# Towards Automatic Detection of Antithesis

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**Abstract.** This paper presents our preliminary work-in-progress on automatic detection of the rhetorical figure, antithesis, including the challenges we have encountered so far.

**Keywords:** Antithesis, Antithesis Detection, Rhetorical figures

## 1 Introduction

Fahnestock [2] defines antithesis as "a verbal structure that places contrasted or opposed terms in parallel or balanced cola or phrases" (p. 46). The parallelism may involve repeated words, similar grammatical structures, and/or acoustic similarity. Antithesis has several argumentative functions [3]. For example, one is Aristotle's argument from opposites: if A and $A^*$ are opposites and B and $B^*$ are opposites, and A is B, then $A^*$ is $B^*$; e.g., if moderation is good then excess (the opposite of moderation) is bad. Another function is to express an argument based upon single-difference experimental design; i.e., if A has outcome B, and $A^*$, which differs from A by some contrasting feature, has outcome $B^*$, which differs from B by some contrasting feature, then there is a causal connection between $A^*$ and $B^*$.

We are interested in exploring the role of rhetorical figures such as antithesis in science policy arguments [5]. In order to develop algorithms for detecting antithesis, it is necessary to provide a precise definition of antithesis and to identify or create a corpus of annotated cases. Since we are not aware of the existence of such a corpus, we have begun to annotate a data set of quotations previously annotated for antimetabole[2] [1]. Antimetabole is defined as "the proximal occurrence of the same two words or word-strings in reverse order" [6]. Harris et al. [7] note that antithesis often occurs in combination with antimetabole and other figures such as parison (syntactic parallelism), e.g., "All compounds are molecules …, but not all molecules are compounds …" (p. 161), in which *compounds/molecules* are related by antimetabole and *all X /not all Y* are related by antithesis. Thus, by starting with a dataset of antimetabole cases, we hoped to find a rich source of antithesis cases as well.

This paper presents a working definition of antithesis for annotation, a preliminary algorithm for detecting antithesis and challenges encountered so far.

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[2] Available at https://github.com/mardub1635/corpus-rhetoric.

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## 2 Annotating Antithesis

So far, we have annotated antithesis in the first 500 of the 3000 antimetabole-annotated quotation dataset. Each quotation consists of one or two sentences. The quotations were ordered by Dubremetz's annotators from best to worst instances of antimetabole. After removing duplicates from the first 500, there were 391 quotations and we identified 120 of them as containing antithesis.

As is often the case at the beginning of an annotation task without pre-existing guidelines, annotation and development of guidelines have proceeded in parallel. Due to the exploratory nature of this work, the authors of this paper were also the annotators and standard measures of inter-annotator agreement have not been calculated. The current guidelines are presented below.

The following three types of antithesis structures were annotated.

1. Opposed terms (A, B) in parallel phrases P1, P2, where A and B are corresponding syntactic constituents in P1 and P2, respectively. Note there may be more than one pair of opposed terms. Example (a "double antithesis"):
   The {A1: young} would choose an exciting {A2: life};
   the {B1: old} [would choose] a happy {B2: death}.[3]
   Antithesis pairs: (A1, B1), (A2, B2)
2. Opposed terms (A1, B1) in phrase P1 and opposed terms (A2, B2) in parallel phrase P2, where A2=B1 and B2=A1, and A1 and A2 are corresponding syntactic constituents of P1 and P2, respectively, and B1 and B2 are corresponding constituents of P1 and P2, respectively. In this case, the antithesis terms also have been coded for antimetabole by Dubremetz. Example:
   There are only two kinds of man.
   The {A1: righteous} who think they are {B1: sinners} and
   the {A2: sinners} who think they are {B2: righteous).[4]
   Antithesis pairs: (A1, B1), (A2, B2). Antimetabole pairs: (A1, B2), (B1, A2).
3. A constituent and its negation in a parallel phrase, i.e., a constituent of one of two parallel phrases is negated in the corresponding syntactic constituent of the other phrase. Example (with antimetabole in the scope of negation):
   We {A1: do not} build services to make money.
   We {B1: [do]} make money to build services.[5]
   Antithesis pair: (A1, B1)

Opposed terms were defined based upon the following list of semantic relations used in descriptions of antithesis and opposites from a variety of sources.[6] Since the distinctions between some of the relations were unclear, we abandoned an early attempt to annotate the type of opposition. Also, for the sake of simplicity we excluded phrases and hyphenated or multiword lexemes from the definition for now. We defined T1 and T2 as opposed terms if they have the same part-of-speech and their lemmas are related by any of the following semantic relations:

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[3](7) in [6]. In this and the other quotations, elided words have been added in square brackets.
[4] Quotation *1* in Dubremetz's dataset.
[5] (17) in [7].
[6] Contraries, contradictories, and correlatives are from [2]; reversives, antipodals, and disjoint opposites are from Wikipedia's entry for "opposites (semantic)".

- Polar (contraries, gradable): opposite ends of a scale, e.g. good/evil, hot/cold.
- Binary (contradictories): alternatives with no intermediate values, e.g. in/out, known/unknown, exhale/inhale, all/none
- Reciprocal (correlatives): refer to relationship from opposite point of view, e.g. father/child, buy/sell
- Reversives: opposing processes, where one is the reverse of the other, e.g. rise/fall, accelerate/decelerate, shrink/grow.
- Antipodals: opposite ends of a literal or figurative axis, e.g. left/right, up/down, first/last, beginning/end
- Disjoint opposites (incompatibles): "members of a set which are mutually exclusive but which leave a lexical gap unfilled," e.g. red/blue, one/ten, Monday/Friday.
- Pronouns: pairs of pronouns referring to different entities, e.g. I/you
- Contingent opposites: two definite NPs referring to entities in opposition in the real world, e.g. Democrats/Republicans

Note that some of the above categories may not be disjoint since they were culled from different sources. We added pronouns, and defined contingent opposites after seeing an example of a category named 'local' in [2]. We assume that while the first six categories ought to be accessible via lexical resources, the category of contingent opposites would require a source of world knowledge.

Finally, we defined parallel phrases as follows. P1 and P2 are syntactically parallel phrases if they are of the same phrasal category (e.g. NP, VP, S) and the corresponding parts of P1 and P2 (phrasal category, part-of-speech, or repeated words) are identical, except possibly for omitted words in elliptical grammatical phrases.

## 3 Antithesis Detection

Lawrence et al. [8] presented an algorithm for detection of antithesis in dialogue which had been previously analyzed in terms of argument components. The algorithm searched for antithesis in each turn of dialogue by first removing common English stop words and searching WordNet (wordnet.princeton.edu) for antonyms of the remaining words. If an antonym was found, the argument structure of the turn was considered to contain antithesis.

We are interested in a broader definition of antithesis, as outlined in the annotation guidelines in the previous section. Our current algorithm removes common English stop words and then searches for antonyms of each remaining word (lemma) in the quotation. The lexical search for antonyms is broader than the approach in [8]. First, a list of antonyms of each word is constructed using both WordNet and ConceptNet (conceptnet.io). Then the antonym list is expanded by searching WordNet and ConceptNet for all synonyms of the antonyms. For example, if the quotation contains 'good', then the antonym list might contain 'bad'. Adding synonyms of 'bad' could expand the antonym list to include 'awful'. If searching the resulting expanded antonym list is not successful, then the algorithm searches for a lemma in WordNet consisting of the original word (e.g. 'tie') with a negative suffix (e.g. 'un-'). The algorithm does not yet identify contrasting pronouns as outlined in the guidelines (which, however, would be relatively easy to implement). Also, it does not yet handle all the forms of negation described in the annotation guidelines, but searches for patterns such as 'no W' or 'not W' where W is a lemma.

Applying the current algorithm to the dataset (having a total of 327 annotated pairs of antithesis) resulted in 81 true positives, 116 false positives, and 130 false negatives, i.e., a precision of 41.1% and recall of 38.4%. Of the 130 false negatives, 36 were cases involving negation, which was not surprising since our annotation guidelines are more ambitious than the current algorithm. Note that using WordNet alone resulted in fewer true positives (67) and fewer false positives (63). Thus, adding ConceptNet as a lexical resource was worthwhile for increasing the rate of detecting antithesis. More work is necessary to analyze why it also increased the false positives.

One practical challenge was the large time cost of making remote calls to ConceptNet. Therefore, to speed up the algorithm during development, repeated calls to ConceptNet were avoided by caching the results in a Python map. To reduce the time cost so that the detection algorithm could be used in an interactive application on arbitrary text in the future, several approaches are possible. One would be to download a local copy of the semantic network. However, the raw file is very large (10GB). Another approach would be to limit the use of lexical resources by first applying constraints such as syntactic parallelism, which has not yet been implemented in our algorithm. Gawryjolek [4] suggested applying a sentiment analysis tool to identify spans with positive and negative polarity and use polarity as a constraint on search.

## 4 Challenges

There are quite a few challenges in detection of antithesis. As noted above, for the time being our current definition does not include phrases or multi-word or hyphenated lexemes. Also, our current algorithm does not address most negative constructions, which would require syntactic analysis. A related challenge also requiring syntactic analysis is ellipsis. To circumvent that problem for now, we added elided words to the dataset.

Another issue is that the current publically available lexical resources that we found, WordNet and ConceptNet, are incomplete in their coverage of opposite lexical concepts. The following list of false negatives illustrates some of the annotated antithesis pairs that were not found using WordNet and ConceptNet antonym lists: righteous/sinners, perfected/begun, theory/experience, fiction/life, action/inspiration, emotion/thought, here/there, born/dying, robots/people. Some of the false positives, antithesis pairs found by the algorithm that were not annotated, do not fit our definition of opposites, e.g.: thumb/finger, go/meet, first/second, vision/sound, good/service.

To partially offset the incomplete coverage of antonyms in lexical resources, our algorithm adds synonyms of antonyms as described above. In the future the algorithm could follow additional paths through ConceptNet, such as following the Related Words link. However, for reasons noted above, broadening the search would incur an increasingly high time cost. Also, it may increase the rate of false positives. In addition to challenges related to lexical resources, for antithesis involving Contingent Opposites a source of world knowledge will be required.

A serious challenge is that to cover some of the interesting examples of antithesis that we found in science policy articles [5], a broader definition of antithesis is required to encompass semantic/pragmatic interpretation of phrases in those articles. For example, we annotated *great advances/steep price* as antithesis. 'Great' is not the opposite of 'steep', nor is 'advance' the opposite of 'price'. However *great advances* has a positive connotation, while *steep price* has a negative connotation, and they signify a kind of trade-off. In the example given earlier in this paper, "The young would choose an exciting life; the old a happy death", the analysis given in [7] is one of double antithesis: *young/old, life/death*. However, we contend that although 'exciting' and 'happy' are not opposites, there is a contrast between the concepts of an exciting life and a happy (i.e. peaceful) death.

In short, antithesis cannot be detected until we decide what counts as antithesis. This is related to the more general problem of defining what counts as the occurrence of a rhetorical figure. Some have treated rhetorical figures as fuzzy categories [1, 8], while others have argued that intuitive rankings of goodness of fit can be attributed to the presence of multiple reinforcing rhetorical figures in the same span, such as the co-occurrence of parison, antimetabole, and antithesis [7].

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