Automated Resolution of Noisy Bibliographic References

Markus Demleitner\textsuperscript{1,2}, Michael Kurtz\textsuperscript{2}, Alberto Accomazzi\textsuperscript{2}, Günther Eichhorn\textsuperscript{2}, Carolyn S. Grant\textsuperscript{2}, Steven S. Murray\textsuperscript{2}

\textsuperscript{1} Lehrstuhl für Computerlinguistik der Universität Heidelberg, Karlstr. 2, 69117 Heidelberg, Germany
\textsuperscript{2} NASA Astrophysics Data System, Harvard-Smithsonian Center for Astrophysics, 60 Garden Street, Cambridge, MA 02138, USA

Summary. We describe a system used by the NASA Astrophysics Data System to identify bibliographic references obtained from scanned article pages by OCR methods with records in a bibliographic database. We analyze the process generating the noisy references and conclude that the three-step procedure of correcting the OCR results, parsing the corrected string and matching it against the database provides unsatisfactory results. Instead, we propose a method that allows a controlled merging of correction, parsing and matching, inspired by dependency grammars. We also report on the effectiveness of various heuristics that we have employed to improve recall.

1 Introduction

The importance of linking scholarly publications to each other has received increasing attention with the growing availability of such materials in electronic form (see, e.g., van de Sompel, 1999). The use of citations is probably the most straightforward approach to generate such links.

However, most publications and authors still do not give machine readable publication identifiers like DOIs in their reference sections. The automatic generation of links from references therefore is a challenge even for recent literature. Bergmark (2000), Lawrence et al. (1999) and Clavaz et al. (2001) investigate methods to solve this problem under a record linkage point of view.

For historical literature, the situation is even worse in that not even the “clean” reference strings as intended by the authors are usually available. In 1999, the NASA Astrophysics Data System (ADS, see Kurtz et al., 2000) began to gather reference sections from scans of astronomical literature and subsequently processed them with OCR software. This has yielded about three million references (Demleitner et al., 1999), many of them with severe recognition errors. We will call these references noisy, whereas references that were
wrong in the original publication will be denoted *dangling*. Noisy references show the entire spectrum of classic OCR errors in addition to the usual variations in citation style. Consider the following examples:

Bidelman, W. P. 1951, Ap. J. "3, 304; Contr. McDonald Obs., No. 199.
Eggen, O. J. 1950a, Ap. J. III, 414; Contr. Lick Obs., Series II, No. 27.
—1950b, ibid. 112, 141; ibid., No. 30.
Huist, H. C. van de. 1950, Astrophys. J. 112,1.
Stromgren, B. 1956, Astron. J. 61, 45.
Morando, B. 1963, "Recherches sur les orbites de resonance," in Pro-
ceedings of the First International Symposium on the Use of Artificial
Satellites for Geodesy, Washington, D. C. (North-Holland Publishing
Company, Amsterdam, 1963), p. 42.

While our situation was worse than the one solved by the record linkage
approaches cited above, we had the advantage of being able to restate the
problem into a classification problem, since we were only interested in resolving references to publications contained in the ADS’ abstract database – or decide that the target of the reference is not in the ADS. This is basically a classification problem in which there are (currently) 3.5 million categories.

A method to solve this problem was recently developed by Takasu (2003)
using Hidden Markov Models to both parse and match noisy references
(Takasu calls them “erroneous”). While his approach is very different from ours, we believe the ideas behind and our experiences with our resolver may benefit other groups also facing the problem of resolution of noisy references.

In the remainder of this paper, we will first state the problem in a rather
general setting, then discuss the basic ideas of our approach in this frame-
work, describe the heuristics we used to improve resolution rates and their
effectiveness and finally discuss the performance of our system in the real
world.

2 Statement of the Problem

![Fig. 1. A noisy channel model for references obtained from OCR.](image)

Fig. 1 shows a noisy channel model for the generation of a noisy reference from an original reference that corresponds to an entry in a bibliographic database. In principle, the resolving problem is obtaining
argmax\( P_m(F' | F) P_p(S' | F') P_r(S | F), \quad S \in \Sigma^*, F' \in (\Sigma^*)^{nf}(1) \)

for a given noisy reference \( S' \). Here, \( \Sigma \) is the base alphabet (in our case, we normalize everything to 7-bit ASCII) and \( nf \) is the number of fields in a bibliographic record. The domain of random variable \( F \) is the database plus the special value \( \emptyset \) for references that are missing from the database but nevertheless valid.

The straightforward approach of modeling each distribution mentioned above separately and trying to compute \( (1) \) from back to front will not work very well. To see why, let us briefly examine each element in the channel.

Under a typical model for an OCR system, \( P_r(S' | S) \), will have many likely \( S \) for any \( S' \), since references do not follow common language models and are hard to model in general because of mixed languages and (as text goes) high entropy.

In contrast, the “parsing” distribution \( P_p(S | S') \) is sharply peaked at few values. Although reference syntax is much less uniform than one might wish, even regular grammars can cope with a large portion of the references, avoiding ambiguity altogether. Even if the situation is not so simple in the presence of titles or with monographs and conferences, the number of interpretations for a given value of \( S \) with nonvanishing likelihood will be in the tens.

In the matching step modeled by \( P_m(F' | F) \), we have a similar situation. For journal references, ambiguity is very low indeed, and even for books this record linkage problem is harmless with \( P_m(F' | F) \) sharply peaked on at worst a few dozen \( F \). The main complication here is detecting the case \( F = \emptyset \).

So, while \( P_m \) and \( P_p \) have quite low conditional entropies, the one of \( P_r \) is very high. This is unfortunate, because in computing \( (1) \) one would generate many \( S \) only to throw them away when computing \( P_p \) or \( P_m \).

In this light, an attempt to resolve noisy references along the lines of Accomazzi et al. (1999)’s suggestion for clean references – which boils down to computing \( \text{argmax}_F P_m(F' | F) \text{argmax}_{F'} P_p(F' | S') \) – is bound to fail when extended to noisy references.

It is clear that there have to be better ways since the conditional entropy of \( P(F' | S') \) is rather low, as can be seen from the fact that a human can usually tell very quickly what the correct interpretation for even a very noisy reference is, at least when equipped with a bibliographic search engine like the ADS itself.

Takasu (2003) describes how Dual and Variable-length output Hidden Markov Models can be used to model a combined conditional distribution \( P_{p,r}(F' | S') \), thus exploiting that many likely values of \( S \) will not parse well and therefore have a low combined probability. The idea of combining distributions is instrumental to our approach as well.

\(^3\) To give an example, the sequence “L1” will have a very low probability in normal text, but, depending on the reference syntax employed by authors, could occur in up to 2.5% of the references in our sample (it is actually found in 1.7% of the OCR’d strings).
3 Our Approach

3.1 Core resolution

One foundation of our resolver comes from dependency grammars (Heringer, 1993) in natural language processing, which are based on the observation that given the “head” of a (natural language) phrase (say, a verb), certain “slots” need to be filled (e.g., eat will usually have to be complemented with something that eats and something that is eaten).

In the domain of reference resolving, the equivalent of a phrase is the reference. As the head of this phrase, we chose the publication source, i.e., a journal or conference name, a book title, a hint that a given publication is a Ph.D. thesis or a preprint. This was done for three reasons. Firstly, it is easy to robustly extract this information from references in our domain, secondly, there are relatively few possible heads (disregarding monographs), and thirdly, the publication source governs the grammar of the entire reference.

For example, in addition to the publication year and authors references to most journals need a volume and a page, while a Ph.D. thesis is complemented by a name of an institution, and reports or documents from the ArXiv preprint servers may just take a single number.

Let us for now assume that references follow the regular expression Author+ Year Rest, where Rest contains a mixture of alphabetic and numeric characters, and a title is not given for parts of article collections – in astronomy, almost all references follow this grammar. A simple regular expression can identify the year with very close to 100% recall and precision even in noisy references, yielding a robust fielding of the reference.

To find the head as defined above, we simply collect all alphabetic characters from the Rest. The remaining numeric information, i.e., all sequences of digits separated by non-digits, are the fillers required by the head. This exploits that fillers are almost always numeric and avoids dependency on syntactic markers like commas that are very prone to misrecognition. Heads that have non-numeric fillers (mostly theses and monographs) receive special treatment.

This head is matched against an authority file that maps Nt full titles and common abbreviations for the sources known to the ADS to a “bibstem” (cf. Grant et al., 2000). We select the n-best matching of these, where n = 5 proved a good choice. To assess the quality of a match, a string edit distance suffices. The one we use is

\[ 1 - \left( \frac{\Delta(a, h) - |a|}{|h|} \right) L(a, h), \]

where \( a \) and \( h \) are a string from the authority file and the head, respectively, \( \Delta(a, h) \) denotes the number of matching trigrams from \( h \) that are found in \( a \), \( L(a, h) \) is the plain Levenshtein distance (Levenshtein, 1966) and \(| . |\) is the length of the string. The worst-case runtime of this procedure is
$O(|h| \max(|a|) N_t \log N_t)$, but since we compute trigram similarities first and compute Levenshtein distances only for those $a$ having at least half as many trigrams in common with $h$ as the best matching $a$, typical run time will be of order $O(|h|^2 \log |h|)$.

This corresponds to maximizing $P_{p,r}(\ldots, source, \ldots) | S')$, i.e., we derive a distribution on publication sources directly from the noisy reference. The conditional entropy of this distribution is relatively low, because there are few possible sources (order $10^4$) and the edit distance induces a sharply peaked distribution.

For each bibstem, the number of slots and their interpretation is known\footnote{Actually, we have an exception list and normally assume two slots, volume and page.}, and we can simply match the slots with the fillers or give educated guesses on insertion or deletion errors based on our knowledge of the fillers expected. In the noisy channel model, this corresponds to greedily evaluating $P_{p,r}(F'| S', \ldots, source, \ldots)$. While in principle, the distribution would have a rather high conditional entropy (e.g., many readings for the numerals would have to be taken into account), it turns out that most of these complications can be accounted for in the matching step, alleviating the need to actually produce multiple $F'$, even more so since parsing errors frequently resemble errors made by authors in assembling their references, which are modeled in $P_a$.

If filling the slots with the available fillers is not possible, the next best head is tried, otherwise, we have a complete fielded record $f'$ that can be matched against the database using a $P_m$ to be discussed shortly. If this matching is successful, the resolution process stops, otherwise, the next best head is tried.

The matching has to be a fast operation since it is potentially tried many times. Fortunately, the bibliographic identifiers (bibcodes, see Grant et al., 2000) used by the ADS are, for serials, computable from the record in constant time, and thus, matching requires a simple table lookup, taking $O(\log N_r)$ time for $N_r$ records we have to match against.

Due to the construction of bibcodes, the plain bibcode match only checks the first character of the first authors’ last name. The numbers below show that the entropy of references with respect to the distribution implied by our algorithm is so low that this shortcoming does not impact precision noticeably – put another way, the likelihood that OCR errors conspire to produce a valid reference is very small even without using most of the information from the author field.

The core resolving process typically runs in $O(\log N_r |h|^2 \ln |h|)$ time. On a 1400 MHz Athlon XP machine, a python script implementing this resolves about 100 references per second and already catches more than 84% of the total resolvable references in our set of 3,027,801 noisy references.
3.2 Reference Matching

For journals for which the database can be assumed complete \( P_m(F | F') \) is nontrivial, i.e., different from \( \delta_{F,F'} \). The single most important ingredient is a mapping from volume numbers to publication years and vice versa, because even if one field is wrong because of either OCR or author errors, the other can be reconstructed. We also scan the surrounding page range (authors surprisingly frequently use the last page of an article) and try swapping adjacent digits in the page number. Finally, we try special sections of journals (usually letter pages). The definition of this matching implies that \( P_m(F = f | F' = f') = 0 \) if \( f \) and \( f' \) differ in more than one field.

While these rules are somewhat ad hoc, they are also straightforward and probably would not profit from learning. They alone account for 8% of the successfully resolved references without further source string manipulation.

When any of these rules are applied, the authors given in the reference are matched against those in the database using a tailored string edit distance. It is computed by deleting initials, first names and common non-author phrases (currently “and”, “et”, and “al”) and then evaluating

\[
\text{fault} = \sum_{w' \in A'} \min_{w \in A} L(w', w),
\]

where \( L \) is the Levenshtein distance with all weights one and \( A \) and \( A' \) the author last names for the paper in the database and from the reference, respectively. The edit distance then is \( d_a = 1 - \text{fault}/\text{limit} \), where \( \text{limit} \) is given by allowing 2 errors for each word shorter than 5 characters, 3 errors for each word shorter than 10 characters and 4 errors otherwise. This reflects that OCR language models do much better on longer words than on shorter ones, even if they come from non-English languages. Unless we have reason to be stricter (usually with monographs), we accept a match if \( d_a > 0 \).

If, after all string manipulations described below have not yielded a match, we relax \( P_m \) for all sources and also try to match identifiers with a different first author (in case the author order is wrong), scan a page range of plausible mis-spellings and try identifiers with different qualifiers\(^5\). 7.8% of the total resolved references were only accepted after this. We have not attempted to ascertain how many of these references were dangling in the original publication.

3.3 Monographs and Theses

The procedures described above are useful for serials and article collections of all kinds. Two kinds of publications have to be treated differently.

\(^5\) This is necessary if there is more than one article mapping to the same bibcode on one page, for details see Grant et al. (2000).
As mentioned above, theses have alphabetic fillers. Thus, we use keyword spotting (a hand-tailored regular expression for possible readings of “Thesis”) to identify the head within the rest. Together with the first character of the author’s last name and the publication year, we select a set of candidates and match authors and granting institutions analogous to the author matching procedure described above.

Monographs are completely outside this kind of handling. For them, a set of candidates is selected based on the first character of the author name and the publication year, and authors and titles are matched. Since this is a very time-consuming procedure, it is only attempted if the resolving to serials failed.

Note that using authors as heads as is basically done with monographs would probably most closely mimic the techniques of human librarians. However, given the fragility of author names both in the OCR process and in transliteration, we doubt that a low-entropy distribution would result from doing so.

4 Heuristics

Takasu (2003) conjectured that the comparatively unsatisfactory performance of his method could be significantly improved through the use of a set of heuristics. We find that the same is true for our approach. Almost 16% of the total resolved papers only become resolvable by the algorithm outlined above after some heuristic manipulations are performed on the noisy reference.

We apply a sequence of such manipulations ordered according to their “daringness” and re-resolve after each manipulation. These manipulations – typically regular-expression based string operations – model a noisy channel, but of course it would be very hard to write down its governing distribution. Still, it may be useful to see what heuristics had what payoff.

In a first step, we correct the most frequently misrecognized abbreviations based on regular expressions for the errors. We concentrate on abbreviations because misrecognitions in longer words usually do not confuse our matching algorithm. While better models may have a higher payoff, our method only contributes 0.6% of the total resolved references.

The second step is more effective at 1.7% of the total resolved references. We code rules about common misreadings of numerals in a set of regular expressions, including substituting numerals at the beginning of the reference using a unigram model for OCR errors, fixing numerals within the reference string using a hand-crafted bigram model and joining single digits to a preceding group to make up for blank insertion errors.

At 4.9% of the total still more effective are transformations on the alphabetic part behind the year, including attempts to remove additional specifications (e.g., “English Translation”), and mostly very domain-specific operations with the purpose of increasing the conformity of journal specifications.
with the authority information used by the source matcher. The most important measure here, however, is handling very short publication names (“AJ”) that are particularly hard for the OCR. From these experiences we believe a learning system will have to have a special mode for short heads.

The last fixing step is dissecting the source specification along separators (we use commas and colons) and try using the part that yields the best match against the authority file as the new head. This usually removes bibliographic information primarily in references to conference proceedings. 0.9% of the total resolved references become resolvable after this. Note that this step would be more important if we had to frequently deal with title removal.

Further, less interesting, heuristics are applied to bring references into the format required by the resolver including title removal – for astronomy references, this is rarely needed –, reconstruct references that refer to other reference’s parts, and to split reference lines containing two or more references. This last task only applies to the rare entries consisting of two separate references listed together by the author. The resolver makes no attempt to discover errors in line joining that were made earlier in the processing chain.

5 Application

Our dataset from OCR currently contains 3,027,801 references (some $10^4$ of which actually consist of non-reference material misclassified by the reference cutting engine). Of these, 2,552,229 (or about 84%) could be resolved to records in the database.

In order to assess recall and precision of the system described here, we created a subset of 852 references by selecting each reference with a probability of 0.00025, which yielded 118 references that were not resolved and 734 that were resolved. We then manually resolved each selected reference, correcting dangling references as best we could. Thus, the following numbers compare the resolver’s $P(F | S')$ with a human’s $P(F | S')$.

The result was that two of the 734 resolved records were incorrectly resolved. In both cases, the correct record was not in the ADS, which illustrates that the $F = \emptyset$ problem dominates the issue of precision. Of the non-resolved records, 94 were not in our database, while 23 were, though six of these were marked doubtful by the human resolvers. Counting doubtful cases as errors, we thus have a precision of more than 99% and a recall of about 97%. Of the 17 definite false negatives, 7 are severely dangling or excessively noisy references to journals, while 6 are references to conference proceedings and the rest monographs.

Note that it is highly unlikely that any of the drawn references were ever inspected during the development of the heuristics. Still, one might question if evaluating the resolver with data that at least might have been used to “train” it is justified. Since during development we mainly inspected resolving failures rather than possibly incorrectly resolved references, we would expect the fact
the we did not hold back pristine reference data for evaluation purposes to impact recall more than precision.

For journal literature between 1981 and 1998, we also compared the resolver result with data purchased from ISI’s science citation index. Randomly selecting 1% of the articles covered by ISI and removing references to sources outside the ISI sample, we had 10832 citing-cited pairs, of which 311 were missing in the OCR sample and 1151 were missing from ISI.

A manual examination of the citing-cited pairs missing from the OCR sample revealed that 112 were really attributable to the resolver, 107 were due to incorrect reconstructions of reference lines, and 86 references were missed because the references were not found by the reference zone identification.

Of the references apparently missing from ISI, 2 were due to resolver errors, and less than 20% were dangling references that ISI did not correct, but were clearly identifiable nevertheless. We have not attempted to identify why the other (correct) pairs were missing from our ISI sample; most problems probably were introduced during the necessarily conservative matchup between records from ISI and the ADS, and possibly in the selection of our data set from ISI’s data base.

For journal articles (others are, for the most part, not available from ISI), we can thus state a recall of 99% and a precision of 99.9% for our resolver and a recall of about 97% for the complete system.

6 Discussion

In this paper we contend that robust interpretation of bibliographic references, as required when resolving references obtained by current OCR techniques, should integrate as much information obtainable from a set of known publications as possible even in parsing and not delay incorporating this information to a “matching” or linkage phase.

Our approach has been inspired by dependency grammars, in which a head of a phrase governs the interpretation of the remaining elements. For (noisy) references, it is advantageous to use the name or type of the publication as head. The existence of bibliographic identifiers that are for most references easily computable from fielded records has been instrumental for the performance of our system.

While we believe some of the rather ad hoc string manipulations and edit distances employed by our current system can and should be substituted by sound and learning algorithms, it seems evident to us that a certain degree of domain-specific knowledge (most notably, a mapping between publication dates and volumes) is very important for robust resolving.

---

6 See [http://www.isinet.com/](http://www.isinet.com/)

7 Actually, in one case the OCR conspired to produce an almost valid reference to a wrong paper, in the second case, incorrect line joining resulted in two references that were mangled into a valid one.
The system discussed here has been in continuous use at the ADS for the past four years, for noisy references from OCR as well as for references from digital sources. The ADS in turn is arguably the most important bibliographic tool in astronomy and astrophysics. The fact that the ADS has received very few complaints concerning the accuracy of its citations backs the estimates of recall and precision given above.

Acknowledgement. We wish to thank Regina Weineck for help in the generation of validation data.

The NASA Astrophysics Data System is funded by NASA Grant NCC5-189.

References

1. Accomazzi, A., Eichhorn, G., Kurtz, M., Grant, C., and Murray, S. (1999). “The ADS Bibliographic Reference Resolver.” In *Astronomical Data Analysis Software and Systems VIII*, R. L. Plante, and D. A. Roberts (eds.), Vol. 172 of *ASP Conference Series* p. 291-294

2. Bergmark, D. (2000). *Automatic Extraction of Reference Linking Information from Online Documents*. Technical Report TR 2000-1821, Computer Science Department, Cornell University

3. Claivaz, J.-B., Meur, J.-Y. L., and Robinson, N. (2001). “From Fulltext Documents to Structured Citations: CERN’s Automated Solution,” *HEP Libraries Webozine* 5 [http://doc.cern.ch/heplw/5/papers/27](http://doc.cern.ch/heplw/5/papers/27)

4. Demleitner, M. and Accomazzi, A. and Eichhorn, G. and Grant, C. S. and Kurtz, M. J. and Murray, S. S. (1999). “Looking at 3,000,000 References Without Growing Grey Hair,” *Bulletin of the American Astronomical Society* 31, 1496

5. Grant, C. S., Accomazzi, A., Eichhorn, G., Kurtz, M. J., and Murray, S. S. (2000). “The NASA Astrophysics Data System: Data holdings,” *Astronomy and Astrophysics Supplement* 143, 111-135

6. Heringer, H. J. (1993). “Dependency syntax – basic ideas and the classical model.” In *Syntax - An International Handbook of Contemporary Research*, volume 1, J. Jacobs, A. von Stechow, W. Sternefeld, and T. Venneman (eds.), Walter de Gruyter, Berlin, New York, pp 298–316.

7. Kurtz, M. J., Eichhorn, G., Accomazzi, A., Grant, C. S., and Watson, J. M. (2000). “The NASA Astrophysics Data System: Overview,” *Astronomy and Astrophysics Supplement* 143, 41–59

8. Lawrence, S., Giles, C. L., and Bollacker, K. (1999). “Digital Libraries and Autonomous Citation Indexing,” *IEEE Computer* 32(6), 67–71

9. Levenshtein, V. I. (1966). “Binary codes capable of correcting deletions, insertions and reversals,” *Soviet Physics Doklady* 10, 707–710

10. Takasu, A. (2003). “Bibliographic attribute extraction from erroneous references based on a statistical model.” In *Proceedings of the third ACM/IEEE-CS joint conference on Digital libraries*, pp 49–60

11. van de Sompel, H. V. and Hochstenbach, P. (1999). “Reference Linking in a Hybrid Library Environment,” *D-Lib Magazine* 5(4)