology **declares** it to be fantastic, irrational and ineffective… (negative)
(3) …When war was first **declared**, and she was co-opted into the military…(neutral)

Negative words are more prone to collocate DECLARE(SHEN and YANG 2019). According to this conclusion, sentiment is set as one predictor. The classification rule not only focuses on the center variants and their windows, but also the whole sentences or even the whole paragraphs. According to this rule, the sentences where variants are are defined positive, negative or neutral. Pre-processing for the observations on sentiment classification relies on sentiment analysis API which is provided by Tencent Cloud as well as manual corrections. The specific proportion of sentiment classification is shown below(Figure 3). It basically shows that DECLARE weighs more in negative than ANNOUNCE, and ANNOUNCE, in turn, is more likely used in positive situations.

	DECLARE	ANNOUNCE	SUM
positive	39	73	112
neutral	158	227	385
negative	67	36	103
SUM	264	336	600

Figure 3 Classification of observations on predictor "sentiment"

4.3 The Predictor "objectivity"

When observations are manually processed, I find that the subject may be able to be served as a predictor. There are example sentences:

(1) …the Licensing Authority **announced** that the revocation of licences would be permanent… (org)
(2) …In her outlandish, simple dialect she had **declared,** Me, Lindi! Me, Lindi Soon the seven-year-old girl had killed an older pupil who mocked her… (pers)

According previous case study, it lists out the frequent subjects for DECLARE and ANNOUNCE(Effendi, Amalia and Lalita 2020), which inspires me to do such experiment with subject words. According to the observations, subjects of variants can be roughly divided into two categories: organization(org) and person(org), and this predictor is defined as "objectivity". The rule to distinguish org and pers is that:

org:
(1) official or public organizations and authorities, such as country, government, organizations, groups, company, etc
(2) People who can represent an official organization, such as statesman, prime minister, president, etc
(3) objective facts, things bound to happen
(4) no personal emotions

pers:
(1) Individuals who say or do personal things
(2) subjective feelings
(3) uncertainty, such as speculation, using "may", "can", etc
(4) things do not happen, such as "should do", "need to be", appealing, etc

The categorization of observations for objectivity is fully manual, and the data for this predictor can be seen below(Figure 4).

	DECLARE	ANNOUNCE	SUM
org	164	193	357
pers	100	143	243
SUM	264	336	600

Figure 4 Classification of observations on predictor "objectivity"

4.4 The Predictor “type”

For the case study itself, to analyze DECLARE and ANNOUNCE has few relations with corpus structure, i.e. publication years, authors, authors’ ages, author’s nationalities, target audiences, etc., but registers of source texts. Therefore, two major classifications haven been made as follows:

(1) **<wtext>** Classify written text genres

In written-typed texts: there are 5 subsidiaries(Figure 5):

genre	meaning
ACPROSE	Academic prose.
FICTION	Fiction and verse.
NEWS	Newspapers.
NONAC	Non-academic prose and biography.
OTHERPUB	Other published materials.
UNPUB	Unpublished materials.

Figure 5 Genres of written materials

(2) **<stext>** Classify spoken text genres

In spoken-typed texts: there are 2 subsidiaries(Figure 6):

genre	meaning
CONVRSN	demographically sampled conversation.
OTHERSP	any other spoken text.

Figure 6 Genres of spoken materials

DECLARE and ANNOUNCE rely on contexts and windows. Therefore, the classification focuses on genres. Some genres are combined and removed, and come to form a 4 kinds of genres: ACPROSE(Academic prose); FICTION(Fiction and verse); NEWS(Newspapers); OTHERSP[1](demographically sampled conversation and any other spoken text).

In the processed corpus, sentences are retrieved from 4 genres of texts respectively, and then calculate the proportion of DECLARE and ANNOUNCE in each genre(Figure 7). After that, 150 sentences are randomly selected from the filtered sentences which contain either DECLARE or ANNOUNCE in each genre(Figure 8).

	ACPROSE	FICTION	NEWS	OTHERSP	SUM
DECLARE	821 (63%)	586 (39%)	851 (30%)	148 (44%)	2406
ANNOUUNCE	477 (37%)	925 (61%)	2015 (70%)	185 (56%)	3602
SUM	1298	1511	2866	333	6008

Figure 7 Classification of observations on predictor “type”

	ACPROSE	FICTION	NEWS	OTHERSP	SUM
DECLARE	55 11.4%	92 10%	105 5.2%	84 45.4%	336
ANNOUUNCE	95 11.6%	58 9.9%	45 5.3%	66 44.6%	264
SUM	150	150	150	150	600

Figure 8 Abbreviated Classification of observations on predictor "type"

4.5 The Predictor "emotion"

In some cases, variants are decorated emphasize something by using punctuations like exclamation mark or violent adverbs. Examples with "violent tones" are below. Therefore, this is assumed as one predictor.

(1) …You've had a visitor, by the way, he **announced cheerfully**. He didn't leave his name, but he said he'd call back…
(2)…That was a fabulous meal, she declared enthusiastically after the pudding plates had been cleared away…

For the predictor "emotion", it has two categories: violent and plain.

violent:
(1) violent adverbs decorate variants, such as triumphantly, angrily, etc.
(2) punctuations, like exclamation or question marks, etc.
(3) person's emotion, like angry, happy, excited, disgust, etc.

plain:
(1) to state the fact
(2) not emotional

Specific data is shown below(Figure 9).

	DECLARE	ANNOUNCE	SUM
violent	43	6	49
plain	221	330	551
SUM	264	336	600

Figure 9 Classification of observations on predictor "emotion"

[1] OTHERSP is not the previous one, but contains the data of CONVRSN and OTHERSP.

5. Experiment and Result

The case study uses two models: one with main effects only, and the other with both main effects and interactions.

5.1 Model 1 with "main effects only"

As there are four predictors in the case study, the most direct way is to analyze this four predictors respectively and combine them as one to find out the model's fitting performance. Therefore, the model is built and its relevant parameters are to analyzed.

The model with "main effects only" are analyzed through two ways by using glm() and lrm().

(1) The p-values in the Pr(>|z|) column is all less than 0.01 which means the result is significant and the model is good, except the predictor "objectivity" whose p-value is over 0.1.
(2) Residual deviance, as presented in Figure 10, is 702.30, less than that of null deviance which is 823.12, and this proves that this model is better than intercept-only model. Besides. the evaluation for the difference between the null model and the fitted model by chi-square is 5.192061e-23, small enough to prove this model's fitting is not too bad.
(3) Overdispersion rule stipulates that if residual deviance is much larger than its degrees of freedom, then the model will turn to be a failure, except for the situation that even if the residual deviance is slightly larger than its degrees of freedom, the model can be accepted(Speelman 2012). The result in this model is good, though residual deviance(702.30) is slightly more than residual degrees of freedom(592).
(4) The prediction correction of this model is 0.693

lrm() function's data shares some of the similar data to that of glm() function. Specific data is to be discussed in the 5.3.

This fitted model having been proved good, more details are explained. Different predictors and their variables predict different probabilities for success scale. For example, if sentiment = negative, the mean proportion is 0.817 to predict DECLARE; however, if sentiment = positive, then the proportion is 0.444 to predict DECLARE. There is a plot to clearly display the simple regression model, and it can visualize the partial effects of the predictors on a proportions of success scale as shown in Figure 10.

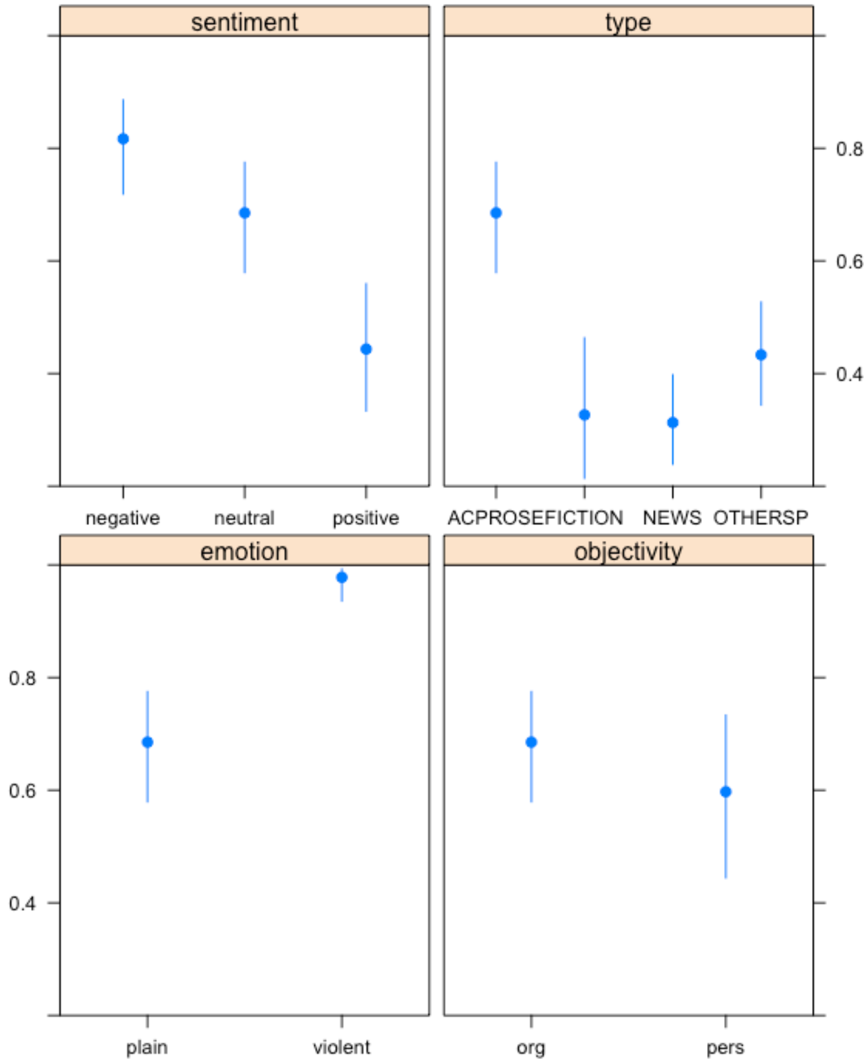

Figure 10 Plot of Model 1 with "main effect only"

5.2 Model 2 with "main effects and interactions"

Apart from each predictors take effect, two predictors can also interact with each other, or to say combine as a new predictor to take effect in logistic regression model, which is called the fitted model with "main effects and interactions" (Speelman 2012). This interactive model shares some similarities with "main effect only model", except to combine two of four predictors together into a new predictor. In this case, what I choose one of the two predictors is "objectivity" with the reason that its p-value is not significant, while the other predictor is "type" which intuitively seems more relevant with "objectivity"than other two predictors. There are analyses for this model as follows.

(1) The interaction predictor pair: objectivity and type

if objectivity = org:

	DECLARE	ANNOUNCE	SUM
ACPROSE	76 (60%)	51 (40%)	127
FICTION	11 (65%)	6 (35%)	17
NEWS	29 (24%)	92 (76%)	121
OTHERSP	48 (52%)	44 (48%)	92

if objectivity = pers:

	DECLARE	ANNOUNCE	SUM
ACPROSE	19 (83%)	4 (17%)	23
FICTION	47 (35%)	86 (65%)	133
NEWS	16 (55%)	13 (45%)	29
OTHERSP	18 (31%)	40 (69%)	58

Figure 11 Data of Interaction between predictor "objectivity" and predictor "type"

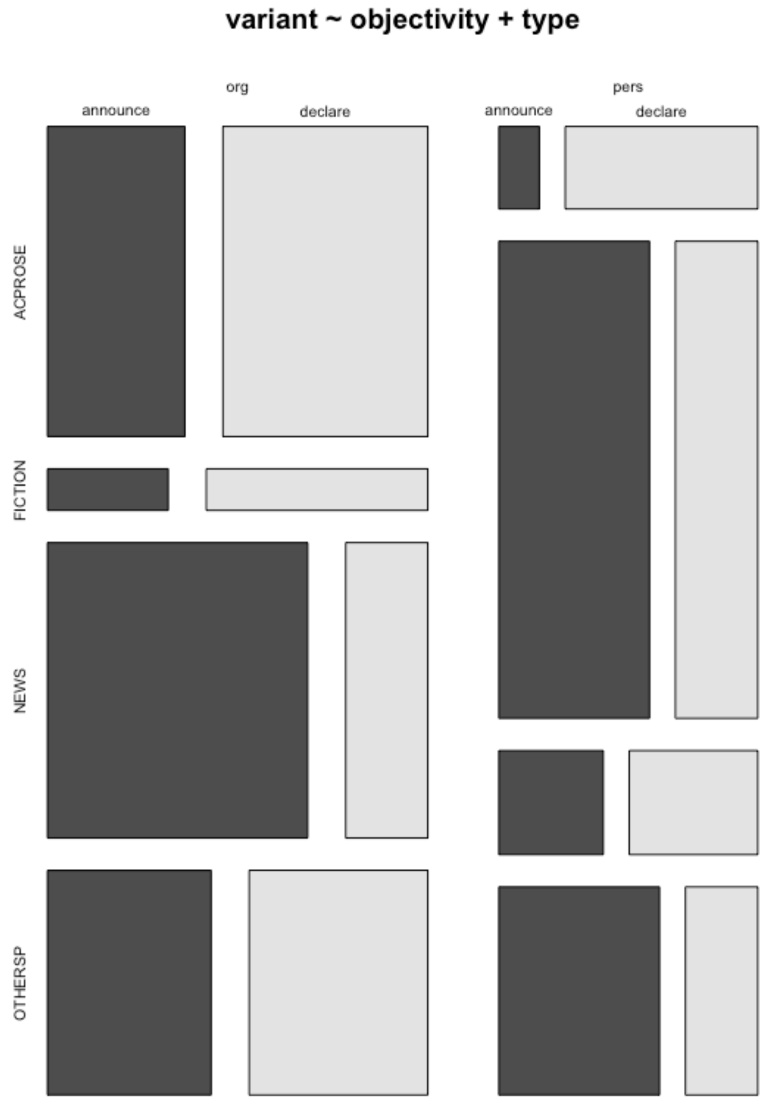

Figure 12 Mosaic plot of Interaction between predictor "objectivity" and predictor "type"

Figure 11 and Figure 12 clearly display how "objectivity" and "type " interact with each other. From Figure 12, the specific proportions are marked when objectivity = org and objectivity = pers respectively. If the subject is organizations ("org"), DECLARE are more used when type = ACPROSE and type = NEWS; when the subject is persons("pers"), DECLARE is less used than ANNOUNCE except when type = ACPROSE.

(2) Some p-values in the Pr(>|z|) column are all less than 0.01; however, some p-values are over 0.5 which is not significantly fitting.
(3) Residual deviance in Figure 10 is 667.23, less than that of null deviance which is 823.12, and this proves that this model is better than intercept-only model. Besides, from the perspective of overdispersion, the residual diviance(667.23) is slightly more than residual degrees of freedom(589), which means the model is acceptable.
(4) drop1() function presents that three predictors, namely sentiment, emotion and objectivity:type are all significant with their p-values are less than 0.001.
(5) the prediction correction of this model is 0.72.

5.3 Model 1 vs Model 2

There is data comparison between these 2 fitted models. From the table(Figure 13), it is obviously to see that Model 2 performs better than Model 1.

Specifically,

(1) Model 2's AIC(689.23) is much less than that of Model 1(718.3), and Model 2 is more significantly fitted than Model 1;
(2) The larger the values of LR chi2(model chi squared) generalized R squared are respectively, the better the fitted model will be(Speelman 2012), and Model 2's LR chi2 is larger than that of Model 1. Therefore, on these two points, Model 2 performs better than Model 1;
(3) Model 2's p-value(5.192061e-23) is smaller than Model 1's(2.285927e-28). That is another aspect to say that Model 2 is better than Model 1;
(4) on the value of prediction correction, Model 2 owns more accurate number than Model 1;
(5) the number of concordance pairs C improves from 0.735 of Model 1 to 0.780 of Model 2.

summary statistic	Model 1 with main effects only	Model 2 with main effects and interactions
number of observations	600 (of which 264 “declare” and 336 “announce”)	
null deviance	823.12 (on 599 df)	
residual deviance	702.3 (on 592 df) [AIC is 718.3]	667.23 (on 589 df) [AIC is 689.23]
model chi squared	120.81 (on 7 df)	155.89 (on 10 df)
p-value (chi squared)	5.192061e-23 $p < 0.0001$	2.285927e-28 $p < 0.0001$
simple proportion of correct predictions in original dataset (cut-off probability set to 0.5)	0.693	0.72
generalized R squared	0.244	0.307
C (area under ROC curve)	0.735	0.780

Figure 13 Statistic data comparison between Model 1 and Model 2

5. Conclusions

Through multiple logistic regression, the four hypothetical predictors play significant roles in the models. Although predictor “objectivity” is not significant in the model with “main effects only”, its interaction with predictor “type” makes the model with “main effects and interactions” significant and better fitted.

On the other side, the prediction correction is not as expected with only 72%. One fundamental reason is that the three of the four predictors(except “type”) are classified manually with much subjectivity. That it to say, the classification rule is not that strict; instead, the classification of observations for these 3 predictors relies on intuition, which may lead to the inaccuracy of the data and undesirable fitted model. Fortunately, the result and the model is not that bad. The data pre-processing is a defect for this case study, and this will contribute to a further study to optimize the performance of the model, and possibly finding a more suitable model for the choice of DECLARE and ANNOUNCE.

Reference

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