

# Evaluate

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## 1 Introduction

This code uses either an online (i.e. from the web) WordNet API (via HTTP RESTful API) or an offline synonym-lookup, via the nltk Python package. If you have the Python package available, a far faster implementation is available.

It is worth noting that the two syn-nets vary slightly.

## 2 Improvement Strategies

### 2.1 Baseline

The baseline provided had an accuracy rate of 0.449312, which means that it functioned slightly better than chance (which would have chosen uniformly from  $-1, 0, 1$  with probability 0.33.... This strategy uses a sort of word-union calculation, where the only metric for calculating accuracy is the intersect of words that occur in a hypothesis and its reference sentence.

More formally, for reference sentence  $r$  and hypothesis  $h$ :

$$A = |\{w | w \in h, w \in r\}|$$

I provide several modifications in this assignment, as well as advantages and disadvantages for each.

### 2.2 WordNet Synonym Lookup

This strategy is a very slight modification of the previous implementation, wherein a word is counted as a +1 if it exists in both sentences ( $h$  and  $r$ ), and a word  $w$  from a hypothesis is counted as a  $+p$  (for some  $p \in 0..1$ ) if  $synonym(w) \in r$ .

$synonym(w)$  is defined using Princeton's WordNet system, accessed via RESTful API endpoint through [thesaurus.altervista.org](http://thesaurus.altervista.org).

### 2.2.1 Advantages

This protocol supposedly casts a wider net to find more sentences that may have simply mistranslated a word but still retain the ‘gist’ of a sentence — such as in cases where “ball” is replaced with “sphere”, etc.

### 2.2.2 Disadvantages

Because this system relies on an internet connection and the WordNet API, it is very slow to execute (in my trials, it took nearly nine wallclock minutes to run 100 sentences). Moreover, accuracy is diminished, as it appears that this ‘dragnet’ approach considers too many sentences to be correct.

When using the downloaded nltk version (in the absence of which, the Python execution should fail gracefully), a very small weight in the WORDNET function, along with a small weight in the Quorum function (explained below) results in better-than-METEOR-alone performance.

### 2.2.3 Results

See Table 1. From the above information, it is likely that the strategy used here is useful for tie-breaking, but is not a viable strategy as a standalone device.

## 2.3 METEOR

For this implementation, I use the METEOR formula as described in the homework prompt [mt-class.org/jhu/hw3.html](http://mt-class.org/jhu/hw3.html), namely:

$$\ell(h, e) = \frac{P(h, e) \cdot R(h, e)}{(1 - \alpha)R(h, e) + \alpha P(h, e)}$$

The only deviation I implemented handles the case of  $P(h, e) = R(h, e) = 0$ , wherein my implementation (intuitively, at least to me) returns 0, indicating zero correlation.

### 2.3.1 Advantages

This system has clear advantages over the baseline strategy — namely, it maximizes the cases in which two sentences are similar enough to be considered ‘close’ while still minimizing those cases due to chance. It is essentially a sliding-scale version of the baseline implementation. However, the pure METEOR implementation can be improved upon, as I will explore below.

### 2.3.2 Disadvantages

METEOR is naïve and still fails on cases where sentences use synonyms. It also fails to accommodate sentence structure in any way, so the sentences *the the the the the* and *the the* are weighted equally.

Table 1: WordNet Sentence Intersect Results

Pred. y=-1	y=0	y=1	
True y=-1	19	7	18
True y= 0	7	7	9
True y= 1	19	2	12

$$A = 0.380000 \quad (n=100)$$

### 2.3.3 Results

This implementation functions notably better than the baseline implementation, reaching approximately 50% accuracy on the provided dataset. For further evaluation statistics, see *Figure 1*.

## 2.4 Quorum

After performing the above implementations, I decided to try to improve the accuracy at the expense of performance by running multiple algorithms and having them reach ‘quorum’. To do this, I modified the `evaluate` function to take an array of tuples for `eval_fns`, in the form:

$$(function, weight)$$

Using only METEOR and  $n = 20$ , I arrived at an accuracy of 0.5. Using the Quorum implementation mixing METEOR at 75% weight and WORDNET at 25% weight, I arrived at an accuracy of 0.55.

### 2.4.1 Advantages

On  $n = 20$ , accuracy from METEOR alone (0.5) was improved by combining with WORDNET (combined, led to  $A = 0.55$ ).

### 2.4.2 Disadvantages

Naturally, the combined algorithm takes considerably longer to run, and if WORDNET is among the utilized algorithms, it performs far slower (as WORDNET requires HTTP calls).

To improve timing, I added a dynamic element that added words and their synonyms to a dictionary (local) as it encountered them over HTTP, so that subsequent calls ran faster. For timing figures, see *Figure 2*.

Table 2: METEOR			
Pred.	y=-1	y=0	y=1
True y=-1	6315	899	3748
True y= 0	1722	487	1724
True y= 1	3642	841	6190
A = 0.508135    ( $\alpha = 0.75$ )			

Figure 1: A plot of  $\alpha$  values ( $x$ ) against accuracy ( $y$ ).

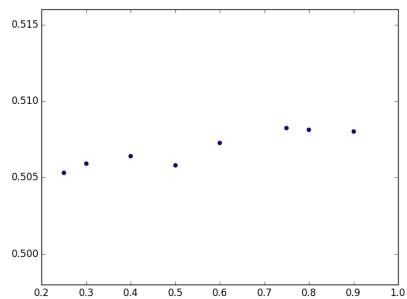


Figure 2: Naive speeds when running WORDNET (red) compared with dynamic version (blue), which saves the encountered words to a local dictionary for faster lookup.

