# A Pairwise Document Analysis Approach for Monolingual Plagiarism Detection

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#### Introduction

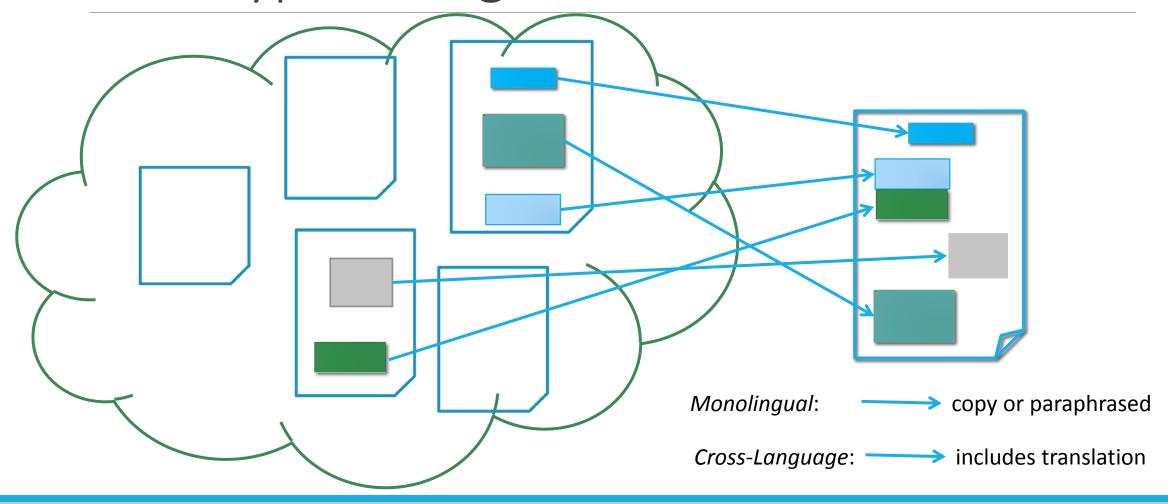
#### Plagiarism:

Unauthorized use of <u>Text</u>, code, idea, ...

Plagiarism detection research area has received increasing attention

- The rapid growth of documents in different languages
- Increased accessibility of electronic documents

## Prototypical Plagiarism



#### Problem definition has two steps

#### Candidate document retrieval

- D: set of source documents
- $\circ$  d': suspicious document with fragments  $d'_f$

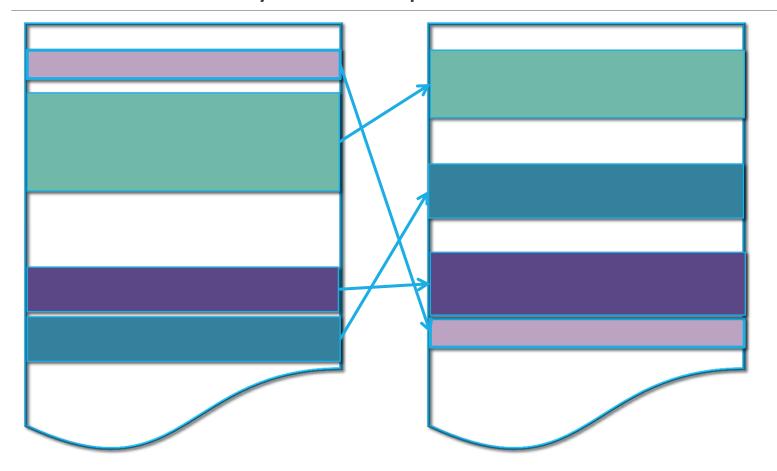
Candidate documents  $(D, d') = \{ d \in D \mid d_f \subseteq d, d'_{f'} \subseteq d', Sim(d_f, d'_{f'}) > \alpha \}$ 

#### Pairwise document similarity

- d: source document with fragments  $d_f$
- d': suspicious document with fragments  $d'_{f'}$

Copied pairs 
$$(d, d') = \{ \langle d_f, d'_{f'} \rangle | d_f \subseteq d, d'_{f'} \subseteq d', Sim(d_f, d'_{f'}) \rangle \beta \}$$

#### Detailed analysis in a pair of documents



Possible errors in detecting plagiarism:

- Text that is not plagiarized might be erroneously reported
- Part or whole of plagiarized source or target text might be unreported
- Parts of one plagiarism case might be reported as separate cases

#### **Evaluation Metrics**

 $\circ$  S: set of true plagiarism cases, R: set of detections reported

$$Precision(R,S) = \frac{1}{|R|} \sum_{r \in R} \frac{\left| \bigcup_{s \in S} (s \cap r) \right|}{|r|} \quad Recall(R,S) = \frac{1}{|S|} \sum_{s \in S} \frac{\left| \bigcup_{r \in R} (s \cap r) \right|}{|s|}$$

Fraction of reported detections (at character level) that are truly plagiarized

Granularity(R,S) = 
$$\frac{1}{|S_R|} \mathop{\mathring{a}}_{s \hat{l} S_R} |R_s|$$

Average number of reported detections per detected plagiarism case

$$Recall(R,S) = \frac{1}{|S|} \sum_{s \in S} \frac{\left| \bigcup_{r \in R} (s \cap r) \right|}{|s|}$$

Fraction of plagiarism cases (at character level) that are detected

$$Granularity(R,S) = \frac{1}{|S_R|} \underset{s \in S_R}{\circ} |R_S| \qquad Plagdet(R,S) = \frac{F_1(R,S)}{\log_2(1 + Granularity(R,S))}$$

Combined metric

# Two phase algorithm for identifying plagiarized text fragments

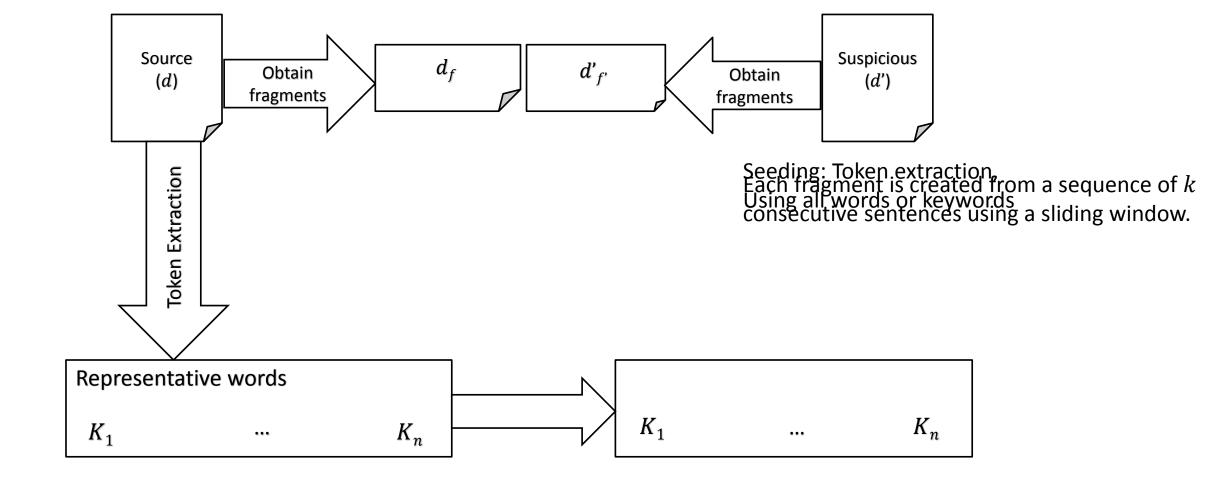
Candidate sentence selection:

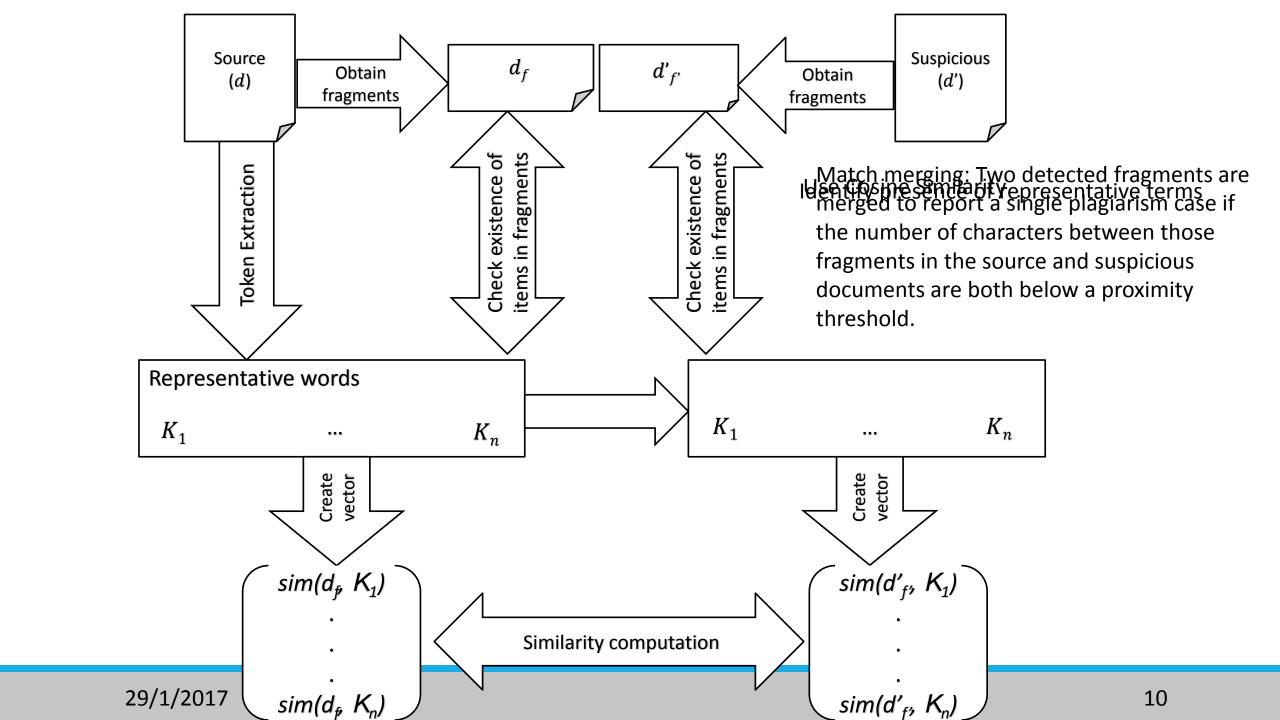
- Finds many possibly plagiarized fragments
- Focusing on recall

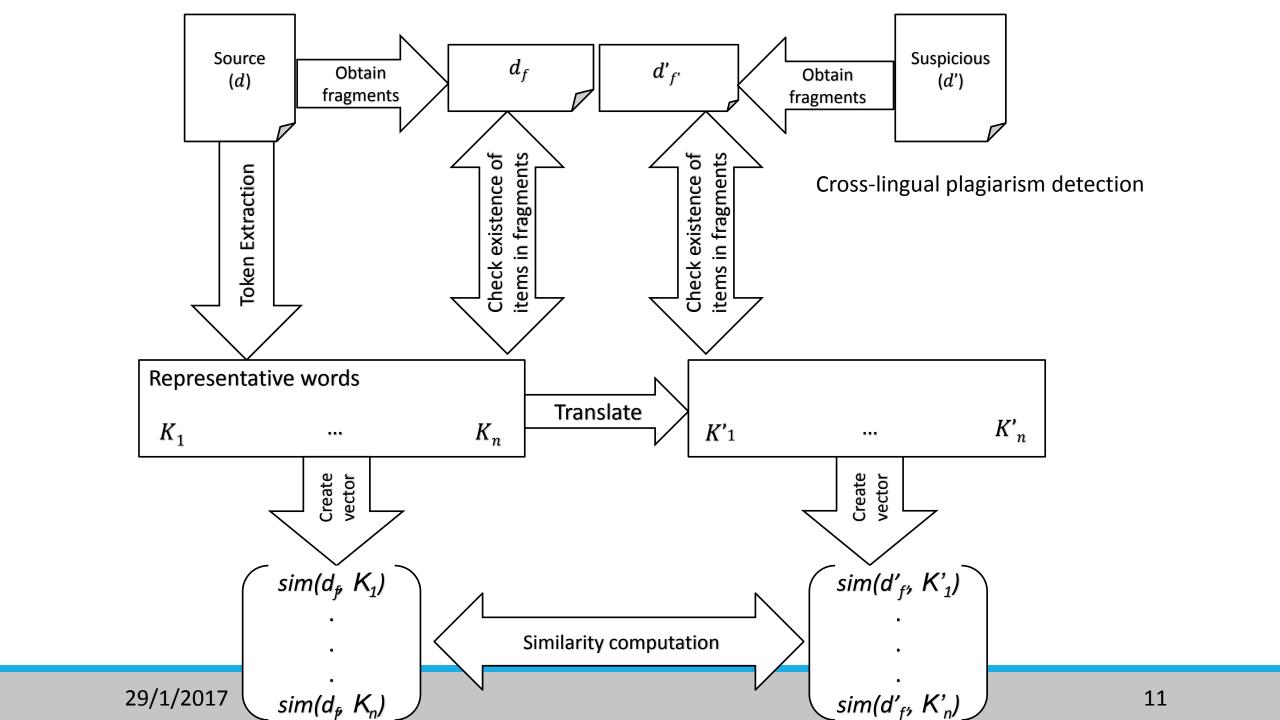
Result filtering:

- Finds alignments between the identified passages
- Focusing on precision

# Step 1: Candidate Sentence Selection



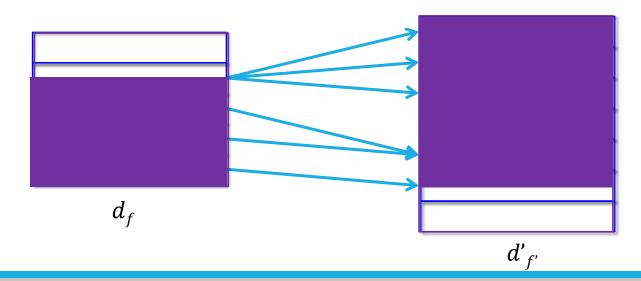




# Step 2: Result Filtering

#### Aligning segments within fragment pairs

- Fragment pair from the first step retrieved
- Fragments split into smaller segments
- Segments aligned using a dynamic programming algorithm
  - allowing 1:0, 0:1, 1:1, 2:1, 1:2, 3:1 and 1:3 alignments
  - exclude sentences at start or end of fragment with >50% content in 1:0 or 0:1 alignments



## Alignment details

```
S(i,j) = max \begin{cases} S(i-1,j) \\ S(i,j-1) \\ S(i-1,j-1) + sim(susp_i, src_j) \\ S(i-1,j-2) + sim(susp_i, src_{j-1:j}) \\ S(i-1,j-3) + sim(susp_i, src_{j-2:j}) \\ S(i-2,j-1) + sim(susp_{i-1:i}, src_j) \\ S(i-3,j-1) + sim(susp_{i-2:i}, src_j) \end{cases}
```

where S(i,j) represents the score of the optimal alignment from the beginning of the fragment to the  $i^{th}$  suspicious segment and the  $j^{th}$  source segment

 To penalize 1-0 and 0-1 alignments and also to make all scores comparable, we keep track of the number of alignments obtained so far, and the score in each step is normalized by the number of alignments.

## Granularity level of alignment

#### Sentence level:

Using sentences as the granularity level of alignment

#### *n*-gram level:

- A plagiarized fragment may omit pieces from the source, but it is likely that at least some of the smallest units are preserved
- *n* is the expected number of terms in each segment

#### Results

Result of detailed analysis sub-task using PersinaPlagdet2016 training corpus t = Similarity threshold, n=Number of sentences

	Precision	Recall	Granularity	Plagdet
(t = 0.2, n = 5)	0.4004	0.8151	1	0.5370
(t = 0.3, n = 5)	0.7630	0.7486	1	0.7557
(t = 0.4, n = 5)	0.8532	0.5357	1	0.6582
(t = 0.3, n = 3)	0.7867	0.8304	1	0.8080
(t = 0.4, n = 3)	0.8604	0.6567	1	0.7449

Result of detailed analysis sub-task using PersinaPlagdet2016 test corpus

	Precision	Recall	Granularity	Plagdet	Runtime
(t = 0.3, n = 5)	0.7496	0.7050	1	0.7266	00:24:08

#### Results

Evaluation of the second phase, result filtering step:

$$t = 0.3, n = 3$$

	Precision	Recall	Granularity	Plagdet
Without result filtering	0.6029	0.8602	1	0.7087
After result filtering	0.7867	0.8304	1	0.8080

#### Results

Evaluation of the seeding phase, using keywords:

	Precision	Recall	Granularity	Plagdet
(t = 0.3, n = 3)	0.5118	0.8858	1	0.6487
(t = 0.4, n = 3)	0.6431	0.8928	1	0.7476
(t = 0.5, n = 3)	0.7475	0.8862	1	0.8110
(t = 0.6, n = 3)	0.8117	0.8459	1	0.8282
(t = 0.7, n = 3)	0.8522	0.7531	1	0.7996

# Cross-lingual detailed analysis for plagiarism detection

Ehsan, N., Tompa, F.W., Shakery, A.: Using a dictionary and n-gram alignment to improve fine-grained cross-language plagiarism detection. In: *Proceedings of the 2016 ACM Symposium on Document Engineering*. pp. 59–68. ACM (2016).

	Precision	Recall	Granularity	Plagdet
Using PAN2012 English-German dataset	0.9301	0.8193	1	0.8712

#### Summary

- The proposed method is a two phase approach for identifying plagiarized fragments
- The first phase tries to find possibly plagiarized fragments
- The second phase tries to improve the precision metric
- The framework is applicable in any language
- The approach could be adapted for cross language domain

