Newer method of string comparison: the Modified Moving Contracting Window Pattern Algorithm

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Abstract
This paper presents a new algorithm, the Modified Moving Contracting Window Pattern Algorithm (CMCWP), for the calculation of field similarity. It strongly relies on previous work by Yang et al. (2001), correcting previous work in which characters marked as inaccessible for further pattern matching were not treated as boundaries between subfields, occasionally leading to higher than expected scores of field similarity. A reference Python implementation is provided.

Keywords: field similarity, string similarity, string comparison.

1 Introduction
Assessing string similarity (or, as commonly referred in the literature, “field similarity”), is a recurrent problem in computer science, particularly when dealing with natural language and genetic data. A review of relevant literature on the topic is presented by Yang et al. [13], which stresses the importance of these methods in applications such as data searching and cleansing, Web searching, computational biology, and data compression.

These areas of research were considered by the authors before introducing their method for field comparison, the Moving Contracting Window Pattern Algorithm (MCWPA). MCWPA is fundamentally different from the general methods for field comparison based in measures of “edit distance” (such as the one proposed by Wagner et Fischer [14]), which expand initial work by Vladimir Levenshtein [8]. These methods, commonly referred to under the single label of “Levenshtein Distance”, are generally defined as counts of the minimum number of single character “edits” required to mutate a field \( F_X \) into a field \( F_Y \), where “edit” is defined as either an insertion, a deletion, or a substitution of a single character; in general, no difference in weight for the various types of “edit” is specified. The method for this computation of field similarity is closely related to pairwise field alignment and usually implemented after the aforementioned Wagner-Fischer algorithm or through dynamic programming approaches such as the one proposed by Guseld [4].

The algorithm proposed by Yang et al. extends and generalizes an alternative “token–based” approach by Lee et al. [7], developed in the context of
data cleansing. In their paper, the authors present a pseudo-code for the algorithm, claiming that their solution “not only achieve[s] higher accuracy but also gain[s] the time complexity $O(knm)$ ($k < 0.75$) for worst case”, comparing the accuracy of their proposal with the one of the method by Lee et al. and concluding that “[t]heoretical analysis, concrete examples and experimental result show that [the proposed] algorithms can significantly improve the accuracy and time complexity of the calculation of Field Similarity”.

In the course of a research conducted around 2005 with extensive usage of the Natural Language Toolkit (NLTK), a Python library and framework for Natural Language Processing by Bird et al. [2], the author of the current paper needed to perform hundreds of field comparisons for sorting lists of fields according to their similarity to a number of reference field, usually short strings containing natural language data. Levenshtein distance, the most recommended method, proved slow when computed without dynamic methods and, more importantly, was found to be unsuitable for a considerable number of cases, as its scores of similarity, adjusted to ratios between 0.0 and 1.0, failed to match the magnitude of similarity that most speakers of the natural languages in study would expect or report. A theoretical investigation suggested that the obstacle was an intrinsic limitation of the algorithm itself given by its focus in general field comparison (i.e., with no a priori assumptions on the entropy of both fields), and was triggered by idiosyncrasies of the morphology and the orthography of the languages in analysis. While the difficulties could in part be circumvented with a combination of orthographic, phonological and, exceptionally, morphological mappings, the decision rested in adopting new methods. A bibliographic research suggested the paper by Yang et al., and, while for our purposes the new algorithm performed better than the edit distance method, its results were occasionally unexpected and, eventually, worse than Levenshtein distance for some corner cases. The author wrote a revised version that partially solved the deviations, and the Python module which implemented them was eventually included among the “contributions” to NLTK.

When needing to perform a similar task almost a decade after that first revision, the author decided to write a new version which fully and correctly implemented the revised method, presenting the algorithm and its implementation in this paper.

2 Background

A brief but throughly description of the “token-based” approach for the computation of field similarity proposed by Lee et al. is given in the second section of Yang et al., from which the outline of the current section is developed.

Let a field $X$ of length $n$ be composed of tokens (such as “words”) $T_{X_1}, T_{X_2}, \ldots, T_{X_n}$ and the corresponding field $Y$ of length $m$ be composed of tokens $T_{Y_1}, T_{Y_2}, \ldots, T_{Y_m}$. Each token $T_{X_i}$, where $1 \leq i \leq n$, is compared with each token $T_{Y_j}$, where $1 \leq j \leq m$. Let $DoS_{X_1}, DoS_{X_2}, \ldots, DoS_{X_n}, DoS_{Y_1}, DoS_{Y_2}, \ldots, DoS_{Y_m}$ be the maximum degree of similarity for tokens $O_{X_1}, O_{X_2}, \ldots, O_{X_n}, O_{Y_1}, O_{Y_2}, \ldots, O_{Y_m}$, respectively. The Field Similarity between $F_X$ and $F_Y$ is computed as follows:

\footnote{The module has apparently been removed from newer versions of NLTK, but can be easily found in public forks based on older versions of the toolkit.}
The algorithm proposed by Yang et al. generalizes the “tokens” employed by Lee et al., essentially words in natural languages, into “window patterns”, which are defined as subfields of minimal length equal to 1. As in the first example given in their paper, for the string "abcde", considering a window of size 3 sliding from left to right, the series of patterns obtained is composed of "abc", "bcd", and "cde". The field similarity in MCWPA is given by the sum of the squares of the number of the same characters, or minimal units, between fields $F_X$ and $F_Y$, which is defined as the cumulative sum of the square of combined length of minimal units matched in both fields, i.e. twice the length of the pattern; the sum is accumulated while marking already matched subfields as inaccessible for further comparisons.

Thus, in MCWPA, let a field $F_X$ of $n$ characters and a field $F_Y$ of $m$ characters; the field similarity between the two fields, which “approximately reflects the ratio of the total number of the common characters in two fields to the total number of characters in two fields”, where SSNC represents the Sum of the Square of the Number of Same Characters between $F_X$ and $F_Y$, is computed as follows:

$$SIM_{F(X, Y)} = \sqrt{\frac{\text{SSNC}}{n+m}}$$

The algorithm is described in depth by Yang et al., with a number of examples and graphical representations of the inner workings of the sliding window approach.

### 3 Changes to MCWPA

The author of the current paper first implemented the MCWPA algorithm in Python following the pseudo-code given in Figure 1 in Yang et al. While the authors did not offer actual code or reference values to test implementations of their algorithms, all the examples could be matched, suggesting that the implementation was correct.

When testing the implementation in production code, however, it was verified that for some corner cases the results returned were unsuitable, with scores generally higher than what was expected by human reviewers. The author also experimented with some random strings used in imitation of genetic data, generated by an ad hoc weighted random function according to a table of DNA codon frequencies for the human genome; for a restricted number of test samples the results were considered equally unsatisfactory.

An investigation of the algorithm did not prove sufficient for identifying any theoretical limit as a source for the unsatisfactory scores. After implementing the algorithm in multiple and different ways, by a trial and error methodology an hypothesis was developed that the problem resided in a simplification of the original implementation, which can be found in the pseudo-code itself and might have been intentional, as MCWPA is less computationally expansive than the
revised method here proposed and the limitation affected a small number of cases.

In detail, while the theoretical description of the paper and the pseudo-code correctly call for marking characters in $F_X$ and $F_Y$ as “inaccessible” after a given pattern matching, the implementation was apparently not marking inaccessible characters as a boundary for future pattern matchings, thus allowing new windows to “jump over them”. The limitation might have been introduced when adapting the method from a token based to a character based approach, as the implementation in Lee et al. doesn’t seem to allow non contiguous tokens to be matched. This hypothesis cannot be verified without access to the original source code.

To illustrate the difference of the algorithm here proposed, the implementation yielding results considered wrong would, when matching the strings "A123B" and "123AB", first match the pattern of characters "123", but after the deletion of this pattern in both fields it would not treat the residual characters as groups of non-overlapping and non-contiguous subfields ("A" and "B" for the first field, "" and "AB" for the second), but as two identical "AB" strings. When reducing the length of the window from 3 to 2, the implementation would incorrectly find a match of a substring of length 2, when, from the theoretical stand point of the algorithm, it would be supposed to identify two different matches of length 1, with a lower final score.

The Python implementation presented in the following section solves this problem by replacing the operation of string concatenation of the first version by operations on lists, introducing the concept of “sub-fields”, i.e., non-overlapping and non-contiguous factors resulting after the removal of a specific factor (the pattern being matched) from a starting field or subfields. When the algorithm matches a pattern, it returns two subfields, i.e., the characters that precede and the characters that follow the matched pattern, if any. As the subfields might be empty, when the match includes the first or the last character in the string, a check is performed to filter out such empty subfields from the list of subfields.

As stated, the distortion was only found in corner cases, and actual scores were higher than the expect only to a reduced limit. However, as bibliographical research did not find any mention or correction to Yang et al., even though their paper has a considerable number of citations, the author found it useful to publish this corrected implementation under the name of MMCPWA (Modified Moving Contracting Window Pattern Algorithm). The author wishes to publicity note that his implementation distributed with old versions of NLTK at the time of writing is still affected by the problem describe above, and should be replaced whenever possible by the one presented here.

4 Python implementation

A stand-alone Python implementation for the algorithm is presented in this section. As per the terms of the “MIT License”, permission is hereby granted, free of charge, to any person obtaining a copy of this software and associated documentation files (the “Software”), to deal in the Software without restriction, including without limitation the rights to use, copy, modify, merge, publish, distribute, sublicense, and/or sell copies of the Software, and to permit persons to whom the Software is furnished to do so, subject to the following conditions:
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Listing 1: CMCWPA

```python
def mmcwpa(f_x, f_y, ssnc):
    """
    An implementation of the Modified Moving Contracting Window Pattern Algorithm (MMCMWP) to calculate string similarity, returns a list of non-overlapping, non-contiguous fields Fx, a list of non-overlapping, non-contiguous fields Fy, and a number indicating the Sum of the Square of the Number of the same Characters. This function is intended to be "private", called from the "public" stringcomp() function below.

    @param f_x: A C{list} of C{strings}.
    @param f_y: A C{list} of C{strings}.
    @param ssnc: A C{float}.

    @return: A C{list} of C{strings} with non-overlapping, non-contiguous subfields for Fx, a C{list} of C{strings} with non-overlapping, non-contiguous subfields for Fy, and a C{float} with the value of the SSNC collected so far.

    @rtype: C{list} of C{strings}, C{list} of C{strings}, C{float}
    """

    match = False
    new_f_x, new_f_y = [], []
```

# the boolean value indicating if a total or partial # match was found between subfields of Fx and Fy; when # a match is found, the variable is used to cascade # out of the loops of the function
match = False

# the variables where to store the new collections of # subfields, if any match is found; if these values # are not changed and the empty lists are returned, # stringcomp() will break the loop of comparison,
# calculate the similarity ratio and return its value
new_f_x, new_f_y = [], []
# search patterns in all subfields of Fx; the index of
# the subfield in the list is used for upgrading the
# list, if a pattern is found
for idx_x, sf_x in enumerate(f_x):
    # 'length' stores the length of the sliding window,
    # from full length to a single character
    for length in range(len(sf_x), 0, -1):
        # 'i' stores the starting index of the sliding
        # window in Fx
        for i in range(len(sf_x) - length + 1):
            # extract the pattern for matching
            pattern = sf_x[i:i+length]

            # look for the pattern in Fy
            for idx_y, sf_y in enumerate(f_y):
                # 'j' stores the starting index in Fy; the
                # Python find() function returns -1 if there
                # is no match
                j = sf_y.find(pattern)
                if j > -1:
                    # the pattern was found; set 'newFx' and
                    # 'newFy' to version of 'fx' and 'fy' with
                    # the patterns removed, update the SSNC and
                    # set 'match' as True, in order to cascade
                    # out of the loops
                    tmp_x = [sf_x[:i], sf_x[i+length:]]
                    tmp_y = [sf_y[:j], sf_y[j+length:]]
                    new_f_x = f_x[:idx_x] + tmp_x + f_x[idx_x+1:]
                    new_f_y = f_y[:idx_y] + tmp_y + f_y[idx_y+1:]

                    ssnc += (2*length)**2

                    match = True
                    break

            # if the current pattern was found, end search
            if match:
                break

        # if a match was found, end sliding window
        if match:
            break

        # if a match was found, end Fx subfield enumeration
        if match:
            break

    # remove any empty subfields due to pattern removal
new \_f\_x = [sf for sf in new \_f\_x if sf]
new \_f\_y = [sf for sf in new \_f\_y if sf]

return new \_f\_x, new \_f\_y, ssnc

def stringcomp(str\_x, str\_y):
    len\_x, len\_y = len(str\_x), len(str\_y)

    f\_x, f\_y = [str\_x], [str\_y]

    ssnc = 0.0
    while True:
        f\_x, f\_y, ssnc = mmcwpa(f\_x, f\_y, ssnc)
        if len(f\_x) == 0 or len(f\_y) == 0:
            break

    return (ssnc / ((len\_x+len\_y)**2.))**0.5

5 Evaluation

Table 1 provides some reference scores as returned by the Python implementation given in the previous section. Besides some new examples, we reproduce all the string comparison employed by Yang et al. when presenting the MCWPA.

| FX       | FY         | SIMF(X,Y) |
|----------|------------|-----------|
| abc      | def        | 0.0000    |
| abcd     | abedef     | 1.0000    |
| Austria  | Australia  | 0.6731    |
| Python   | python     | 0.8333    |
| a123b    | ab123      | 0.6982    |
| 129 Industry Park | 129 Industry Park | 0.6101    |
| abc de   | abc k de   | 0.6388    |
| de abc   | de abc     | 1.0000    |
| abc de   | de abc     | 0.6236    |
| Fu Hui   | Mr Fu Hui  | 0.8000    |
| Fu Hui   | Fu Mr Hui  | 0.5962    |
| abcdefgh ijklnmop | abcdefgh ijklnmop | 0.8843    |
| akabc axyz mo | aabc axyz mo | 0.7768    |
| abcdefagha | aijklamabc | 0.3316    |
| Gao Hua Ming | Gao Ming Hua | 0.5892    |
| zeng zeng | zeng hong  | 0.5983    |
6 Conclusion

This paper presented a new algorithm, Modified Moving Contracting Window Pattern Algorithm (MMCWPA) for the calculation of field similarity, strongly relying on previous work by Yang et al. (which are in no way associated with this work). As for MCWPA, theoretical analysis, concrete examples, and experimental results indicate that MMCWPA improves the accuracy and efficiency of the calculation of field similarity and should be considered alongside with other field metrics, particularly when dealing with short strings representing natural language.

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