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# End-to-End page-Level assessment of handwritten text recognition

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The evaluation of Handwritten Text Recognition (HTR) systems has traditionally used metrics based on the edit distance between HTR and ground truth (GT) transcripts, at both the character and word levels. This is very adequate when the experimental protocol assumes that both GT and HTR text lines are the same, which allows edit distances to be independently computed to each given line. Driven by recent advances in pattern recognition, HTR systems increasingly face the end-to-end page-level transcription of a document, where the precision of locating the different text lines and their corresponding reading order (RO) play a key role. In such a case, the standard metrics do not take into account the inconsistencies that might appear. In this paper, the problem of evaluating HTR systems at the page level is introduced in detail. We analyse the convenience of using a two-fold evaluation, where the transcription accuracy and the RO goodness are considered separately. Different alternatives are proposed, analysed and empirically compared both through partially simulated and through real, full end-to-end experiments. Results support the validity of the proposed two-fold evaluation approach. An important conclusion is that such an evaluation can be adequately achieved by just two simple and well-known metrics: the Word Error Rate (WER), that takes transcription sequentiality into account, and the here re-formulated Bag of Words Word Error Rate (bWER), that ignores order. While the latter directly and very accurately assess intrinsic word recognition errors, the difference between both metrics ($\Delta$WER) gracefully correlates with the Normalised Spearman's Foot Rule Distance (NSFD), a metric which explicitly measures RO errors associated with layout analysis flaws. To arrive to these conclusions, we have introduced another metric called Hungarian Word Word Rate (hWER), based on a here proposed regularised version of the Hungarian Algorithm. This metric is shown to be always almost identical to bWER and both bWER and hWER are also almost identical to WER whenever HTR transcripts and GT references are guarantee to be in the same RO.



## 1. Introduction

Archives and libraries throughout the world hold billions of historical manuscripts. Many of these documents are already digitised into images, but their access is limited because the contents are not available in a symbolic format that would allow modern treatment of textual matters such as editing, indexing, and retrieval. Handwritten Text Recognition (HTR)[1] is the cornerstone in this situation which aims to provide automatic ways of transcribing these documents [25].

In classical HTR laboratory experiments, the text lines are assumed to be given. Therefore, the performance is evaluated at the line level. Traditional evaluation measures for line-level HTR are the Character Error Rate (CER) and the Word Error Rate (WER), borrowed from the Automatic Speech Recognition field. These metrics indicate the length-normalised number of elementary editing operations needed to produce a reference (correctly transcribed) sequence from the HTR hypothesis, at the character (CER) or word (WER) level. Under the premise of a line-level formulation, it is generally acknowledged that these metrics provide a good measure of performance.

Due to recent advances in the field, especially brought about by the intensive use of deep neural networks, line-level HTR is con-

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[1] While all the problems and methods discussed in this paper equally apply to *printed* text and OCR transcripts, we keep the main focus on *handwritten* text, where the problems become more insidious and the solutions more relevant.

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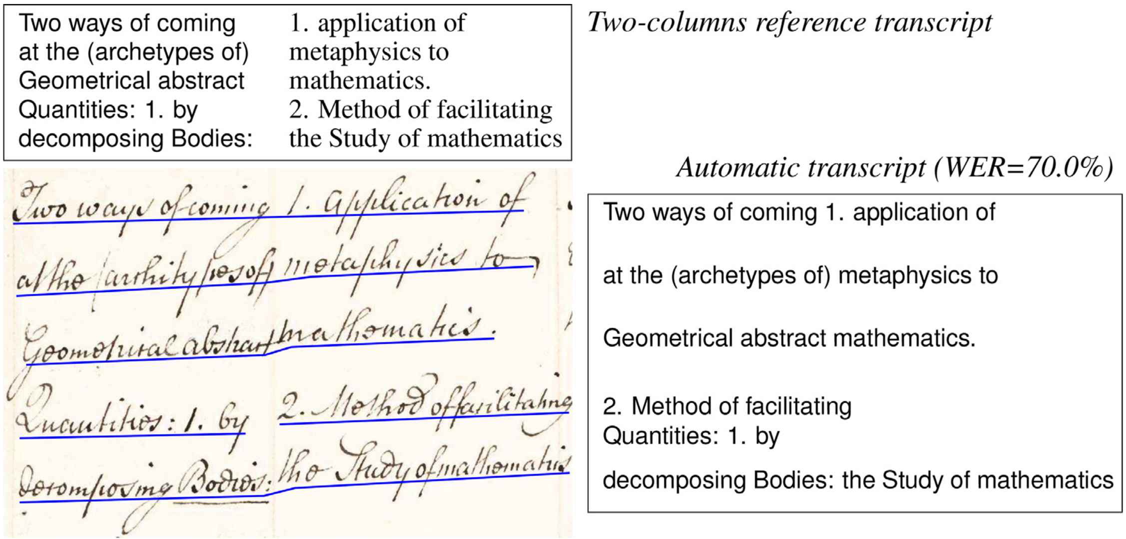


**Fig. 1.** Example of misleading WER evaluation, caused by wrong reading order due to text-line detection flaws. While all the words in the automatic transcript are perfectly correct, the WER is 70% (13 matching words, 13 substitution errors, 4 insertions and 4 deletions). The image is part of a page of the Bentham Papers collection (see Section 3).

sidered practically solved, or close to. Therefore, the field is experiencing a paradigm shift towards end-to-end full-page scenarios. In a page-level application, lines are not given. Instead, images are usually processed to first extract single lines, under a process generally known as Layout Analysis (LA).[2] Then, each line is transcribed independently with line-level HTR. Furthermore, some works do not explicitly include any LA step and aim to obtain the transcription hypothesis by processing whole pages or paragraphs [2,9].

Despite moving from the line-level to the page-level HTR scenario, the traditional CER and WER metrics are still generally used for assessment. However, this evaluation protocol is too naive: full-page real applications do suffer from LA errors which systematically lead to inconsistencies when evaluating the model using such metrics. Fig. 1 shows a real example of this kind of issues related to LA (see other examples in Figs. 2, 7, and 10). While all the words are perfectly recognised, the WER is 70%, which is absolutely misleading. Clearly, if this figure is meant to reflect anything, it is a LA problem — nothing related with word recognition errors! This kind of problems become even more insidious in approaches that bypass the LA step. When researchers were hard-pressed to obtain acceptable performance values, questioning the traditional evaluation protocol did not seem relevant. However, with an increasing number of effective page-level transcription workflows, we see the need to ask ourselves about the nature of its evaluation and whether the traditional line-level evaluation faithfully represents a proper indicator of page-level transcription performance.

The difficulties underlying the evaluation of page-level HTR results boil down to a Reading Order (RO) problem [7,26,30,33]. A number of recent proposals try to heuristically weight and combine both word recognition and LA geometric errors into a single scalar value [10,19]. Unfortunately, this hinders the capability to sort out the nature of the corresponding errors and thereby making a comprehensive, useful assessment. Here we instead advocate for a two-fold evaluation approach which decouples the impact of word (and character) recognition errors from the influence of wrong RO and, furthermore, it is largely agnostic to geometry-related flaws.

One possibility to assess page-level word recognition accuracy regardless of RO is to rely on the Bag of Words concept, as proposed and used in early works by Antonacopoulos, Clausner and Pletschacher [4–6,30] (see also [8]), and later by other authors [37]. Here we will argue that a properly defined WER based on the Bag of Words concept can not trivially consist on just counting how many words do not appear both in the reference and HTR transcripts. So we (re-)define a bag-of-words WER (bWER) so that it becomes faithfully comparable with the traditional WER and proves to be a very convenient page-level RO-independent word error metric.

However, the bWER approach does not allow measuring character-level error, nor it provides the word alignment information needed to compute RO assessment metrics. Instead, both word- and character-level RO-independent recognition accuracy can be precisely computed using the well-known Hungarian Algorithm (HA) [3,16]. Here we introduce a regularised version of the HA which provides HA-based WER values (hWER) that are almost identical to those of bWER and, moreover, are also practically equal to those of the classical WER when the reference and HTR transcripts are in the same RO. In addition, it further provides the information needed to compute RO assessment metrics such as the Normalised Spearman's Footrule Distance (NSFD) [17,33].

In this work, we study all these related approaches to separately assess at the page-level both the HTR word (and character) recognition accuracy and the quality of the RO. The problems considered and the proposed solutions will be presented along with empirical results obtained on a semi-artificial task, where the typically expected LA errors and associated RO problems are simulated. The proposed assessment methods will be then applied to a series of real page-level end-to-end HTR experiments, considering both LA-based and holistic page-level transcription approaches.

Our experiments will show that: i) in the traditional line-level setting, bWER and WER are typically almost identical; ii) the WER based on the regularised HA is almost the same as the bWER and both accurately approach page-level WER in the traditional line-level evaluation setup; iii) the difference between WER and bWER highly correlates with the NSFD and is much more efficient than using the HA, needed to compute the NSFD.

[2] Many present-day HTR systems use simplified forms of LA which only focus on detecting the text-lines of each image. In the sequel, the term LA will be used indistinctly to refer to proper LA as well as to just line detection.

The remainder of this work is structured as follows. Classical WER and CER measures are reviewed in Section 2; the RO problem and the NSFD measure are discussed in Section 3; the proposed bWER and hWER metrics are described in Section 4 and 5, respectively; and a summary of the different metrics considered is provided in Section 6. Then, simulated and real experiments are reported and analysed in Section 7 and 8, respectively. We close the article by outlining related works in Section 9 and concluding in Section 10. Finally, Appendix A presents detailed examples of the computation of the different metrics proposed and Appendix B provides details for public access to the datasets and software tools used and developed in this work.

## 2. Word & character error rates based on the edit distance

Traditional HTR assessment is based on line-level WER and CER. As commented above, this ignores possible line detection and/or extraction errors made by the LA stage in real automatic transcription tasks. This section reviews this evaluation approach, as an introduction to the forthcoming sections, where we propose new approaches for fair page-level end-to-end HTR assessment.

### 2.1. Edit distance, WER and CER for word sequences

Let the word sequences $x = x_1, \dots, x_{|x|}$ and $y = y_1, \dots, y_{|y|}$ be a reference text and a HTR hypothesis, respectively. The word *edit distance* from $x$ to $y$, $\mathrm{d}(x, y)$, is the minimum number of word insertion, substitution and deletion edit operations that transform $x$ into $y$ [46]. Edit operations define a “trace” or alignment between word instance positions of $x$ and $y$, which may be formulated in several equivalent ways. Here we loosely follow the work of Marzal and Vidal [24] and define an alignment $\mathcal{A}(x, y)$ as a sequence of ordered pairs of integers (word indices), $(j, k)$, $1 \le j \le |x|$, $1 \le k \le |y|$, such that for every two distinct pairs $(j, k), (j', k') \in \mathcal{A}(x, y)$, $j < j' \Leftrightarrow k < k'$. In what follows, word alignments which fulfil this *sequentiality constraint* will be denoted as $\mathcal{T}(\cdot,\cdot)$, leaving the notation $\mathcal{A}(\cdot,\cdot)$ only for unconstrained alignments.

$\mathcal{T}(x, y)$ can be conveniently extended to explicitly represent word insertions and deletions. To this end, a *dummy* position, denoted by $\epsilon$, is assumed in both $x$ and $y$ which points to the *“empty word”*, $\lambda$; that is, $x_\epsilon = y_\epsilon \stackrel{\text{def}}{=} \lambda$. The edit distance from $x$ to $y$ is thus formally defined as:

$$\mathrm{d}(x, y) = \min_{\mathcal{T}(x,y)} \sum_{(j,k)\in\mathcal{T}(x,y)} \delta(x_j, y_k) \tag{1}$$

where $\delta(a, b)$ is defined to be 1 if $a \ne b$ and 0 otherwise. With these editing costs, it is often called Levenshtein distance. For the above sequentiality constraint to still be meaningful, we assume that the predicate $j < j'$ is *true* for any $j, j'$ such that $j$ or $j'$ are $\epsilon$.

By analysing the pairs in the optimal trace $\mathcal{T}(x, y)$, the sum in Eq. (1) can be decomposed into separate counts for insertions, substitutions and deletions; i.e., $\mathrm{d}(x, y) = i + s + d$. Example 1 in A.1 illustrates the computation of the word edit distance and the corresponding trace[3] for $x$ = “To be or not to be, that is the question” and $y$ = “to be oh! or not to be: the question”, with $i = 1, s = 2, d = 2$ and $\mathrm{d}(x, y) = 5$.

[3] To avoid nonessential complications such as (language-dependent) tokenization and capitalisation, any character sequence delimited with withe space is considered a “word”. Therefore: $\delta$(be, be,) = $\delta$(be, be:) = $\delta$(The, the) = 1.

The WER of $y$ with respect to $x$ is defined as the edit distance, normalised by the length of the reference text,[4] $n = |x|$:

$$\mathrm{WER}(x, y) \;=\; \frac{\mathrm{d}(x, y)}{n} \;\equiv\; \frac{i + s + d}{c + s + d} \tag{2}$$

where $c$ is the number of correct words (those which do not need editing). In Example 1 (A.1), $\mathrm{WER}(x, y) = (1 + 2 + 2)/(6 + 2 + 2) = 5/10 = 50\%$.

The CER is defined similarly, by just assuming that $n$ is the total number of characters in $x$ and $i, s, d, c$ are *character*, rather than *word* edit operations and correct matching counts.

### 2.2. Traditional, line-based page level WER and CER

Let $\mathcal{I}$ be a text image and $X$ the reference GT transcript of $\mathcal{I}$. Let $Y$ be the transcription hypothesis provided by an HTR system for $\mathcal{I}$. Both $X$ and $Y$ are made up of the same number $M$ of individual text-lines $x^1, x^2, \cdots, x^M$ and $y^1, y^2, \cdots, y^M$, respectively, where each text-line is a sequence of words. Each pair of text-lines $x^\ell$ and $y^\ell$ are transcripts of the same image line, which is simply denoted as $\ell$, $1 \le \ell \le M$. In the traditional setting, page-level WER is then computed as:

$$\mathrm{WER}(X, Y) \;=\; \frac{\sum_{\ell=1}^{M} \mathrm{d}(x^\ell, y^\ell)}{N} \;\equiv\; \frac{\sum_{\ell=1}^{M} (i_\ell + s_\ell + d_\ell)}{\sum_{\ell=1}^{M} (c_\ell + s_\ell + d_\ell)} \tag{3}$$

where $N = |X|$ is the total number of word instances of $X$.

Another way to compute $\mathrm{WER}(X, Y)$ is to concatenate all the $M$ lines of $X$ and $Y$ in any arbitrary order (the same order for $X$ and $Y$) and directly compute the edit distance between the concatenated texts. Except for small possible differences in the text-line boundaries, the editing operations obtained by this computation will be essentially the same as those involved in the $M$ edit distances $\mathrm{d}(x^\ell, y^\ell)$, $1 \le \ell \le M$ of Eq. (3). Therefore:

$$\mathrm{WER}(X, Y) \;\approx\; \frac{\mathrm{d}(X, Y)}{N} \;\equiv\; \frac{i' + s' + d'}{c' + s' + d'} \tag{4}$$

where $i', s', d'$ and $c'$ are now counts of word edit operations and matchings involved in the computation of $\mathrm{d}(X, Y)$ for the *whole* texts $X$ and $Y$.

As in Section 2.1, the CER is defined similarly by just assuming that $N$ is the total number of characters in $X$ and $i, s, d, c, i', s', d', c'$ are *character*, rather than *word* edit operation and correct matching counts.

### 2.3. Page-level end-To-End assessment using traditional WER and CER

In a realistic scenario, image-lines may be given for the GT reference transcript, $X$. But these lines may not correspond one-to-one with lines automatically detected in the text image $\mathcal{I}$. Moreover, the number of text-lines in $X$ and $Y$ might be different.

To overcome this hurdle, it is often ignored that the lines of $Y$ may *not* be in the same *reading order* (RO) as those of $X$ and the WER is thus naively computed for the whole texts in $X$ and $Y$ as in Eq. (4). This is the approach often followed in experiments which aim to provide end-to-end performance assessment such as [2] and [35] (Sec.8, Test-B2).

[4] Note that, defined in this way, it may happen that $\mathrm{WER}(x, y) > 1$, which prevents WER to be properly interpreted as an error probability. For the same reasons a Word Accuracy can not be defined just as $1 - \mathrm{WER}$. The Normalised Edit Distance [24,44] would overcome these drawbacks but, following time-honoured tradition in ASR and HTR alike, we stick with the conventional normalisation by the length of the reference sequence.

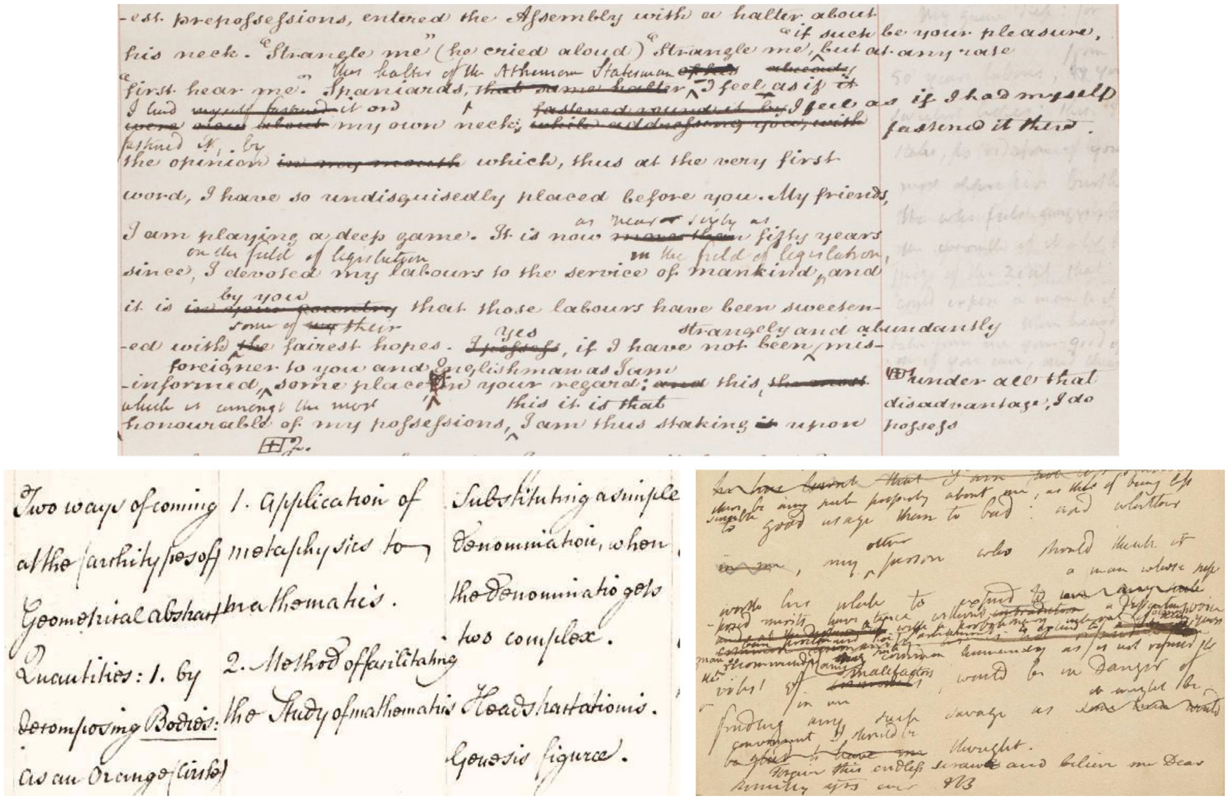

**Fig. 2.** Examples of frequent reading order issues, from the Bentham Papers collection.

## 3. The reading order problem

The RO of a sequence of words $W = w_1, \ldots, w_n$ is just the linear sequence $1, \ldots, n$ of the *positions* of these words in $Z$. Loosely speaking, two transcripts $X$ and $Y$ of an image $\mathcal{I}$ are said to be in a similar RO if a sequential, monotonous correspondence (i.e., a trace) exists between the positions of the matching words of $X$ and $Y$. Note that this applies to documents written in occidental or latin-derived left-to-right writing style, as well as to other scripts where writing follows right-to-left or top-to-bottom directions.

As noted in Section 1, assuming that reference and hypothesis transcripts are in similar RO is generally unrealistic. This is particularly the case in many historical handwritten text images such as those shown in Fig. 2.[5] If Eq. (4) of Section 2.3 is applied in this scenario, the resulting WER figures will reflect an uncontrolled combination of actual word recognition failures and errors due to inaccurate RO generally due to poor LA.

On the other hand, it is important to realise that the RO provided by reference transcripts and/or other layout GT annotations is generally only one among several possible RO annotations which would be all correct. Therefore, mixing RO and word recognition errors into a single assessment measure (as in [10,19]) does not seem the best idea for understanding which are the inner issues of an end-to-end full-page HTR system.

These facts lead us to propose a two-folded evaluation approach which completely decouples the RO from word recognition errors, while also providing a simple, comprehensive picture of the end-to-end system performance.

Research on RO has some tradition for printed documents [7,18,26]. More recently, RO analysis has also been considered for handwritten documents, where RO issues are specially relevant. In the work of Quiros and Vidal [33], effective methods to learn line RO in handwritten text images from examples are proposed and empirically assessed.

### 3.1. Assessing reading order: Normalised Spearman's footrule distance

RO assessment issues are discussed in [33], where two metrics are finally proposed and used in the experiments: the Kendall's Tau rank distance (also called bubble-sort distance) [15] and the Normalised Spearman's Footrule Distance (NSFD) [17]. Here we adopt the latter because it measures not only how many elements are not placed in the correct position within the expected order, but also how far these elements are from their correct positions. Thereby it provides reasonable estimates of the human effort that would be needed to render a sequence of elements in a correct order given by a reference sequence. The NSFD can be defined as:

$$\rho(X,Y) = \frac{1}{\lfloor \frac{1}{2} N^2 \rfloor} \sum_{(j,k) \in \mathcal{A}(X,Y)} |j-k| \qquad (5)$$

where $\mathcal{A}(X,Y)$ is an alignment between the reference text $X$ and the HTR hypothesis $Y$, and $N = \max(|X|,|Y|)$ is the number of words of the longest text. Note that the alignment $\mathcal{A}(X,Y)$ does *not* need to fulfil the sequentiality constraint used in Section 2.1 to define the word edit distance. In what follows, we assume that the alignment used in Eq. (5) will be provided by the methods discussed in Section 5. Example 2 in A.2 illustrates the computation of the NSFD for $X=$ "To be or not to be, that is the question" and $Y=$ "The big question: to be or not to be", with $\rho(X,Y) = 27/50$ (54%).

From a user point of view, insertions and deletions do not typically affect the RO in a substantial way. Therefore, in Eq (5) we just assume that $|j-\epsilon| = |\epsilon - k| \stackrel{\text{def}}{=} 1 \ \forall j,k$. However, insertions and deletions may indirectly affect significantly the result of Eq. (5), because of the contribution of subsequent values of $|j-k|$. This is

[5] From the Bentham Papers collection. See, e.g.: http://prhlt-kws.prhlt.upv.es/bentham

illustrated in Example 2 as well, along with the approach we propose to circumvent this problem by just renumbering the positions of words of $Y$ and/or $X$ according to the inserted or deleted words specified in $\mathcal{A}(X, Y)$.

## 4. Bag of words WER

In Section 2, $X$ and $Y$ were considered sequences where the order of text-lines and words is relevant for computing word errors. However, in page-level performance assessment, once we have a specific metric to measure RO, it is desirable to largely ignore the order of words in $X$ and $Y$ to measure word recognition performance.

A simple way to achieve this goal is to rely on the "Bag of Words" concept, as discussed in Section 1. To this end, $X$ and $Y$ are now considered multi-sets (or "bags") of words and the number of instances of each word can be used to compute a metric which is fairly closely related to the WER.

Let $V_X$ and $V_Y$ be the respective sets of different words (vocabularies) of $X$ and $Y$, and $V = V_X \cup V_Y$. For each word $v \in V$ let $f_X(v)$ and $f_Y(v)$ be the number of instances of $v$ in $X$ and $Y$, respectively. The "bag of words distance" between $X$ and $Y$ is defined as:

$$\mathrm{B}(X, Y) = \sum_{v \in V} |f_X(v) - f_Y(v)| \tag{6}$$

Then, if $N$ is the number of words in the reference $X$, a simple "BoW WER" can be rather naively defined as:

$$\beta\mathrm{WER}(X, Y) \;=\; \frac{B(X, Y)}{N} \;\equiv\; \frac{1}{N} \sum_{v \in V} |f_X(v) - f_Y(v)| \tag{7}$$

As defined in Eq. (6), $\mathrm{B}(X, Y)$ is the number of word instances of $X$ which fail to appear in $Y$ plus the number of word instances in $Y$ which are not in $X$. This can be properly interpreted in terms of editing operations just as the total number of word insertions and deletions that would be needed to transform $X$ into $Y$, *without allowing for word substitutions*.

In the classical WER, a combined deletion and insertion pair of edit operations can be achieved by a single substitution. So, if $X$ and $Y$ are in the same RO, the bag of words distance will always be larger than or equal to the corresponding word edit distance; that is, $\mathrm{B}(X, Y) \geq \mathrm{d}(X, Y)$. If word substitution were allowed, many pairs of the $\mathrm{B}(X, Y)$ insertions and deletions could be advantageously exchanged by single substitutions. In the best case, the number of these word substitutions would be exactly $\mathrm{B}(X, Y)/2$. However, if $|X| \neq |Y|$, it is unavoidable that a number of words $b = \big|\,|X| - |Y|\,\big|$ have to be actually deleted or inserted, without any possible pairing for interpretation as single substitutions. We will say that these insertions or deletions are *unavoidable*.

Therefore, to define a "bag of words WER" which can be fairly compared with the traditional WER, we assume that each insertion/deletion pair, except those unavoidable, is equivalent to a single substitution. Formally speaking, the above definition of bag of words distance needs to be revamped into $\mathrm{B}'(X, Y) = b + \lfloor(\mathrm{B}(X, Y) - b)/2\rfloor$. Since $\mathrm{B}(X, Y) - b$ is always even, the *bag of words WER* is thus defined as:

$$\begin{aligned} \mathrm{bWER}(X, Y) &= \frac{\mathrm{B}'(X, Y)}{N} \\ &= \frac{1}{2N}\left(\big|N - |Y|\big| \;+\; \sum_{v \in V} |f_X(v) - f_Y(v)|\right) \end{aligned} \tag{8}$$

Through the computation of Eq. (8), the *number* of word insertions, deletions and (implicit) substitutions can be easily derived, even though which specific words are involved in the different operations remain unknown. This becomes a significant drawback, because it prevents to derive any kind of word-to-word or position-to-position alignment that could be used to compute the NSFD or any other metric to assess RO mismatch. For the same reason, a CER associated with bWER can neither be properly computed. (Note that a "bag of characters" error rate would be overtly deceptive, and therefore is not an option). The examples in A.3 illustrate the computation of $\beta$WER and the reformulated version here proposed bWER (Eq. (8)), along with their relation with the classical WER.

It is important to note that the WER is based on sequentially constrained alignments (see Section 2.1), while the bWER does not. Therefore, bWER can be (much) lower than WER, especially if the RO of $X$ and $Y$ are very different. Even without the RO issue, the bWER can underestimate word errors. Example 3a in A.3 shows a simple case of this. However, based on empirical evidence presented in Sections 7 to 8, these cases are rare in practice. The page-level bWER (Eq. (8)), therefore, becomes a good approximation to the corresponding WER in traditional experimental settings where RO is not an issue. This is interesting because bWER is much simpler and cheaper to compute than WER.

## 5. CER, WER and NSFD based on bipartite graphs and the hungarian algorithm

As discussed above, determining RO-independent word and character recognition accuracy at the full-page level, requires words and/or word positions from the reference transcript $X$ to be freely aligned or paired with corresponding words of the transcription hypothesis $Y$. Edit distance computation provides word alignments (traces) as a byproduct, but the trace sequentiality restriction leads to alignments which lack the freedom needed for RO-independent word pairing. A proper formulation of the required kind of word alignments is given by the so-called *"minimum-weight matching or assignment problem"* [3].

Let $G = (V, E)$ be a *bipartite graph*, where the set of nodes $V$ is composed of two disjoint subsets $A, B$, $A \cup B = V$, $A \cap B = \emptyset$, and the set of edges $E$ is a subset of $V \times V$ such that $(u, v) \in E \Rightarrow u \in A \,\wedge\, v \in B$. A *matching* $\mathcal{M} \subset E$ is a set of pairwise non-adjacent edges; that is, no two edges share a common node. A node is matched if it is an endpoint of one of the edges in the matching. Otherwise, the node is unmatched. $\mathcal{M}$ is said to be *maximum* if it contains the largest possible number of edges and it is a *perfect matching* if all the vertices of the graph are matched. Every perfect matching is also maximum. A bipartite graph $G = (V, E)$ is *weighted* if a real-valued weight $g(u, v)$ is assigned to each edge $(u, v) \in E$. Then, the weight of a matching $\mathcal{M}$ is the sum of the weights of the edges in $\mathcal{M}$. Given a weighted bipartite graph, the assignment problem is to find a perfect matching with minimum weight. An efficient solution to this problem is provided by the *Hungarian Algorithm* (HA) [16].

In our HTR assessment task, $A$ and $B$ are, respectively, the word instances of the reference transcript $X$ and the HTR hypothesis $Y$ of a page image; $E = \{(X_j, Y_k), 1 \leq j \leq |X|, 1 \leq |Y|\}$ is the set of all pairs of word instances in $X$ and $Y$, and the weight $g(X_j, Y_k)$ is the character edit distance between the $j$-th word of $X$ and the $k$-th word of $Y$. Word insertions and deletions are represented by assignments to "dummy" nodes, which represent the empty word $\lambda$. These nodes need to be added to *both* sets, not only because in general $|X| \neq |Y|$, but also because we need to simultaneously support *both insertions* and *deletions* for any given pair of transcripts. The cost of an edge connecting a dummy node with a word $v$ is thus defined as $g(v, \lambda) = g(\lambda, v) = \frac{1}{2}|v|$, where $|v|$ is the number of characters of $v$ and, as in Section 4, the factor $\frac{1}{2}$ is introduced to balance the cost of a word substitution with that of an equivalent combined word insertion and deletion.

The assignment problem is to pair each (maybe empty) word instance of $X$ with a (maybe empty) word instance of $Y$ so that the sum of character edit distances between the paired words is mini-

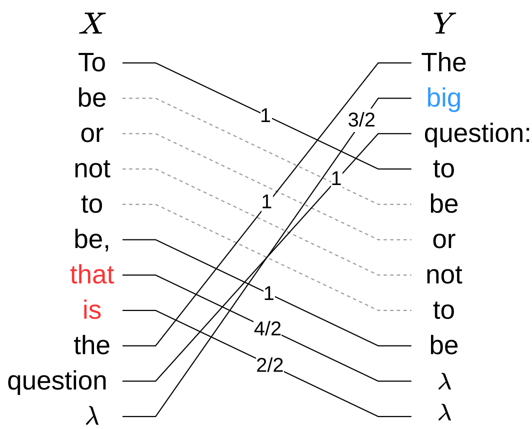


**Fig. 3.** Assignment obtained by the Hungarian algorithm for a bipartite graph corresponding to the word sequences $X$ and $Y$. Dotted edges have a null cost and coloured words are insertions or deletions. For this assignment, $\mathrm{d_h}(X,Y) = 1+1+4/2+2/2+1+1+3/2 = 8.5$.

mum. Therefore, the HA yields what could be called "HA Character Edit Distance":

$$\mathrm{d_h}(X,Y) \;=\; \min_{\mathcal{A}} \sum_{(j,k)\in\mathcal{A}(X,Y)} g\big(X_j, Y_k\big)\,; \tag{9}$$

Fig. 3 illustrates all the above concepts for a pair of word sentences.

The optimal alignment $\hat{\mathcal{A}}(X,Y)$ associated with Eq. 9 is a set of pairs $(j,k)$, $1 \le j \le |X| = N$, $1 \le k \le |Y|$, along with two additional sets of pairs of the form $(j,\epsilon)$ and $(\epsilon,k)$ to account for word deletions and insertions, respectively. Let $D$ be the number of these dummy pairs in $\hat{\mathcal{A}}(X,Y)$ and, as in Eq. (8), let $b = \big|\,|X| - |Y|\,\big|$. Since both insertions and deletions are allowed in $\hat{\mathcal{A}}(X,Y)$, $D \ge b$. So, as in the case of Eq. (8) for the bWER, the (now typically few) $D-b$ excess pairs of insertions and deletions, can be interpreted as single substitutions. Then, the "HA WER" (hWER) can be defined as:

$$\mathrm{hWER}(X,Y) \;=\; \frac{1}{N} \sum_{(j,k)\in\hat{\mathcal{A}}(X,Y)} \delta(X_j, Y_k) \;-\; \frac{(D-b)}{2N} \tag{10}$$

where $\delta(\cdot,\cdot)$ is the 0/1 function introduced in Section 2.1. Also using $\hat{\mathcal{A}}(X,Y)$, the NSFD $\rho(X,Y)$ can be computed straightaway as in Eq. (5).

To compare hWER with bWER, note that the optimisation of Eq. (9) ensures a word alignment with minimum sum of *character edit distances* between the paired words. But this alignment may not always lead to a minimum *word edit distance*. Thus, while it can be easily shown that $\mathrm{bWER}(X,Y) \le \mathrm{hWER}(X,Y)\ \forall X,Y$, the strict equality may not hold in some cases.

The examples in A.4 further illustrate the computation of hWER for the more realistic texts used in Example 3. It is worth noting that the values of hWER in these examples are identical to the corresponding bWER values of Example 3 (A.3).

When multiple instances of some word exist in $X$ and/or in $Y$, as in the examples of A.4, the HA is free to pair any matching instances, as long as the values of $\mathrm{d_h}(\mathrm{X},\mathrm{Y})$ are the same. In other words, there may be multiple alignments which provide the same optimal result for Eq. (9) and the HA has no means to decide which one would be more consistent with the positions of these words in the RO of the compared texts.

This is discussed in detail in A.5 for one of the examples of A.4. Because of unlucky tie breaks, the NSFD between two example sentences $X$ and $Z$ which are almost in the same RO is $\rho(X,Z) = 13.3\%$. However, if ties are broken more favourably (and in a more natural way), the resulting NSFD is $\rho(X,Z) = 1/\lfloor 14^2/2 \rfloor =$ 1.0%, which much better reflects the very minor RO discrepancy between $X$ and $Z$.

To avoid this kind of ties, we propose to regularise the HA cost with a term which measures the contribution of each pairing to increase the NSFD. That is, we propose changing Eq. (9) into:

$$\mathrm{d_h}(X,Y) \;=\; \min_{\mathcal{A}} \sum_{(j,k)\in\mathcal{A}(X,Y)} \left( g(X_j, Y_k) \;+\; \gamma\, \frac{|j-k|}{N} \right) \tag{11}$$

where $\gamma$ is the regularisation factor and, as in Eq. (5), it is assumed that $|j-\epsilon| = |\epsilon - k| = 1\ \forall j,k$.

If $\gamma$ is close to 0, the HA will just behave as usual, yielding hWER values very close or identical to those of bWER, but alignments $\hat{\mathcal{A}}(\cdot,\cdot)$ not ideal for assessing RO discrepancies. On the other extreme, for large $\gamma$ the HA will tend to provide alignments which do not change word order; that is, alignments close to the sequential trace $\mathcal{T}(\cdot,\cdot)$ of the traditional edit distance (cf. Eq. (1)), with NSFD values close to 0. For small values of $\gamma$ it is expected that the hWER result provided by Eq. (10) and Eq. (11) will be very close or identical to those obtained with $\gamma = 0$; but the alignment $\hat{\mathcal{A}}(\cdot,\cdot)$, when used in Eq. (5), will result is NSFD values which more fairly reflect RO discrepancies.

To define a proper "HA character error rate" (hCER), note that the HA score $\mathrm{d_h}(X,Y)$ is not directly suitable because of the regularisation and the special treatment of word insertions and deletions. However, a simple approximation can be easily computed as $\mathrm{hCER}(X,Y) \stackrel{\text{def}}{=} \mathrm{CER}(X,\tilde{Y})$, where $\mathrm{CER}(\cdot,\cdot)$ is the standard character error rate (see Section 2.2) and $\tilde{Y}$ is obtained by reordering the word hypothesis $Y$ according to the optimal alignment of Eq. (11). The values obtained in this way for the examples in A.4 are: $\mathrm{hCER}(X,Y) = 8.1$, $\mathrm{hCER}(X,Z) = 16.1$,

## 6. Summary of the different metrics proposed

This section summarises the properties of the most important evaluation metrics discussed above. In all the cases, it is assumed that $X$ is a full-page reference transcript, with $N$ running words, and $Y$ a corresponding HTR hypotheses with $O(N)$ running words.

- $\mathrm{WER}(X,Y)$: The traditional Word Error Rate, defined in Eqs. (1), and (4), with a computational cost in $O(N^2)$. If $Y$ is in the same RO as $X$, the WER just measures the word recognition error rate. Otherwise, this metric is expected to grow monotonically with the amount of RO mismatch between $X$ and $Y$, with an offset that reflects the actual word recognition failures. This offset can accurately be estimated by the bWER or the hWER.
- $\beta\mathrm{WER}(X,Y)$: An early, naive notion of "bag of words error rate" defined as $\mathrm{B}(X,Y)/N$, where $\mathrm{B}(X,Y)$ measures text discrepancies in terms of only word insertions and deletions (Eq. (6)). It can be computed in $O(N)$ time. When $Y$ is in the same RO as $X$, the classical WER yields (much) lower values than the $\beta$WER, but if the RO is very different, WER is expected to be much larger. The use of this metric is, therefore, not appealing.
- $\mathrm{bWER}(X,Y)$: A redrafted version of $\beta$WER, given in Eq. (8), which exactly estimates how many word insertions and deletions can be equivalently resolved with word substitutions. It can be computed in $O(N)$ time. When $Y$ is in the same RO as $X$, it is expected to yield values which are only slightly lower than those of the classical WER but, in contrast to WER, it is completely insensible to RO mismatch. A drawback of this metric is that it does not provide any word-to-word alignment, thereby preventing to compute a character error rate or to be used as a basis to estimate a RO mismatch metric.

**Table 1**
hWER and NSFD results (in percentage) for increasing values of the regularisation factor $\gamma$. The corresponding WER and bWER results were 42.6% and 12.4%, respectively.

| $\gamma$ | 0 | $10^{-4}$ | 0.1 | 1 | 2 | 5 | 10 | 20 | 50 | 100 |
|---|---|---|---|---|---|---|---|---|---|---|
| $\rho$ | 14.7 | 12.9 | 12.9 | 12.8 | 12.6 | 11.5 | 9.0 | 5.3 | 1.6 | 0.9 |
| hWER | 12.4 | 12.4 | 12.4 | 12.4 | 12.5 | 13.8 | 17.9 | 25.4 | 36.5 | 42.7 |

hWER$(X,Y)$: The "Hungarian Algorithm Word Error Rate", defined in Eq. (10) based on a RO-independent word alignment obtained as a byproduct of computing Eq. (11). Its computational cost is $O(N^3)$. In terms of word error rate, hWER is almost identical to bWER, but it may provide slightly higher values than bWER in some cases. In contrast with bWER, hWER does provide word alignments which allow computing a character error rate and can be used to estimate a RO mismatch (with the NSFD, e.g.).

$\rho(X,Y)$: Normalised Spearman Footrule Distance (NSFD), defined in Eq. (5) to explicitly estimate the amount of RO mismatch between $X$ and $Y$. It requires a word-to-word alignment which is assumed to be available as a byproduct of computing the hWER. Its computational cost is $O(N)$, but taking into account the cost of obtaining the required alignment, the overall cost is $O(N^3)$. The values of NSFD are expected to grow monotonically with the degree of RO mismatch. It is also expected that these values be closely correlated with the values of the classical WER, after discounting the offset due to actual word recognition errors which, as previously mentioned, can be accurately estimated by the bWER or the hWER.

## 7. Simulation experiments

A first series of experiments were carried out to check and empirically analyse the properties of the proposed metrics under controlled conditions. To this end a simple HTR dataset was adopted and real full-page HTR transcription results were artificially altered in order to simulate typical conditions that are expected to affect the different evaluation results.

### 7.1. A Basic Dataset for testing different assessment approaches

The well known and widely used ICFHR14 dataset was adopted. This is a small subset of selected manuscripts from the Bentham Papers collection,[6] mostly written by the English philosopher and reformer Jeremy Bentham.[7]

The ICFHR14 dataset contains text-line images extracted from around 433 page images, some examples of which are shown in Fig. 4. It was first used in the ICFHR-2014 HTR competition [39] and is now freely available for research purpose at ZENODO (see Appendix B).

This early dataset was carefully prepared by the ICFHR14 organisers so as to avoid the need of LA and to simplify "non-essential" HTR matters as much as possible. To this end, text lines were manually detected and extracted and small pieces of text such as marginalia were ignored. Thus, all the benchmarking results reported so far for this dataset have been based only on conventional WER, exactly as discussed in Section 2.2. That is, the given training text-line images and their corresponding GT transcripts were directly used for model training and the WER was evaluated on the results achieved for the independent set of test line images.

**Table 2**
Test set main statistics of the evaluated datasets. Except for ICDAR17, the running words and lexicon sizes correspond to untokenized "words", which may include punctuation marks.

| | ICFHR14 | IAMDB | ICFHR16 | ICDAR17 | FCR |
|---|---|---|---|---|---|
| Number of pages | 33 | 336 | 50 | 57 | 100 |
| Number of lines | 860 | 2 915 | 1 138 | 1 412 | 6 183 |
| Running words | 6 966 | 23 406 | 3 546 | 14 460 | 33 999 |
| Running chars | 38 474 | 123 090 | 22 396 | 80 568 | 214 785 |
| Lexicon | 2 278 | 6 398 | 1 834 | 4 648 | 9 890 |
| Alphabet size | 82 | 75 | 80 | 104 | 83 |

Here we will use the test-set line images to simulate different shortcomings typically expected both from HTR and LA. Main statistics of this test set are reported later in Table 2.

### 7.2. General settings to analyse the proposed metrics

For each test-set page, the transcripts of the different text-lines were concatenated into a single word sequence,[3] following the RO specified in the GT of that page. From this sequence, WER, bWER and hWER can be computed according to Eqs. (4), 8) and (10), respectively. NSFD, in turn, can be determined according to Eq. (5), using the alignment derived from the computation of hWER, after the position renumbering described in Section 3.1. Finally, CER and hCER can be calculated as explained in Section 2.2 and at the end of Section 5.

To obtain global values of these metrics for a whole test set of $K$ page images, let $\mathcal{C} = \{(X_1, Y_1), (X_2, Y_2), \ldots, (X_K, Y_K)\}$ be the set of page-level pairs of reference and transcription hypothesis. We perform "micro-averaging" that somewhat minimises the impact of the relative page sizes (number of words or characters). For any metric $m(\cdot,\cdot)$, the global micro-average, $\bar{m}(\mathcal{C})$, can be expressed as the weighted sum of values of $m$ computed for each page:

$$\bar{m}(\mathcal{C}) \;=\; \frac{\sum_{k=1}^{K} N_k\, m(X_k, Y_k)}{\sum_{k=1}^{K} N_k} \tag{12}$$

where $m(\cdot,\cdot)$ can be one of the following page-level metrics: WER, bWER, hWER, CER, hCER or NSFD. That is, page metric values are weighted by the corresponding number of reference words (or characters) in the page, $N_k$, accumulated over all the test-set pages, and finally normalised by the total number of reference words (or characters for CER).

Among the proposed metrics, only hWER has a tunable parameter; namely, the regularisation factor of Eq. (11), $\gamma$. Throughout several tests, it has been consistently found that this parameter does not require critical tuning. For one of these typical tests, Table 1 reports NSFD and hWER results for increasing values of $\gamma$. These results were obtained in a controlled RO–alteration experiment, described in Section 7.4, where random swaps were applied to 4 text lines of each image, at distances ranging from 4 to 7 lines apart.

As discussed in Section 5, $\rho$ actually decreases monotonically with $\gamma$, while hWER is almost constant and identical to bWER for a wide range of $\gamma < 5$. According to these and other similar results,

[6] The full collection (searchable using PrIx [42]) is here: http://prhlt-kws.prhlt.upv.es/bentham

[7] http://blogs.ucl.ac.uk/transcribe-bentham/jeremy-bentham.

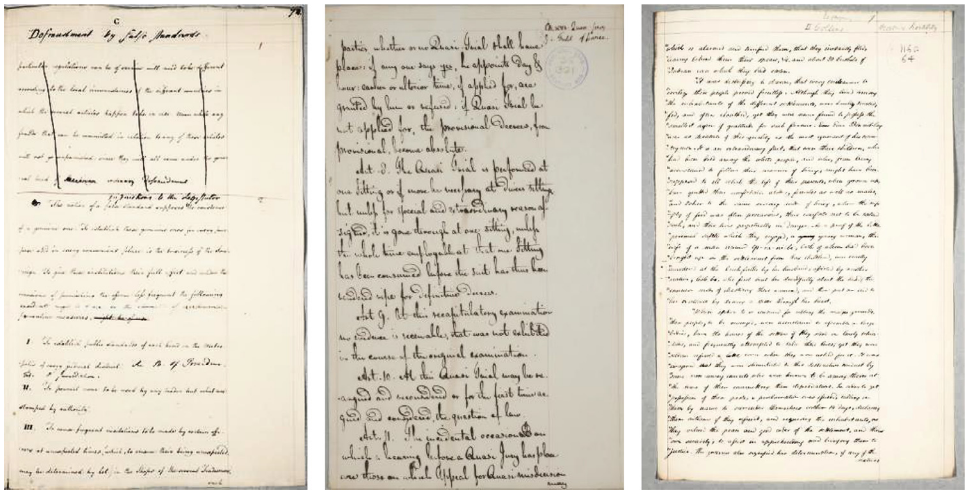

**Fig. 4.** Page images of the ICFHR14 dataset.

the regularization factor was set to $\gamma = 1.0$ for all the experiments presented in this paper.

### 7.3. Inducing word-level character errors, while the RO is kept essentially unchanged

In this experiment we applied increasingly higher character-level insertions, deletions and substitution distortion to the test-set reference transcripts, while keeping text lines in their original (correct) RO. Two different settings were considered: 1) *"line-level"*, where white-space editing operations are allowed to separate or join words, and 2) *"word-level"*, where white-space was excluded from editing operations in order to keep the number of running words unchanged.

The lowest distortion was chosen so as to induce a CER of 3.25%, which is the CER of real HTR transcripts obtained in a regular experiment (see Table 8.2). Increasing distortion was then progressively applied according to $\text{tCER}(n) = 3.25n$, $n \in \{1, 2, \ldots, 6\}$, until reaching an induced (or "theoretical") tCER of 19.5%. The distribution of the total tCER into the different character error types was set proportional to the observed proportions of substitutions, insertions and deletions. Further, for line-level distortion, the proportion of white-space characters was set according to the character error distribution observed in the real HTR experiment.

Fig. 5 plots the empirical WER, bWER and hWER results, along with the theoretical values of induced CER (tCER, dotted-line) and WER (tWER, dashed-line, calculated according to $\text{tWER}(n) = 4.65 \cdot \text{tCER}(n)$, where 4.65 is the average word length in the reference transcripts).

Results for the word-level distortion are shown in Fig. 5-left. As the RO in this case is not altered at all, the theoretical NSFD (tNSFD) is 0 (horizontal dash-dotted line). As expected, all the empirical NSFD values are also very close to 0. Moreover, the empirical values of WER, bWER and hWER all grow almost identically for increasing tCER. This also holds for CER and hCER.

For line-level distortion the results are shown in Fig. 5-right. In this case, for large tCER, the empirical NSFD results become significantly larger than 0, and CER is also somewhat larger than hCER. This is clearly due to the white-space editing operations which, for large tCER, results in significant variations in the number of words. The HA need to accommodate these variations by means of insertions and/or deletions, which explicitly increases the NSFD, albeit only moderately.

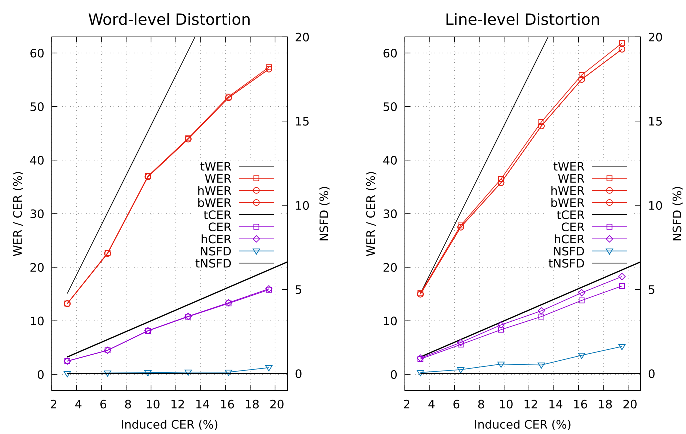


**Fig. 5.** Evaluation results for increasingly distorted transcripts, as a function of the CER artificially induced by the distortion process. Left: words are distorted individually avoiding induced white space errors to break or join words. Right: distortion is applied at full line level, allowing white space to be deleted/inserted between/within words. Curves with very similar or identical values are depicted with the same colour and/or point shape. The prefix "t" in tCER, tWER and tNSFD indicates the corresponding values are theoretically computed.

### 7.4. Altering text line RO for HTR transcripts with fixed word errors

Here we evaluated the impact of altering the RO of the real HTR transcripts produced in a regular HTR experiment (namely, the one whose results are reported in the first row of Table 8.2 of Section 8.2). For the sake of simplicity, alterations considered in this section are limited to whole-line swapping. This aims to simulate typical failures in text-line ordering, often caused by poor (implicit or explicit) LA of images with multi-column text blocks, marginalia, etc.

For each test-set page with $M$ text lines, the order of line transcription hypotheses is changed by swapping a given number of line pairs, $S$, at a given distance or range, $r$. Line pairs are randomly selected, but lines already swapped are not candidate for further swapping. For a given $S$, depending on the value of $r$, the actual number of possible swapping on a page may be lower than $S$. For example, the maximum number of swappable line pairs of a page with $M = 8$ lines, at a distance $r = 7$, is only one: the first line with the last one of that page.

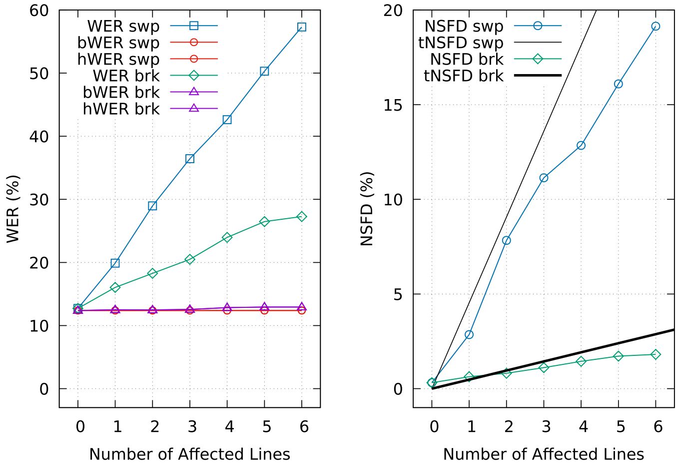


**Fig. 6.** Evaluation results on actual HTR transcripts where the line order is distorted by random line swaps and breaks. Curves with almost identical values are depicted with the same colour and symbol. tNSFD corresponds to theoretically computed values. The "swp" and "brk" labels denote line swap and split, resp. (see Section 7.4 and 7.5).

For a given range of swap distances $r \in [R', R]$, and a given number of pages, $K$, the expected NSFD induced by this process, $\tilde{\rho}$, can be approximated as:

$$\tilde{\rho}(K, S, R', R) \;\approx\; \frac{S(R'+R)}{K} \sum_{k=1}^{K} \frac{1}{\lfloor M_k^2/2 \rfloor} \tag{13}$$

where $M_k$ is the number of lines of the $k$-th page. In our experiments, $K = 33$, $R' = 4$, $R = 7$, and $\sum_{k=1}^{K} 1/\lfloor M_k^2/2 \rfloor = 0.136$, yielding: $\tilde{\rho}(S) = 0.045\,S$. In the right plot of Fig. 6 shows these expected NSFD values as the dashed line labelled "tNSFD swp").

The left plot of Fig. 6 shows WER values obtained for different (maximum) numbers of swapped lines, where each value is the average over a range of swap distances [4,7]. As expected, while WER increases quickly with the number of swapped lines, the corresponding bWER and hWER remain almost constant. On the other hand, the right plot shows how the empirical NSFD values also grow as the number of line swaps increases, more or less closely following the expected linear tendency (tNSFD swp). Fig. 6 also includes WER and NSFD results of the experiments discussed in the next subsection.

### 7.5. Impact of text line splitting errors

Finally we check the effect of randomly inserting line-breaks in the HTR transcripts. This aims to simulate (implicit or explicit) line detection errors which lead to wrong intra-line text ordering. To this end, the following procedure was carried out for the HTR transcripts of each test page: 1) $S$ lines are randomly selected. 2) For each selected line a splitting position is randomly chosen; it can be at character or word level, with a chance of 1 to 4 respectively. 3) The split line fragments are relocated according to one of these three equiprobable options: i) the line suffix goes before the prefix, ii) the line suffix goes after the line next to the selected one, or iii) the line prefix goes after the line next to the selected one. These cases correspond to relatively common flaws of (implicit or explicit) LA, which may happen mainly with highly skewed text images, as illustrated in Fig. 7 (see also Fig. 2).

As in Section 7.4, we can estimate the impact of these RO alterations on the NSFD metric. Ignoring the effect of word breaks, the NSFD induced for $K$ page images can be approximated as:

$$\tilde{\rho}(S) \;\approx\; \frac{7}{6}\frac{S}{K} \sum_{k=1}^{K} \frac{N_k/M_k}{\lfloor M_k^2/2 \rfloor} \tag{14}$$

where, as before, $M_k$ and $N_k$ are respectively the number of lines and words of the $k$-th page image. For our $K = 33$ page images, this leads to $\tilde{\rho}(S) = 0.0048\,S$. The dotted line labelled "tNSFD brk" in the right plot of Fig. 6 shows these expected NSFD values.

Note that, unlike the RO alteration simulation of Section 7.4, here not only the RO is changed (in this case at a range distance $r = 1$), but also some words are distorted because a line split point may happen to fall within a word, thereby producing two word fragments. Such word splits happen with probability $S\,(K/4)/\sum_{k=1}^{K} N_k$ and for each split, two word errors are expected. In our case, $K = 33$ and, for the transcription hypotheses, $\sum_{k=1}^{K} N_k = 6955$. Therefore, the expected increase of bWER (and hWER) is $0.0023\,S$ ($0.23\,S$ in %), which explains the tiny increase of bWER-brk and hWER-brk observed in Fig. 6.

### 7.6. WER–NSFD Correlation and computational costs

In Section 7.3 (Fig. 5) we have seen that, when the amount of character (and word) errors increases without changing the word order, the NSFD remains essentially constant and close to 0. In contrast, all the word and character error metrics grow almost linearly with the amount of induced character errors. Moreover, the three word error metrics (WER, bWER and hWER) yield almost identical values in all the cases. On the other hand, we have seen in Section 7.4 (Fig. 6) that if the amount of word errors is kept constant but the RO of the transcripts is increasingly perturbed, both WER and NSFD (and also CER) grow fairly linearly with the amount of induced RO mismatch. In contrast, now bWER (and hWER) remain practically constant and equal to the value of WER when HTR and reference transcripts are in the same RO.

All these results (those of Fig. 6 in particular) suggest a strong correlation between NSFD and WER, with an offset given by bWER (or hWER). This is explicitly put forward in Fig. 8, where values of $\Delta\text{WER} \overset{\text{def}}{=} \text{WER} - \text{bWER}$ (and also WER − hWER) are plotted against the corresponding values of NSFD. We also include in this plot a few points corresponding to real end-to-end evaluation results of some of the experiments that will be presented in Section 8 (Table 8.2). It can be seen that these points also show a fair linear correlation between ΔWER and NSFD.

Regarding the relative costs of the different metrics, computing times are plotted in Fig. 9 as a function of the number of words per page. All the times were measured on the same computer, using the C++ implementations of WER, bWER, and hWER described in Appendix B. The points correspond to real end-to-end evaluation of individual pages and the least-square fitted curves clearly show the different time complexities of each method.

## 8. Examples of real end-to-End evaluation

The proposed evaluation metrics have been applied to assess end-to-end HTR systems in real scenarios. The HTR datasets considered, the empirical settings and the results obtained are presented in the following subsections.

### 8.1. Datasets and methods

Besides the historical dataset ICFHR14 [39] already used in the preceding sections, four additional datasets were selected to test the proposed evaluation metrics; namely: the traditional modern handwriting benchmark IAMDB [23], and three historical handwriting datasets: ICFHR16 [34] and ICDAR17 [40], compiled for

**Fig. 7.** Real examples from Bentham Papers images 010_003_002, 019_004_003, which illustrate text line splitting errors that affect RO. In the simulation experiments these examples correspond, top to bottom, to Cases 1, 2 and 3.

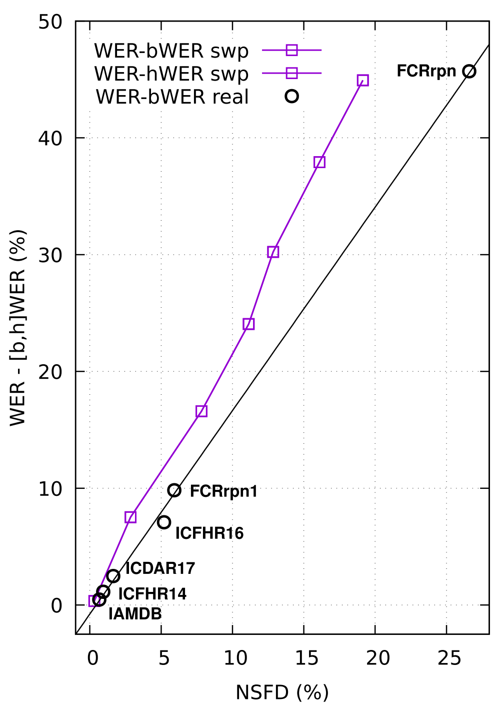


**Fig. 8.** Correlation of WER – bWER (and WER– hWER) with NSFD. Real results from Table 8.2 are included, along with a straight line fitted to these points. Curves with almost identical values are depicted with the same colour and symbol.

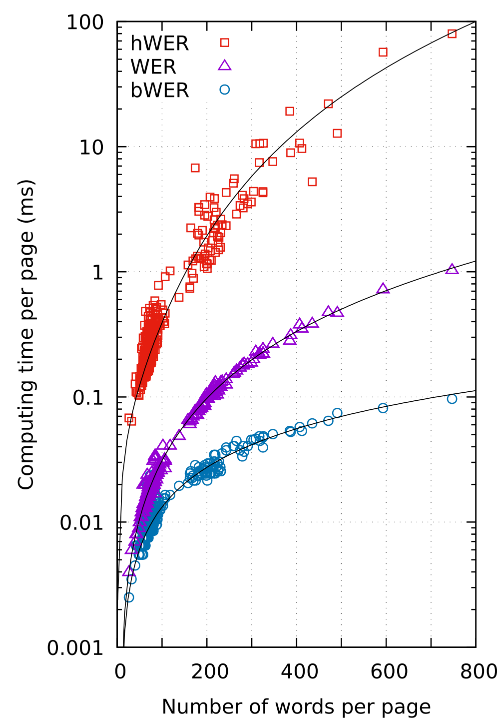


**Fig. 9.** Computing Times of hWER, $O(N^3)$, WER, $O(N^2)$ and bWER, $O(N)$, fitted respectively to polynomials of degrees 3, 2 and 1 (linear).

the ICFHR-2016 and ICDAR-2017 HTR competitions, and the *Finnish Court Records* dataset (FCR) [33] from the “Renovated District Court Records” held by the National Archives of Finland. Information about how to download each of these datasets is given in Appendix B.

IAMDB is a well known modern English handwritten text corpus, gathered by the FKI-IAM Research Group on the base of the Lancaster-Oslo/Bergen text Corpus (LOB) [13]. The last released version (3.0) contains about 1 500 scanned text pages, written by 657 different writers.

The ICFHR16 dataset encompasses 450 page images which are a subset of the Ratsprotokolle collection, written in old German and composed of handwritten minutes of council meetings held from 1470 to 1805. One remarkable characteristic of this dataset is that their text lines are short, each one containing very few (long) words.

The ICDAR17 dataset comprises around 10K page images, most of which taken from the *Alfred Escher Letter Collection*. This collection is mostly written in German, but it also includes pages in French and Italian. Here, the performance evaluation was carried out on the pages corresponding to the partition called "Test-B2" in [40], which was aimed to evaluate not only text recognition accuracy but also (indirectly) LA performance.

Finally, the FCR dataset consists of 500 manuscript images which contain records of deeds, mortgages, traditional lifeannuity, among others. They were written in Swedish by many hands during the 18th century. Here, the evaluation was done on 100 images (48 are double-page images) which are a subset of the test partition used in [45]. For more details about ICFHR14, ICFHR16, ICDAR17 and FCR datasets, refer to [33,35].

It is important to remark that no tokenization (e.g. to separate punctuation marks from words) was applied to text references or HTR transcripts, excepting ICDAR17 whose original references and HTR results obtained in the associated competition were used. Table 2 reports the main statistics *only for the test sets*, which are the focus of the proposed evaluation metrics.

Except ICDAR17 (for which the same transcripts as in [40] were used), for each dataset we trained specific optical character models using the provided training images and the corresponding reference transcripts. Character modelling was based on *Convolutional-Recurrent Neural Networks* (CRNN), trained using the state-of-the-art freely available PyLaia Toolkit.[8] The same setup described in [45] was adopted here to specify the CRNN topology and meta-parameters.

HTR transcripts of test images were obtained through two different ways of line extraction: 1) use the line locations and RO given in the GT; and 2) use a *Region Proposal Network* (RPN) [32] trained to detect and extract lines with a RO given by their positions on image, from top-to-bottom and left-to-right as in [33]. To this end, the same RPN topology and meta-parameter settings as in [32] was adopted. For both ways of line extraction and each dataset, the corresponding CRNN model trained with PyLaia was used to decode the extracted line images. Finally, HTR full-page transcripts were produced by concatenating the predicted text lines according to their RO given by the GT or computed by the RPN.

In addition to the above "classical" HTR experiments, as an example of what we consider the ultimate aim of the proposed metrics, we also test the end-to-end LA + HTR approach named *Simple Predict & Align Network* (SPAN) [9].[9] This model learns to transcribe paragraphs by aligning all the text line representations via a horizontal feature map unfolding. By training with the CTC loss strategy, this model learns how to align input information with the feature map rows and produce a sequential output, without requiring any specific LA preprocessing.

### 8.2. Real end-to-end evaluation results

Table 3 reports performance in terms of the proposed evaluation metrics for different end-to-end HTR approaches, tested on the datasets outlined before. The way of line extraction and ordering, as well as the HTR system adopted, appear on the columns labelled LA+RO and HTR, respectively. Selected values of $\Delta$WER = WER − hWER and NSFD, highlighted in boldface, are plotted in Fig. 8, as already mentioned in Section 7.6.

In all the cases, hWER is slightly higher than or identical to bWER and both are always smaller than WER, as discussed in Sections 4,5 (and summarises in Section 6) – and as expected from the simulation results of Section 7. Also as expected, all the HTR approaches which use the (perfect) text lines and RO given by the GT, achieve lower NSFD and $\Delta$WER, compared with other approaches involving automatic line detection.

Another important general remark is the fairly tight correlation observed between NSFD and $\Delta$WER. It is more clearly seen for results more or less affected by RO issues, specifically those highlighted in boldface which, as commented, are also plotted in Fig. 8. This further endorses the discussion in Section 7.6 and adds empirical support to consider $\Delta$WER as a suitable metric to put forward LA or, in general, RO problems.

IAMDB has a very simple RO structure and no significant differences exist among the different error rate metrics. To a lesser extent, the same can be said for ICFHR14.

The case of ICFHR16 is worth commenting. The WER achieved by RPN–CRNN (33.5%) is significantly higher than the bWER (26.4%), leading to $\Delta$WER = 7.1%. This makes it clear that the RO provided by RPN LA is far from perfect, an issue directly supported by the fairly high value of NSFD (5.20%). As discussed later in more detail, most RO errors are due to marginalia transcripts for which the system fails to place in the correct RO.

Also interesting is the case of FCR, which contains a mixture of single- and double-page images. For double-page images, the regular RPN settings (denoted in the table just as "RPN") dramatically fail to separate the lines of each page and render them in the correct RO. So, even though the individual words are fairly well recognised (with bWER = 26.7%), the conventional WER is exorbitant (72.4%). This leads to a very large $\Delta$WER (45.7%) which clearly shows the massive RO mismatch, also reflected by the very large value of NSFD (26.6%). Of course, this experiment was only aimed at providing a clear illustration of the behaviour of proposed metrics. So we also tested a more reasonable LA approach (called "RPN1" in the table). In this approach, when a double-page is identified, each detected text line is classified as belonging to the left or to the right page and then the usual RPN RO is applied page-wise. This approach provides identical individual word recognition performance (bWER = 26.7%) and greatly solves the RO issues – albeit not completely, as assessed by the still high values $\Delta$WER = 9.8% and NSFD= 5.92%.

Regarding CER and hCER results, in general they reflect similar tendencies as WER and hWER when RO issues are involved. Note however that, as discussed in Section 5, hCER is only an approximation and is not as directly and faithfully comparable with CER as hWER is with WER.

The SPAN (true full-page) approach, was tested on two datasets. Results for IAMDB are comparatively good in terms of word and character error metrics and also in terms of RO as assessed by NSFD and $\Delta$WER.

The SPAN results for ICFHR16 deserve a more detailed analysis. The RO-independent word recognition results (hWER$\approx$bWER= 29.9%) are sensibly worse than those of RPN+CRNN discussed above (hWER$\approx$bWER=26.4%), while the conventional WER is somewhat better (31.5% vs. 33.5%). So the $\Delta$WER for SPAN is significantly lower (1.6% vs. 7.1%) – which is also consistent with NSFD (1.3% vs. 5.2%). This indicates that the transcripts provided by SPAN have more word errors but are in significantly better RO than RPN+CRNN.

To better understand these results, we can gather additional evaluation clues from the distribution of bWER errors. In this case, from bWER=29.9%, 25.7% errors are substitutions, 0.3% insertions and 3.9% deletions. So we observe that SPAN makes many word deletions, around 10 times more than RPN+CRNN (with 0.4% deletions, 0.6% insertions and 25.4% substitutions). A closer look at the SPAN transcripts reveals that, indeed, SPAN almost systematically delete (i.e., fails to detect and recognise) the many marginalia lines existing in the ICFHR16 images. Clearly, while the RO is hardly affected by this fact, there is a noticeable impact on the RO-independent recognition accuracy, evidenced by the relatively larger values of bWER and hWER.

[8] https://github.com/jpuigcerver/PyLaia.

[9] https://github.com/FactoDeepLearning/SPAN.

**Table 3**
Real evaluation results for different datasets, LA and HTR approaches. All values are percentages. ΔWER denotes WER−bWER. RO mismatch (NSFD) and ΔWER values corresponding to points shown in Fig. 8 are marked in boldface. WER, bWER and hWER 95% confidence intervals are narrower than ±1.6% for ICFHR16 and ±1% for all the other datasets. The LA+RO approach "TRB" for ICDAR17 stands for Transkribus platform.

| Dataset \ Metric | LA+RO | HTR | NSFD | ΔWER | WER | bWER | hWER | CER | hCER |
|---|---|---|---|---|---|---|---|---|---|
| ICFHR14 | GT | CRNN | 0.3 | 0.3 | 12.7 | 12.4 | 12.4 | 3.3 | 4.0 |
| | RPN | CRNN | **0.9** | **1.1** | 17.4 | 16.3 | 16.3 | 5.5 | 5.9 |
| IAMDB | GT | CRNN | 0.6 | 0.5 | 27.0 | 26.5 | 26.5 | 7.5 | 8.2 |
| | RPN | CRNN | **0.7** | **0.5** | 27.8 | 27.3 | 27.3 | 7.9 | 8.7 |
| | SPAN | | 0.5 | 0.6 | 26.7 | 25.9 | 26.0 | 7.5 | 8.3 |
| ICFHR16 | GT | CRNN | 0.3 | 0.6 | 27.7 | 27.1 | 27.2 | 5.7 | 6.6 |
| | RPN | CRNN | **5.2** | **7.1** | 33.5 | 26.4 | 26.6 | 13.7 | 6.5 |
| | SPAN | | 1.3 | 1.6 | 31.5 | 29.9 | 30.0 | 10.7 | 10.9 |
| ICDAR17 | GT | CRNN | 1.4 | 2.2 | 18.6 | 16.4 | 16.5 | 6.3 | 6.6 |
| | TRB | CRNN | **1.6** | **2.5** | 20.1 | 17.6 | 17.7 | 7.0 | 7.1 |
| FCR | GT | CRNN | 0.8 | 1.1 | 25.2 | 24.1 | 24.4 | 5.6 | 6.4 |
| | RPN | CRNN | **26.6** | **45.7** | 72.4 | 26.7 | 27.0 | 50.8 | 8.5 |
| | RPN1 | CRNN | **5.9** | **9.8** | 36.5 | 26.7 | 27.0 | 15.1 | 8.2 |

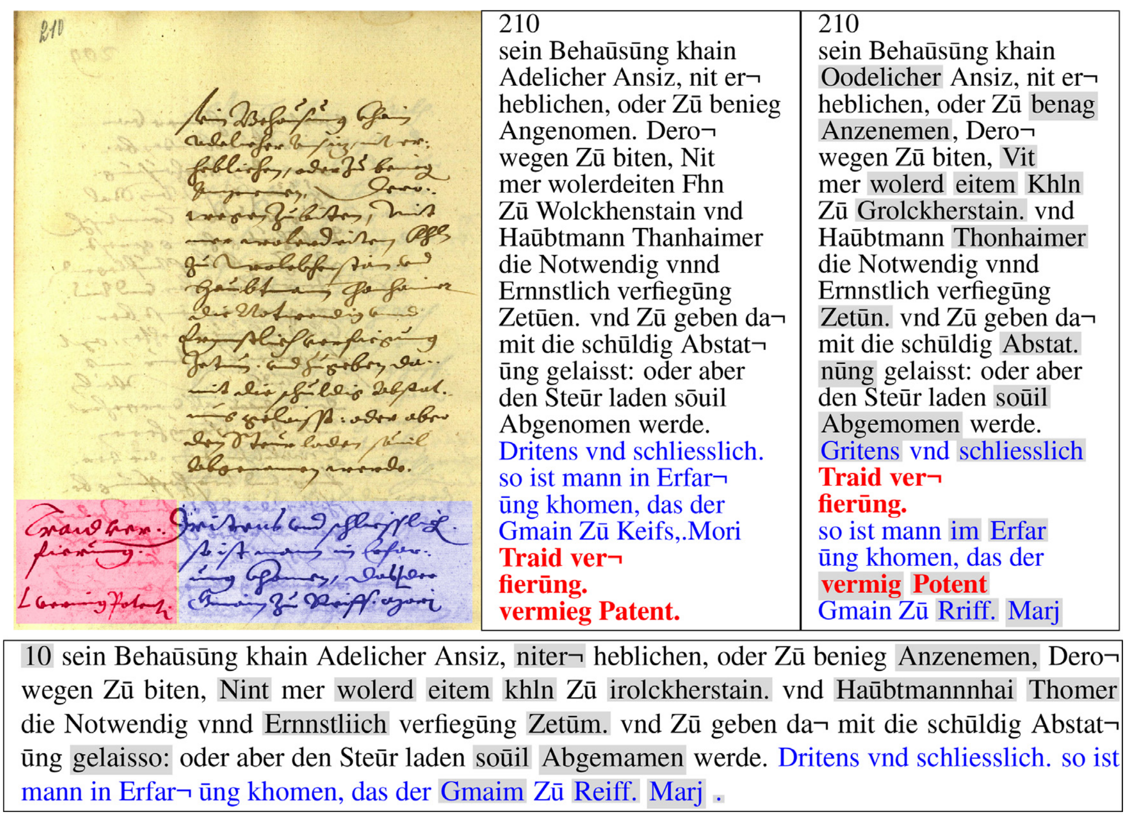


**Fig. 10.** A page from the ICHFR16 dataset (ID: Seite0418). The red and blue texts and shadings correspond to the text blocks affected by RO issues, while word recognition errors are marked with shadowed boxes. The top-middle panel is the reference transcript. The right-panel shows the RPN-CRNN's hypothesis, with bWER = hWER = 31.4% and ΔWER = 10% which fairly reflects the RO errors caused by poor LA. The bottom panel shows the SPAN's hypothesis, which clearly failed to detect and recognise all the marginal note words (in red colour). As compared with RPN-CRNN, SPAN has produced the same amount of word errors (bWER = hWER = 31.4%), but the transcript is in better RO, a fact fairly reflected by ΔWER = 1.4%. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

As a specific example of this general fact, Fig. 10 shows an ICFHR16 page image, along with its GT, RPN+CRNN and SPAN transcripts. In the RPN+CRNN transcript, the lines corresponding to the marginal note (in red) are correctly detected and all their words recognised (with two errors). However, they are mixed with the lines of the last paragraph (in blue). The total number of word errors is 22 (31.4%), but because of the mixed marginal lines, the RO is rather poor, as properly reflected by ΔWER = 10%. For the SPAN transcript, hWER = bWER = 31.4, exactly the same as for RPN+CRNN. But, as suspected, it has completely failed to transcribe the marginal note words. However, all the transcribed words are in good RO, a fact faithfully reflected by ΔWER = 1.4%.

## 9. Related works

The problem of assessing the quality of full-page automatic transcripts, taking into account LA and/or RO errors has been addressed in many previous works. In this section, we briefly review the literature both in HTR and other research fields where alternative metrics have been proposed in this regard. The review is organised into four topics, corresponding to what we consider the four main contributions of our work.

### 9.1. LA and/or RO awareness in HTR metrics

Almost all the works cited in this section consider only *printed* (historical) documents and the task of full-page, end-to-end evaluation is always more or less explicitly linked to (geometric) issues caused by faulty LA—see eg. [26] for a recent work in this category. Going deeper in this direction, Antonacopoulos, Clausner and Pletschacher are among the earlier authors who explicitly put forward the importance of this problem and its relation with RO difficulties — and propose pioneering practical approaches for RO-aware evaluation [7,30].

Note, however, that with the exception of [7,30] (and others discussed in the coming subsections), these works are *not* directly concerned with transcription *evaluation*. Some produce end-to-end transcription results, while others deal with LA and/or RO methods; but all need evaluation metrics and some of them make proposals that seem adequate to assess their results. On the other hand, as far we can tell, none of the cited works makes a convincing assessment of the adequateness of the proposed metrics for general-purpose evaluation and benchmarking of full-page transcripts of text images.

In comparison, our work explicitly analyses and proposes general-purpose metrics which are agnostic of geometry and other details of LA. We also report comprehensive results that support the adequateness of these metrics for unbiased evaluation of the overall quality of end-to-end transcription results of handwritten (or printed) text images.

### 9.2. Metrics related with the bag of words

BoW-based assessment appears in [30] and [37], and it has been used in several ICDAR competitions [4–6]. In these papers and competitions the Bag of Words concept was used to define evaluation measures based on, or related with recall (or missed words) and precision (or falsely detected words), generally combined into a kind of F-measure referred to “success rate” [1]. However, the formal details of these measures are not sufficiently documented and most probably they are largely unrelated with the metrics we are proposing in this paper. Moreover, by relying on misses and false detections, the “success rate” implicitly overlooks word substitutions, thereby making it difficult to establish meaningful relations with the traditional WER.

The definition of bWER in Eq. (8) explicitly considers substitutions, thereby making it almost identical to hWER and allowing for a proper comparison with the WER. This leads to the introduction of ΔWER, which proves to be a very convenient way to measure RO logical mismatch.

It is worth mentioning that our definition of bWER is not new. The idea was first suggested in [27] to obtain a rough measure of the quality of Machine Translation (MT) results disregarding word order. Under the name “Position-independent Error Rate” (PER), that idea was later presented more formally in [31]. By looking closely at the proposed formulation, one can observe that the core computation is indeed essentially the same as that of our Eq. (8).

### 9.3. Metrics related with the hungarian algorithm

The HA has been adopted in many document analysis and recognition tasks, many of them related with full-page, end-to-end training and/or text image recognition [22,41]. It has been proposed as well for other miscellaneous tasks such as invoice analysis [28], pairing different versions of historical manuscripts [14], and reassembling shredded document stripes [20], to name a few. All these works are completely unrelated with evaluation of HTR transcripts, which is the topic of this paper.

Among the works which explicitly deal with evaluation, we should mention an interesting early work in the field of Computer Vision, which considers the evaluation of visual objects detection [21]. Several works on LA make use of the HA to evaluate results of *line detection* and/or *text region segmentation* [12,48]. While this task may seem similar to ours, the overall framework is quite different. In these proposals, the elements to be paired are image regions, and the pairing criterion is strongly based on region geometry information. In contrast, our proposal is applied to transcripts, represented just by character strings. And evaluation is completely blind to the existence of text lines and explicitly ignores geometric features of the text images and/or their GT annotations.

It is worth mentioning that our point of view in this matter is similar to the one adopted in [36] for assessment of video OCR results. However, the metric proposed in [36] aims to assess not only the quality of the transcripts (and their RO), but also the positions of the detected and recognised words in the image. Therefore, this evaluation approach mixes geometric and text criteria, which is contrary to the principles adopted in our work.

Perhaps the most interesting proposal that is close to our work is the so called “Flexible Character Accuracy” metric [8] (FCA). It is based on computing the character edit distance between two chunks of text by iteratively comparing the lines with minimum edit distance, following a greedy strategy. The method is further based on several heuristics which need four weighting factors to control how much relevance is given to the offset and length difference of the matched strings. Additionally, unmatched substrings are considered insertion or deletion operations, so they are added as a penalty to the whole result. This metric was used to assess HTR transcription results in the ICDAR 2019 competition on Recognition of Documents with Complex Layouts [6].

In our opinion, FCA does succeed in providing a reasonable word accuracy score which is fairly RO-independent. Nevertheless, it has two important drawbacks. First, it is just based on a greedy, suboptimal solution to a line matching or assignment problem, for which the here proposed regularised HA would provide an optimal solution. In comparison, the approaches here proposed ensure optimal word pairings and, moreover, they do not need to assume any kind of LA units such as text blocks or lines. Second, FCA heavily depends on several tunable weights. Indeed, in the experiments, the reported results correspond to a best-scoring combination of parameters for each algorithm run. Clearly, this makes the method too dependent on the datasets considered, which would become problematic for general-purpose benchmarking of full-page transcription results.

In addition to the above discussions, perhaps our most important contribution to the use of the HA for HTR evaluation is to introduce a *regularised* HA version. Thanks to the proposed regularisation term, the HA not only minimises the character edit distance between the paired words, but also avoids as far as possible word order mismatch, as measured by the NSFD.

Such an enhancement has allowed us to define a HA WER (hWER) which exhibits all the desired properties: a) it yields essentially the same results as the bag-of-words WER (bWER) and thereby provides a proper RO-independent evaluation of individual word recognition performance; b) it provides practically the same results as the conventional WER, whenever reference and system transcripts are in the same RO; and c) it produces the alignments needed to compute a RO-independent character error rate and used by NSFD to explicitly measure RO mismatch.

### 9.4. Integrating evaluation of WER and reading order mismatch

All the works dealing with full-page, end-to-end HTR need to assess not only word recognition performance, but also the impact of errors due to flaws in (explicit or implicit) LA [2,9,47]. Of course, the main focus in these works is on the proposed HTR methods; so they do not generally pay much attention to how to properly measure the performance they achieve.

A popular idea is to measure LA errors using conventional LA metrics and then make do with conventional WER or CER to measure word or character recognition errors. Finally, both measures are somehow combined to obtain a single scalar figure which hopefully represents an "overall performance" metric [10]. In a similar vein, but explicitly devoted to HTR evaluation, the work presented in [19],goes deeper in the metric combination idea, with daunting mathematical formulation. However, this is a utterly theoretical work which does not provide any empirical evidence that would support the proposed formulation or methods in practice.

As we see it, the metric combination idea has several drawbacks: 1) as discussed throughout this paper, if reference and system transcripts are *not* in the same RO, conventional WER or CER systematically provide misleading word recognition performance values – and any combination of misleading values is obviously also misleading; 2) metric combination requires adequately tuned weights which are impossible to adjust for general-purpose benchmarking; and 3) the required GT is expensive because of the effort entailed by manual annotation of LA geometric details.

Another idea that has been adopted in some works [40,41,47] is to assess the overall quality of system transcripts using the so called "BLEU" measure [29]. It is borrowed from the field of Machine Translation and is based on matching n-gram frequencies of the system transcript with those of the GT reference. While this idea avoids the complications and exceedingly high cost of taking into account LA geometric details, it does suffer form the same problems of directly using the conventional WER; namely, it jumbles errors coming from different flaws and it often fails to provide the kind of insights needed for system improvement.

In contrast with the methods discussed above, the evaluation framework proposed, developed and assessed in this paper, favours a two-fold evaluation approach which completely decouples intrinsic word recognition errors from RO errors caused by poor (explicit or implicit) LA.

Before closing this section it is worth to cite the work presented in [38], which aims at assessing HTR results without resorting to GT reference annotations. While this is indeed an interesting prospect, it is completely unrelated with the aims and methods discussed in this paper.

## 10. Concluding remarks

In classical HTR experiments each relevant text-line image is given and accuracy is adequately assessed using conventional WER and CER. When moving to an end-to-end full-page transcription scenario, page-level accuracy is often being assessed using two very different metrics: geometric accuracy of layout analysis *and* WER/CER. We consider that this assessment approach is doubly misleading. First, geometric accuracy seldom matches well with logical relation between relevant image elements (text lines). Second, WER values are systematically tainted with false word recognition errors caused by well recognised words which are not placed in the "correct" order.

We argue that methods which aim at end-to-end processing, or at full integration of layout analysis with word recognition at page-image level, need assessment criteria which do *not* rely on any kind of geometric accuracy. Having this in mind, we have proposed page-level assessment approaches which: a) are geometry agnostic, b) provide a measure of word recognition accuracy which does not depend on word reading order, and c) provides a measure of logical mismatch of transcription elements (words or lines) which is largely independent on the accuracy with which individual words are recognised.

As a basic, simple and computationally cheap method to assess word recognition errors with independence of reading order, we advocate for a *reformulated* version of the popular bag-of-words WER, which we refer to as bWER. It should be pointed out, however, that the bWER does have some applicability limitations. Specifically, as commented in Section 4 and illustrated in Example 3a (A.3), it can provide optimistically low values if the evaluated transcripts have many word repetitions. Clearly, the probability that a chunk of text contains repeated words grows with the size of the text. Consequently, bWER is prone to become increasingly optimistic as the size of the evaluation sample (e.g., page image transcript) becomes larger. This is thoroughly studied in [43] and the results show that, in general, bWER can be safely used for typical page sizes and text densities, up to a some hundreds words per page, or even much larger in some datasets.

In addition, we have introduced another reading-order independent WER, called hWER, which is based on a *new, regularised* version of the Hungarian Algorithm. Both bWER and hWER provide almost identical results, but hWER is much more computationally expensive. However, the proposed regularised Hungarian Algorithm underlying the hWER also produces word alignments which can be used to compute specific reading-order metrics such as the Normalised Spearman Footrule Distance (NSFD). Moreover, if system and references transcripts are in the same reading order, these alignments very closely approach the traditional word-to-word sequential "traces" underlying the word edit distance assumed in the classical WER.

The proposed methods are analysed both formally and with the help of illustrative examples, as well as through a series of partially simulated experiments. Finally we have applied state-of-the-art line detection and HTR methods to a good number of popular benchmark tasks and assessed the achieved end-to-end accuracy using the proposed metrics.

An important conclusion from both simulated and real assessment experiments is that the bWER is ideal in practice to assess the performance of recognising individual words, with full independence of how these words are ordered in the reference transcripts or in the HTR transcription hypotheses. Moreover, empirical evidence also shows that bWER is almost identical to the classical WER in the classical, simplified HTR experimental setting where the same reading order for reference and system transcripts is (rather artificially) guaranteed.

Another important conclusion is that the difference between WER and bWER ($\Delta$WER) is a very good indicator of the amount of logical or reading-order mismatch between reference and system transcripts. Our experiments show that this difference graciously correlates, almost linearly, with the NSFD, which explicitly measures the reading-order mismatch. Thanks to this correlation, the NSFD (which is rather complex and requires alignments yield by the expensive Hungarian Algorithm) becomes largely unnecessary. So, both the individual word recognition accuracy *and* the degree of logical or reading order mismatch between (page-level) transcripts, can be assessed using just the well-known WER and (the properly redefined version of) bWER.

*Therefore, our closing recommendation for benchmarking end-to-end full-page transcription systems is to provide these two assessment figures:* bWER and $\Delta\text{WER} \stackrel{\text{def}}{=} \text{WER} - \text{bWER}$.

Although both WER and bWER are simple and well known, in Appendix B we provide publicly available software to reliably compute these two metrics, along with the other auxiliary metrics we have used in this work, the Regularised Hungarian Algorithm WER (hWER) and the Normalised Spearman Footrule Distance (NSFD), based on the hWER.

Following the concepts and results here presented, in future works we aim to develop adequate loss functions that allow training end-to-end HTR systems which explicitly optimise the here proposed assessment criteria.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

Data is available from Zenodo

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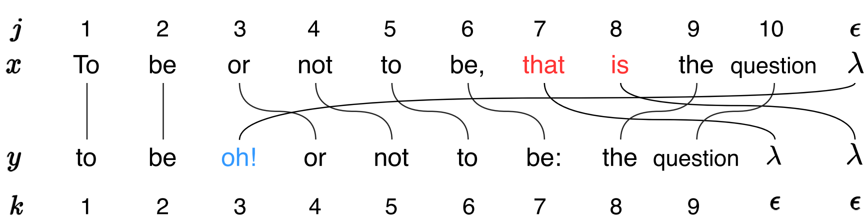
## Appendix A. Examples

### A1. Example 1

Computation of the edit distance $\mathrm{d}(x, y)$ and the corresponding trace $\mathcal{T}(x, y)$. Deleted and inserted words are marked with red and blue colour, respectively. See also footnote 3.

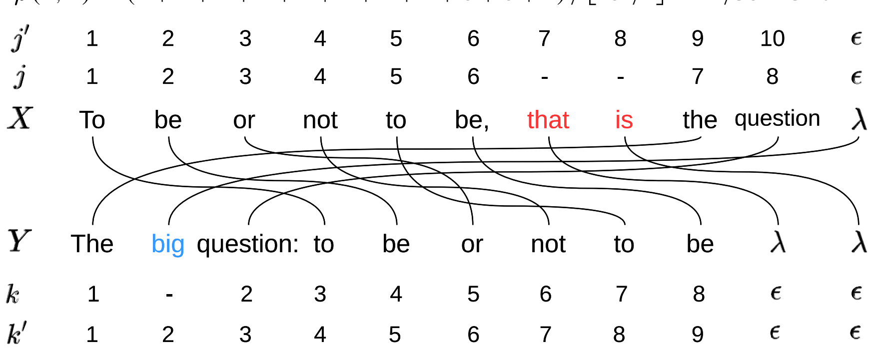
$$\mathcal{T}(x, y) = (1, 1), (2, 2), (\epsilon, 3), (3, 4), (4, 5), (5, 6), (6, 7), (7, \epsilon), (8, \epsilon), (9, 8), (10, 9)$$
$$\mathrm{d}(x, y) = 1 + 0 + 1 + 0 + 0 + 0 + 1 + 1 + 1 + 0 + 0 = 5 \qquad (i = 1, s = 2, d = 2)$$




### A2. Example 2

Computation of the NSFD for a given alignment $\mathcal{A}'$. The original word positions are denoted by $j', k'$, while $j, k$ reflect the renumbering applied to circumvent the indirect effects of deletions and insertions. This converts the original alignment $\mathcal{A}'(X, Y)$ into $\mathcal{A}(X.Y)$, used in Eq. (5) to compute the NSFD. To account for the unit-cost contribution of insertions and deletions, it is assumed that $|-, \epsilon| = |\epsilon, -| = 1$.

$$\mathcal{A}'(X, Y) = (1, 4), (2, 5), (3, 6), (4, 7), (5, 8), (6, 9), (7, \epsilon), (8, \epsilon), (9, 1), (10, 3), (\epsilon, 2)$$
$$\mathcal{A}(X, Y) = (1, 3), (2, 4), (3, 5), (4, 6), (5, 7), (6, 8), (\text{-} \epsilon), (\text{-}, \epsilon), (7, 1), (8, 2), (\epsilon, \text{-})$$
$$\rho(X, Y) = (2 + 2 + 2 + 2 + 2 + 2 + 1 + 1 + 6 + 6 + 1) \,/\, \lfloor 10^2/2 \rfloor = 27/50 = 54\%$$



### A3. Example 3

Computation of bWER Eq. 8) for a reference transcript $X$ and two hypotheses $Y$ and $Z$, and its relation with the naive bag-of-words WER, $\beta$WER (Eq. 7) and with the classical WER (Eq. 2 or (4). In both cases, the number of unavoidable insertions is $b = ||X| - |Y|| = ||X| - |Z|| = 14 - 13 = 1$.

$$
\begin{aligned}
X &= \text{to be or not to be that is the question that needs be answered}\\
Y &= \text{the question that needs be answered is to be or not to be}\\
Z &= \text{to be or not to be, that is the question to be answered}
\end{aligned}
$$

$$
\begin{aligned}
\beta\mathrm{WER}(X,Y) &= 1/14 = 7.1\% \qquad \beta\mathrm{WER}(X,Z) = 5/14 = 35.7\%\\
\mathrm{bWER}(X,Y) &= (1+1)/(2\cdot 14) = 7.1\% \qquad \mathrm{bWER}(X,Z) = (1+5)/(2\cdot 14) = 21.4\%\\
\mathrm{WER}(X,Y) &= (0+11+1)/14 = 85.7\% \qquad \mathrm{WER}(X,Z) = (0+2+1)/14 = 21.4\%
\end{aligned}
$$

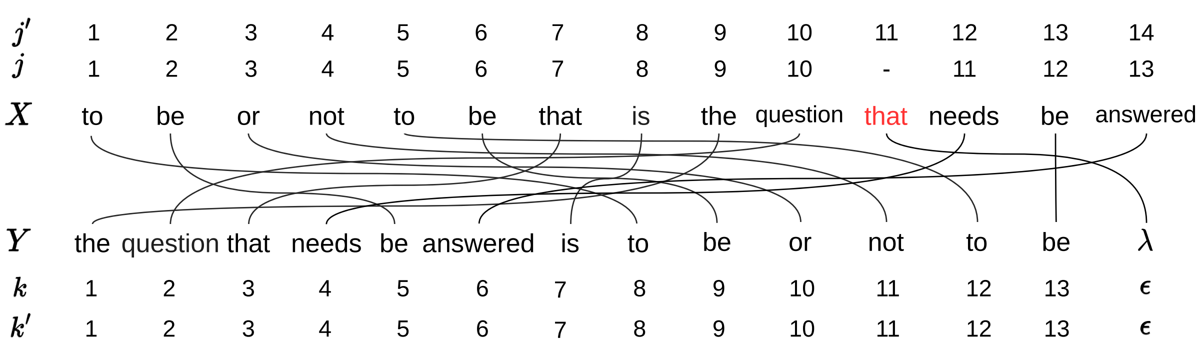
*Example 3a.* The bWER can considerably underestimate what might be considered “true” word recognition errors which, in this example, would be $6/10 = 60\%$:

$$
\begin{aligned}
X &= \text{to be or not to be, that is the question}\\
Y &= \text{to be, to not or be the is that question}
\end{aligned}
$$

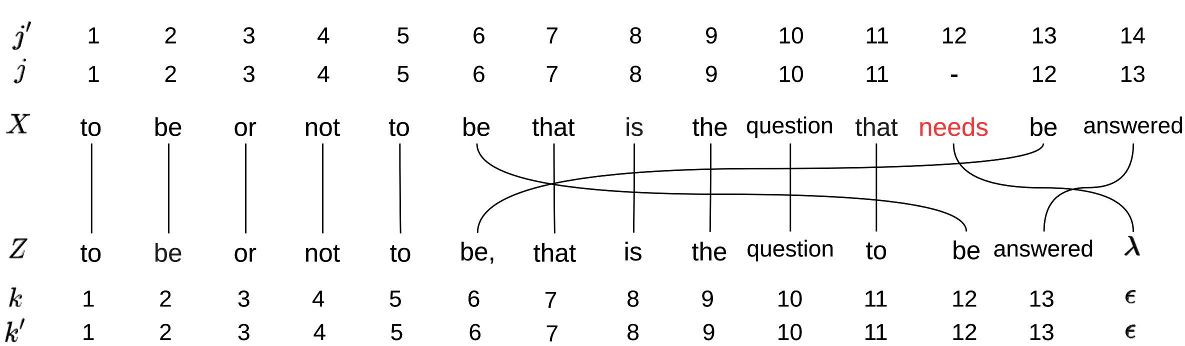
$$\mathrm{bWER}(X,Y) = (0+0)/(2\cdot 20) = 0\%$$

### A4. Example 4

Computation of hWER for the same texts used in Example 3 (A.3). As in Example 2 (A.2), here $\hat{\mathcal{A}}'(\cdot,\cdot)$ are original alignments obtained as a byproduct of Eq. (9) and used in Eq. (10) to compute hWER, and $\hat{\mathcal{A}}(\cdot,\cdot)$ are the ones used to compute NSFDs after word renumbering to circumvent the effects of insertion and/or deletions. Notice that the values of hWER$(X,Y)$ and hWER$(X,Z)$ are identical to the corresponding bWER values of Example 3.




$$
\begin{aligned}
\hat{\mathcal{A}}'(X,Y) &= (1,8),(2,5),(3,10),(4,11),(5,12),(6,9),(7,3),(8,7),(9,1),(10,2),(11,\epsilon),(12,4),(13,13),(14,6)\\
\hat{\mathcal{A}}(X,Y) &= (1,8),(2,5),(3,10),(4,11),(5,12),(6,9),(7,3),(8,7),(9,1),(10,2),(-\epsilon),(11,4),(12,13),(13,6)\\
\mathrm{WER(X,Y)} &= (0+11+1)/14 = 85.7\%\\
\mathrm{hWER}(X,Y) &= (0+\ 0+1)/14 = 7.1\%\\
\rho(X,Y) &= 71/\lfloor 14^2/2 \rfloor \qquad = 72.4\%
\end{aligned}
$$

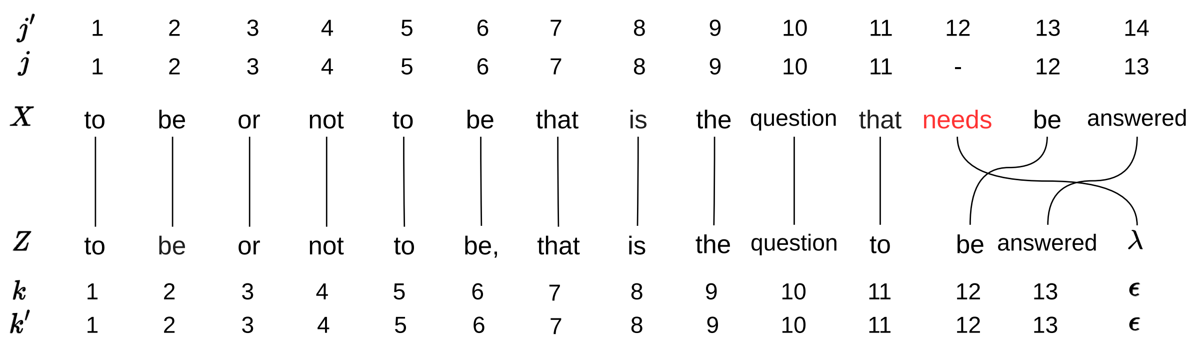


$$\begin{aligned}
\hat{\mathcal{A}}'(X,Z) &= (1,1),(2,2),(3,3),(4,4),(5,5),(6,12),(7,7),(8,8),(9,9),(10,10),(11,11),(12,\epsilon),(13,6),(14,13)\\
\hat{\mathcal{A}}(X,Z) &= (1,1),(2,2),(3,3),(4,4),(5,5),(6,12),(7,7),(8,8),(9,9),(10,10),(11,11),(\;-\epsilon),(12,6),(13,13)\\
\mathrm{WER}(X,Z) &= (0+2+1)/14 = 21.4\%\\
\mathrm{hWER}(X,Z) &= (0+2+1)/14 = 21.4\%\\
\rho(X,Z) &= 15/\lfloor 14^2/2\rfloor \quad = 13.3\%
\end{aligned}$$

*A5. Impact of multiple word instances and ties in NSFD*

When multiple instances of some word exist in $X$ and/or in $Y$, as in the examples of A.4, the HA is free to pair any matching instances, as long as the values of $\mathrm{d_h}(\mathrm{X},\mathrm{Y})$ are the same. In other words, there may be multiple alignments which provide the same optimal result for Eq. (9) and the HA has no means to decide which one would be more consistent with the positions of these words in the RO of the compared texts.

For instance, in Example 4, $\hat{\mathcal{A}}(X,Z)$ pairs $X_6=$"be" with $Z_{12}=$"be" and $X_{13}=$"be" with $Z_6=$"be,". Because of these pairings, the resulting NSFD, $\rho(X,Z)=13.3\%$, is exceedingly high, taking into account that $X$ and $Z$ are almost in the same RO. Clearly, more consistent or "natural" pairings with the same $\mathrm{d_h}(\mathrm{X},\mathrm{Y})$ are: $X_6=$"be" with $Z_6=$"be," and $X_{13}=$"be" with $Z_{12}=$"be". A complete alternative (renumbered) alignment, with identical $\mathrm{d_h}$ (and hWER), would be:




$\hat{\mathcal{A}}(X,Z) = (1,1),(2,2),(3,3),(4,4),(5,5),(6,6),(7,7),(8,8),(9,9),(10,10),(11,11),(-\epsilon),(12,12),(13,13).$

The NSFD of such an alignment is much lower: $\rho(X,Z) = 1/\lfloor 14^2/2\rfloor = 1.0\%$, which better reflects the very minor RO discrepancy between $X$ and $Z$.

## Appendix B. Software Tools and Datasets

The software, with the implementation of the metrics employed to evaluate End-to-End HTR approaches, is freely available to download and use for replicating the results reported in this paper.[10]

Most of its functionalities have been programmed in python, like computation of the NSFD metric and the building of the edit-distance-based cost-matrix with the proposed regularisation factor of Eq. (9) for using with the HA. Regarding the time-critical HA computation, we employ the implementation provided by the *scipy library*[11] implemented in C and with a python-wrapper, which is based on the one described in [11]. For the also time-critical Levenshtein edit-distance computation, it was employed an extended version of `fasterwer`[12] (forked from the original one[13]), a library written in C++ and wrapped in python for ease of use. In this library we have also included support for UTF-8 encoding as well as others time-critical functionalities like the implementation of bag-of-words (see Eq. (8)) based on hashing for faster computation, and the implementation of the backtrace algorithm to obtain the aligning-path through a minimum edit-distance between reference and hypothesis strings.

The datasets used throughout this work can be downloaded most of them from the ZENODO platforms: ICFHR14[14], IAMDB[15], ICFHR16[16], ICDAR17[17] and FCR[18].

[10] https://github.com/PRHLT/E2EHTREval.git
[11] https://docs.scipy.org/doc/scipy/reference/generated/scipy.optimize.linear_sum_assignment.html
[12] https://github.com/PRHLT/fastwer
[13] https://github.com/kahne/fastwer
[14] https://zenodo.org/record/44519
[15] https://fki.tic.heia-fr.ch/databases/iam-handwriting-database
[16] http://doi.org/10.5281/zenodo.1164045
[17] http://doi.org/10.5281/zenodo.835489
[18] https://zenodo.org/record/3945088#.Y3u_tkjMLZ8

## References


[1] A. Antonacopoulos, C. Clausner, PRImA text evaluation tool - User guide, performance evaluation for OCR methods, version 1.4, University of Salford, UK, 2017 Technical report.
[2] T. Bluche, Joint line segmentation and transcription for end-to-end handwritten paragraph recognition, in: Advances in Neural Information Processing Systems 29: Annual Conference on Neural Information Processing Systems 2016, December 5–10, 2016, Barcelona, Spain, 2016, pp. 838–846.
[3] R. Burkard, M. Dell'Amico, S. Martello, Assignment Problems: Revised reprint, SIAM, 2012.
[4] C. Clausner, A. Antonacopoulos, T. Derrick, S. Pletschacher, ICDAR2017 competition on recognition of early indian printed documents - REID2017, in: 14th IAPR International Conference on Document Analysis and Recognition (ICDAR), vol. 01, 2017, pp. 1411–1416.
[5] C. Clausner, A. Antonacopoulos, S. Pletschacher, ICDAR2017 competition on recognition of documents with complex layouts-RDCL2017, in: 2017 14th IAPR International Conference on Document Analysis and Recognition (ICDAR), volume 1, IEEE, 2017, pp. 1404–1410.
[6] C. Clausner, A. Antonacopoulos, S. Pletschacher, ICDAR2019 competition on recognition of documents with complex layouts - RDCL2019, in: 2019 Int. Conf. on Document Analysis and Recognition, ICDAR 2019, Sydney, Australia, September 20–25, 2019, 2019, pp. 1521–1526.
[7] C. Clausner, S. Pletschacher, A. Antonacopoulos, The significance of reading order in document recognition and its evaluation, in: 2013 12th International Conference on Document Analysis and Recognition, IEEE, 2013, pp. 688–692.
[8] C. Clausner, S. Pletschacher, A. Antonacopoulos, Flexible character accuracy measure for reading-order-independent evaluation, Pattern Recognit. Lett. 131 (2020) 390–397.
[9] D. Coquenet, C. Chatelain, T. Paquet, SPAN: a simple predict & align network for handwritten paragraph recognition, in: Document Analysis and Recognition – ICDAR 2021, Springer International Publishing, 2021, pp. 70–84.
[10] D. Coquenet, C. Chatelain, T. Paquet, DAN: a segmentation-free document attention network for handwritten document recognition, IEEE Transactions on Pattern Analysis and Machine Intelligence, 2023.
[11] D.F. Crouse, On implementing 2d rectangular assignment algorithms, in: IEEE Transactions on Aerospace and Electronic Systems, volume 52, 2016, pp. 1679–1696.
[12] A. Garz, A. Fischer, H. Bunke, R. Ingold, A binarization-free clustering approach to segment curved text lines in historical manuscripts, in: 12th International Conference on Document Analysis and Recognition, IEEE, 2013, pp. 1290–1294.
[13] S. Johansson, et al., Lancaster-oslo-bergen Corpus of Modern English (Lob):[Tagged, Horizontal Format], Legacy Collection Digital Museum, 1978.
[14] M. Kassis, J. Nassour, J. El-Sana, Alignment of Historical Handwritten Manuscripts Using Siamese Neural Network, in: 14th IAPR International Conference on Document Analysis and Recognition (ICDAR), volume 1, IEEE, 2017, pp. 293–298.
[15] M.G. Kendall, A new measure of rank correlation, Biometrika 30 (1/2) (1938) 81–93.
[16] H.W. Kuhn, The hungarian method for the assignment problem, Naval Res. Logist. Quarter. 2 (1–2) (1955) 83–97.
[17] R. Kumar, S. Vassilvitskii, Generalized distances between rankings, in: Proceedings of the 19th International Conference on World Wide Web, WWW '10, volume 01, 2010, pp. 571–580.
[18] C.-Y. Lee, C.-L. Li, C. Wang, R. Wang, Y. Fujii, S. Qin, A. Popat, T. Pfister, Rope: reading order equivariant positional encoding for graph-based document information extraction, 2021, (????). ArXiv preprint arXiv:2106.10786.
[19] G. Leifert, R. Labahn, T. Grüning, S. Leifert, End-to-end measure for text recognition, in: 2019 International Conference on Document Analysis and Recognitio n, ICDAR 2019, Sydney, Australia, September 20–25, 2019, IEEE, 2019, pp. 1424–1431.
[20] Y. Liang, X. Li, Reassembling shredded document stripes using word-path metric and greedy composition optimal matching solver, IEEE Trans. Multimed. 22 (5) (2019) 1168–1181.
[21] G. Liu, R.M. Haralick, Optimal matching problem in detection and recognition performance evaluation, Pattern Recognit. 35 (10) (2002) 2125–2139.
[22] S. Long, S. Qin, D. Panteleev, A. Bissacco, Y. Fujii, M. Raptis, Towards End-to-end unified scene text detection and layout analysis, in: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2022, pp. 1049–1059.
[23] U.-V. Marti, H. Bunke, The IAM-database: an english sentence database for offline handwriting recognition, Int. J. Doc. Anal. Recogn. 5 (1) (2002) 39–46.
[24] A. Marzal, E. Vidal, Computation of normalized edit distance and applications, in: IEEE transactions on pattern analysis and machine intelligence, volume 15, 1993, pp. 926–932.
[25] G. Muehlberger, L. Seaward, M. Terras, S.A. Oliveira, V. Bosch, M. Bryan, S. Colutto, H. Déjean, M. Diem, S. Fiel, et al., Transforming scholarship in the archives through handwritten text recognition: transkribus as a case study, J. Document. (2019).
[26] A. Naoum, J. Nothman, J. Curran, Article segmentation in digitised newspapers with a 2d markov model, in: 2019 Int. Conf. on Document Analysis and Recognition (ICDAR), 2019, pp. 1007–1014.
[27] H. Ney, S. Nießen, F.J. Och, H. Sawaf, C. Tillmann, S. Vogel, Algorithms for statistical translation of spoken language, IEEE Trans. Speech Audio Process. 8 (1) (2000) 24–36.
[28] R.B. Palm, O. Winther, F. Laws, Cloudscan-a configuration-free invoice analysis system using recurrent neural networks, in: 14th IAPR International Conference on Document Analysis and Recognition (ICDAR), volume 1, IEEE, 2017, pp. 406–413.
[29] K. Papineni, S. Roukos, T. Ward, W.-J. Zhu, Bleu: a method for automatic evaluation of machine translation, in: Proceedings of the 40th annual meeting of the Association for Computational Linguistics, 2002, pp. 311–318.
[30] S. Pletschacher, C. Clausner, A. Antonacopoulos, Europeana newspapers OCR workflow evaluation, in: Proceedings of the 3rd International Workshop on Historical Document Imaging and Processing, Association for Computing Machinery, New York, NY, USA, 2015, pp. 39–46.
[31] M. Popović, H. Ney, Towards automatic error analysis of machine translation output, Comput. Linguist. 37 (4) (2011) 657–688.
[32] L. Quirós, E. Vidal, Evaluation of a region proposal architecture for multi-task document layout analysis, 2021, (????). CoRR. arXiv: 2106.11797
[33] L. Quirós, E. Vidal, Reading order detection on handwritten documents, in: Neural Computing and Applications, volume 34, 2022, pp. 9593–9611.
[34] J.A. Sanchez, V. Romero, A.H. Toselli, E. Vidal, ICFHR2016 competition on handwritten text recognition on the read dataset, in: 2016 15th International Conference on Frontiers in Handwriting Recognition (ICFHR), IEEE, 2016, pp. 630–635.
[35] J.A. Sánchez, V. Romero, A.H. Toselli, M. Villegas, E. Vidal, A set of benchmarks for handwritten text recognition on historical documents, Pattern Recognit 94 (2019) 122–134.
[36] P. Soundararajan, M. Boonstra, V. Manohar, V. Korzhova, D. Goldgof, R. Kasturi, S. Prasad, H. Raju, R. Bowers, J. Garofolo, Evaluation Framework for Video OCR, in: Computer Vision, Graphics and Image Processing, Springer, 2006, pp. 829–836.
[37] P.B. Ströbel, S. Clematide, M. Volk, How much data do you need? about the creation of a ground truth for black letter and the effectiveness of neural OCR, in: Proc. of the Twelfth Language Resources and Evaluation Conference, Marseille, France, May, European Language Resources Association, 2020.
[38] P.B. Ströbel, M. Volk, S. Clematide, R. Schwitter, T. Hodel, D. Schoch, Evaluation of HTR models without ground truth material, in: Proc. of the 13th Language Resources and Evaluation Conference, LREC 2022, European Language Resources Association, 2022, pp. 4395–4404.
[39] J.A. Sánchez, V. Romero, A.H. Toselli, E. Vidal, ICFHR2014 competition on handwritten text recognition on transcriptorium datasets (HTRtS), in: 2014 14th International Conference on Frontiers in Handwriting Recognition, 2014, pp. 785–790.
[40] J.A. Sánchez, V. Romero, A.H. Toselli, M. Villegas, E. Vidal, ICDAR2017 competition on handwritten text recognition on the read dataset, in: 2017 14th IAPR Int. Conf. on Document Analysis and Recognition (ICDAR), vol. 01, 2017, pp. 1383–1388.
[41] C. Tensmeyer, C. Wigington, Training Full-page handwritten text recognition models without annotated line breaks, in: 2019 Int. Conf. on Document Analysis and Recogn. (ICDAR), 2019, pp. 1–8.
[42] A.H. Toselli, V. Romero, E. Vidal, J.A. Sánchez, Making two vast historical manuscript collections searchable and extracting meaningful textual features through large-scale probabilistic indexing, in: 15th Int. Conf. on Document Analysis and Recognition (ICDAR), 2019.
[43] A.H. Toselli, E. Vidal, Revisiting Bag-of-Word metrics to assess end-to-end text image recognition results, 2023, (????). To be published.
[44] E. Vidal, A. Marzal, P. Aibar, Fast computation of normalized edit distances, in: IEEE Transactions on Pattern analysis and machine intelligence, volume 17, 1995, pp. 899–902.
[45] E. Vidal, A.H. Toselli, Probabilistic indexing and search for hyphenated words, in: International Conference on Document Analysis and Recognition, Springer, 2021, pp. 426–442.
[46] R.A. Wagner, M.J. Fischer, The string-to-string correction problem, J. ACM (JACM) 21 (1) (1974) 168–173.
[47] C. Wigington, C. Tensmeyer, B. Davis, W. Barrett, B. Price, S. Cohen, Start, follow, read: end-to-end full-page handwriting recognition, in: Proceedings of the European Conference on Computer Vision (ECCV), 2018, pp. 367–383.
[48] F. Yin, C.-L. Liu, Handwritten chinese text line segmentation by clustering with distance metric learning, Pattern Recognit. 42 (12) (2009) 3146–3157.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