New Methods, Current Trends and Software Infrastructure for NLP.

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Abstract. The increasing use of ‘new methods’ in NLP, which this conference series exemplifies, occurs in the context of a wider shift in the nature and concerns of the discipline. This paper begins with a short review of this context and significant trends in the field. The review motivates and leads to a set of requirements for support software of general utility for NLP research and development workers. A freely-available system designed to meet these requirements is described (called GATE - a General Architecture for Text Engineering). Information Extraction (IE), in the sense defined by the Message Understanding Conferences (ARPA), is an NLP application in which many of the new methods have found a home (Hobbs; Jacobs ed.). An IE system based on GATE is also available for research purposes, and this is described. Lastly we review related work.

1 Introduction

The central theme of this paper is support software (or software infrastructure) for NLP research and development (R&D). This is not a new concern – witness for example the Alvey tools project (Grover et al.), or the Core Language Engine (Alshawi ed.), or ALEP (Simpkins) – although it is a subject that has appeared in various forms in the literature of new methods in NLP (for example, in this conference series: Nirenburg, FGNLP-2; Cunningham et al., NeMLaP-1). Recent trends in NLP (including, though not limited to, renewed interest in statistical methods, newly available corpora and dictionary resources and tractable automatic learning algorithms) make support software of particular current relevance. Recent work in the European Linguistic Research and Engineering programme (in the MULTEXT project (Thompson; Ballim)) and the US TIPSTER programme (in the TIPSTER architecture project (Grishman)) represent responses to this situation. This paper reports work aimed at promoting and synthesising the results of these programmes.

We begin by reviewing current trends in the field. This review motivates and draws out a set of requirements for the provision of software infrastructure for NLP R&D. GATE (a General Architecture for Text Engineering) is a freely-available system designed to meet these requirements, and is described. Information Extraction (IE), in the sense defined by the Message Understanding Conferences (ARPA), is an NLP application in which many of the new methods have found a home (Hobbs; Jacobs ed.). An IE system based on GATE is also available for research purposes, and this is described. Lastly we review related work.

2 Current trends in Language Engineering R&D

An increasing number of research and development efforts have recently positioned themselves under the banner Language Engineering (LE). This signals a shift away from well-established
labels such as *Natural Language Processing* (NLP) and *Computational Linguistics*. Examples include the renaming of UMIST’s Department of Language and Linguistics (location of the *Centre for Computational Linguistics*) as the Department of Language Engineering, and the naming of the European Commission’s current relevant funding programme *Language Engineering* (the previous programme was called *Linguistic Research and Engineering*). The new journal of *Natural Language Engineering* is another example.

We shall argue here that this shift is more than simple TLA-fatigue. The new name reflects a change of emphasis within the field towards:

– increasing use of quantitative evaluation as a metric of research achievement;
– renewed interest in statistical language models and automatically-generated resources;
– increasing availability and use of large-scale resources (e.g. corpora, machine-readable dictionaries);
– a re-orientation of language processing research to large-scale applications, with a concomitant emphasis on predictability and conformance to requirements specifications (i.e. emphasis on engineering issues).

Several commentators have characterised the broad trend of AI approaches to language as tending towards the “toy problem syndrome”, expressing the view that AI has too often chosen to investigate artificial, small-scale applications of the technology under development.

For example, one of the present authors began a large-scale Prolog grammar project in 1985 (Farwell, Wilks [13]); by 1987 it was perhaps the largest DCG (Definite Clause Grammar) grammar anywhere, designed to cover a linguistically well-motivated test set of sentences in English. Interpreted by a standard parser it was able to parse completely and uniquely virtually no sentence chosen randomly from a newspaper. We suspect most large grammars of that type and era did no better, though reports are seldom written making this point.

The mystery for linguists is how that can be: the grammar appeared to inspection to be virtually complete – it had to cover English, if thirty years of linguistic intuition and methodology had any value. It is a measure of the total lack of evaluation of parsing projects up to that time that such conflicts of result and intuition were possible, a situation virtually unchanged since Kuno’s large-scale Harvard parser of the 1960’s (Kuno, Oettinger [21]) whose similar failure to produce a single, preferred, spanning parse gave rise to the AI semantics and knowledge-based movement. The situation was effectively unchanged in 1985 but the response this time around has been quite different, characterised by:

– use of empirical methods with strict evaluation criteria;
– renewed interest in performance-based models of language, and a corresponding renewal and extension of statistical techniques in the area;
– increased provision and reuse of large-scale data resources;
– greater emphasis on the development of prototype applications of NLP technology to large-scale problems.

With hindsight it may seem obvious that computational linguistics, in the sense of computer programs that seek to exploit the results of linguistic research to make computers do useful things with human language should be subject to empirical criteria of effectiveness. The big problem, of course, is determining precisely what the criteria of success should be. Should we

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1 The editorial of the first issue also discusses the new name (Boguraev, Garigliano, Tait [7]).
2 TLA: three-letter acronym
3 There is, of course, at least one other sense, that of using computational tools to aid linguistic research.
collect video tapes of Star Trek and measure our efforts in comparison to the Enterprise’s lucid conversational computer? There is now a substantial literature on this question (Crouch, Gaizauskas, Netter [1]), and more practical solutions to the evaluation problem have emerged in a number of areas.

Participants in the TIPSTER programme and the MUC (Message Understanding Conference, an information extraction competition) and TREC (Text Retrieval Conference, an information retrieval (or ‘document detection’) competition) competitions (ARPA [1]), for example, build systems to do precisely-defined tasks on selected bodies of news articles. Human analysts are employed to produce correct answers for some set of previously unseen texts, and the systems run to produce machine output for those texts. The performance of the systems relative to human annotators is then measurable quantitatively. Quantitative evaluation metrics bring numerically well-defined concepts like precision and recall, long used to evaluate information retrieval systems, to language engineering.

A related phenomenon is the increasing use of statistical techniques in the field (Jelinek [20]; Church [9]; Church, Mercer [10]). Instead of an introspective process of investigation into the underlying mechanisms by which people process language (or, in Chomsky’s terms, their competence), statistical NLP attempts to build models of language as it exists in practical use – the performance of language.

Statistical methods have had significant successes, and the debate once thought closed by Chomsky’s ‘I saw a fragile whale’ is now as open as it ever has been. Most part-of-speech taggers now rely on statistics and it seems possible that parsers may also go this way, though more conventional methods are also increasing in quality and robustness.

It is possible that there is a natural ceiling to the advance of performance models (Wilks [26]), but the point of relevance for this paper is that the jury is still out on performance vs. competence. Thus, as well as a host of competing linguistic and lexicographic theories, LE is home to a thoroughgoing paradigm conflict. Two important consequences ensue.

First, empirical measurement of the relative efficacy of competing techniques is even more important. Secondly, hybrid models are becoming common, implying a growing need for the flexible combination of different techniques in single systems. Numbers of techniques that have poor performance alone may sometimes be combined to produce a whole greater than the sum of the parts (Wilks, Guthrie, Guthrie, Cowie [27]).

In common with other software systems, LE components deploy both data and process elements. The quality, quantity and availability of shared data resources has increased dramatically during the late 1980s and 1990s. (Extensive discussion of the repositories (LDC, CLR, MLSR etc.) of corpora and lexicon resources and their holdings up to 1994 can be found in (Wilks et al. [28]). More recent developments concerning ELRA (the European Linguistic Resources Association can be found in Elsentis 4.5 (November 1995)).

The sharing of processing (or algorithmic) resources remains more limited (Cunningham, Freeman, Black [12]), one key reason being that the integration and reuse of different components can be a major task. Section 2 noted the increase in scale of the problems that LE research systems aim to tackle. In parallel with this trend, the overhead involved in creating a full-scale IE system, for example, is also increasing. For many research groups the costs are prohibitive. Any method for alleviating the problems of reuse would make a significant contribution to LE research and development.

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4 Machine Translation systems had been subject to evaluation from its earliest days (ALPAC [3]), but this tradition did not spread further until recently.
On a smaller scale, the typical life-cycle of doctoral research in AI/NLP is: have an idea; reinvent the wheel, fire and kitchen sinks to provide a framework for the idea; program the idea; publish; throw the system to the dogs / tape archivist / shelfware catalogue. A framework which enabled relatively easy reuse of past work could significantly increase research productivity in these cases.

With the increasing scale of LE systems, software engineering issues become more important. Just as the construction of the Golden Gate Bridge was a rather different order of problem from that of laying a couple of planks across a farmland ditch, the development of software capable of processing megabytes of text, written by idiosyncratic wetware, in short periods of time to measurable levels of accuracy is a quite different game from that, say, of providing natural language interaction for the control of a robot arm that moves blocks on a table top (Winograd [29]). The nuts and bolts are a lot bigger, and may even be of a completely different fabric altogether. This type of issue has been solved successfully in other areas of computer science, e.g. databases. Failure to address software-level robustness (as opposed to the robustness of the underlying NLP technology), quality and efficiency will be a barrier to transferring LE technology from the lab to marketplace.

Some other requirements relating to the technological foundations of these systems also arise. Module interchangeability (at both the data and process levels), a kind of ‘software lego’ or ‘plug-and-play’, would allow users to buy into LE technology without tying them to one supplier. Also desirable are easy upgrade routes as technology improves. In addition to the reasons noted above, precise quantification of performance measures are also needed to foster confidence in the capability of LE applications to deliver, and robustness and efficiency for large text volumes are prerequisites for many applications. Software multilinguality and operating system independence are also issues. Finally, maximising cross-domain portability will favourably impact delivery costs.

Our discussion of trends in LE concludes with two major LE application areas, Information Extraction (IE) and Machine Translation (MT), which both exhibit the trends discussed above. Recent years have seen significant improvements in the quality and robustness of LE technology. Rapid improvement in robustness (the ability to deal with any input) and quality are evident in the leading systems. In last year’s MUC-6 competition initial results indicate that named-entity recognition can now be performed by machines to performance levels equal those of people (ARPA [2]). The result is that applications of the technology to large-scale problems are increasingly viable.

IE is intended to deal with the rapidly growing problem of extracting meaningful information from the vast amount of electronic textual data that threatens to engulf us. Scientific journal abstracts, financial newswires, patents and patent abstracts, corporate and government technical documentation, electronic mail and electronic bulletin boards all contain a wealth of information of vital economic, social, scientific and technical importance. The problem is that the sheer volume of these sources is increasingly preventing the timely finding of relevant information, a state of affairs exacerbated by the explosive growth of the Internet. Existing information retrieval (Salton [23]) solutions to this problem are a step in the right direction, and the industry supplying IR applications can expect to continue in its current healthy state. IR systems, however, attempt no analysis of the meaningful content of texts. This is a strength of the approach, leading to robustness and speed, but also a weakness, as the information represented by the texts is retrieved in the format of the texts themselves – i.e. in the ambiguous and verbose medium of natural language. Extraction of information in definite formats is an obvious solution and one which can only be achieved through the application of LE technology.

Journalists.
The IE community have been leaders in quantitative evaluation. Statistical methods are widely used, but so is more conventional CL. The need for systematic reuse of both data and processing resources has been recognised, and work funded to facilitate this, and the importance of software engineering matters noted. A similar situation is evident in MT research: Machine Translation Vol. 8 nos. 1-2, Special Issue on Evaluation.

3 GATE

GATE – a General Architecture for Text Engineering – is a project (funded by the EPSRC under grant GR/K25267) that aims to address the infrastructural needs of language engineering in the context of the trends described in the previous section.

GATE is an architecture in the sense of providing a common infrastructure for building LE systems. GATE is a development environment because it provides a variety of data visualisation, debugging and evaluation tools (with point-and-click interface), and a set of standardised interfaces to reusable components.

GATE comprises three principal elements (figure 1):

- a database for storing information about texts and a database schema based on an object-oriented model of information about texts (the GATE Document Manager – GDM);
- a graphical interface for launching processing tools on data and viewing and evaluating the results (the GATE Graphical Interface – GGI);
- a collection of wrappers for algorithmic and data resources that interoperate with the database and interface and constitute a Collection of REusable Objects for Language Engineering – CREOLE.

Figure 1. The three elements of GATE
GDM is based on the TIPSTER document manager (Grishman [16]). TIPSTER have defined a neutral model of information associated with text (see below). It is planned to enhance the SGML capabilities of this model, possibly by exploiting the results of the MULTEXT project (we thank colleagues from ISSCO and Edinburgh for making available documentation and advice on this subject). See section 5 for details of the relationship between GATE and these projects.

GDM provides a central repository or server that stores all information an LE system generates about the texts it processes. All communication between the components of an LE system goes through GDM, insulating parts from each other and providing a uniform API (applications programmer interface) for manipulating the data produced by the system. Benefits of this approach include the ability to exploit the maturity and efficiency of database technology, easy modelling of blackboard-type distributed control regimes and reduced interdependence of components.

GGI is in development at Sheffield. It is a graphical launchpad for LE subsystems, and provides various facilities for viewing and testing results and playing software lego with LE components: interactively stringing objects into different system configurations.

All the real work of analysing texts (and maybe producing summaries of them, or translations, or SQL statements...) in a GATE-based LE system is done by CREOLE modules. Typically, a CREOLE object will be a wrapper around a pre-existing LE module or database – a tagger or parser, a lexicon or ngram index, for example. Alternatively objects may be developed from scratch for the architecture – in either case the object provides a standardised API to the underlying resources which allows access via GGI and I/O via GDM. The CREOLE APIs may also be used for programming new objects.

The initial release of GATE will be delivered with a CREOLE set comprising a complete MUC-compatible IE system (to begin with, more of a pidgin than a creole!). Some of the objects will be based on freely available software (e.g. the Brill tagger (Brill [8])), while others are derived from Sheffield’s MUC-6 entrant, LaSIE (Gaizauskas, Humphreys, Wakao, Cunningham, Wilks [14]). This set is called VIE – a Vanilla IE system. See section 4 for an overview.

The recent MUC competition, the sixth, defined four IE tasks to be carried out on Wall Street Journal articles. Sheffield’s system did well, scoring in the middle of the pack in general and doing as well as the best systems in some areas. Developing this system took 24 person-months, one significant element of which was coping with the strict MUC output specifications. In GATE and VIE we hope to provide an environment where groups can mix and match elements of MUC technology from other sites (including ours) with components of their own, thus allowing the benefits of large-scale systems without the overheads. A parser developer, for example, can replace the parser supplied with VIE.

Working with GATE/VIE, the researcher will from the outset reuse existing components, the overhead for doing so being much lower than is conventionally the case – instead of learning new tricks for each module reused, the common APIs of GDM and CREOLE mean only one integration mechanism must be learnt. And as CREOLE expands, more and more modules and databases will be available at low cost.

As we built our MUC system it was often the case that we were unsure of the implications for system performance of using tagger X instead of tagger Y, or gazetteer A instead of pattern matcher B. In GATE, substitution of components is a point-and-click operation in the GGI

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6 Where very large data sets need passing between modules other external databases can be employed if necessary.
7 Large-Scale IE.
interface. This facility supports hybrid systems, ease of upgrading and open systems-style module interchangeability. Of course, GATE does not solve all the problems involved in plugging diverse LE modules together. There are two barriers to such integration:

– incompatibility of representation of information about text and the mechanisms for storage, retrieval and inter-module communication of that information;
– incompatibility of type of information used and produced by different modules.

GATE enforces a separation between these two and provides a solution to the former based on the work of the TIPSTER architecture group. Because GATE places no constraints on the linguistic formalisms or information content used by CREOLE objects, the latter problem must be solved by dedicated translation functions – e.g. tagset-to-tagset mapping – and, in some cases, by extra processing – e.g. adding a semantic processor to complement a bracketing parser in order to produce logical form to drive a discourse interpreter. As more of this work is done we can expect the overhead involved to fall, as all results will be available as CREOLE objects. In the early stages Sheffield will provide some resources for this work in order to get the ball rolling, i.e. we will provide help with CREOLEising existing systems and with developing interface routines where practical and necessary. We are confident that integration is possible (partly because we believe that differences between representation formalisms tend to be exaggerated) – and others share this view, e.g. the MICROKOSMOS project (Beale, Nirenburg, Mahesh [6]), which seeks to integrate many types of knowledge source in a useable whole, as well as the LexiCadCam experience at New Mexico (Wilks, Guthrie, Slator [28]) which sought to provide core lexical information as needed in a range of user-specified formats.

GATE is also intended to benefit the LE system developer (which may be the LE researcher with a different hat on, or industrialists implementing systems for sale or for their own text processing needs). A delivered system comprises a set of CREOLE objects, the GATE runtime engine (GDM and associated APIs) and a custom-built interface (maybe just character streams, maybe a Visual Basic Windows GUI, . . .). The interface might reuse code from GGI, or might be developed from scratch.

The LE user may upgrade by swapping parts of the CREOLE set if better technology becomes available elsewhere. This model for the commercialisation of LE technology is already beginning to operate in the US, where a number of organisations are preparing TIPSTER-compatible modules for sale or distribution for research. (These organisations include NMSU, SRA, HNC, University of Massachusetts, Paracell, Logicon (Dunning 1995, personal communication).) All TIPSTER-compatible modules will also work with GATE as GATE itself is designed to be a TIPSTER-compatible system. Thus the pool of easily reusable LE resources available to researchers and developers using GATE has the potential to become a large, rich set of modules from a good proportion of the LE community world-wide. Also, it may well become the case that organisations purchasing LE software will require TIPSTER compatibility (this will be true of US government organisations, for example).

GATE cannot eliminate the overheads involved with porting LE systems to different domains (e.g. from financial news to medical reports). Tuning LE system resources to new domains is a current research issue (see also: the LRE ECRAN project). The modularity of GATE-based systems should, however, contribute to cutting the engineering overhead involved.

4 VIE, a Vanilla Information Extraction system

GATE will be distributed with a set of CREOLE objects that together implement a complete information extraction system capable of producing results compatible with the MUC-6 task
definitions. This CREOLE set is called VIE, a Vanilla IE system, and it is intended that participating sites use VIE as the basis for specialising on sub-tasks in IE. By replacing a particular VIE module – the parser, for example – a participating group will immediately be able to evaluate their specialist technology’s potential contribution to full-scale IE applications. Sheffield has access to the MUC-6 scoring tools (and the PARSEVAL software) and will run periodic evaluations of various VIE-based configurations.

The most recent MUC competition, MUC-6, defined four tasks to be carried out on Wall Street Journal articles: named entity (NE) recognition, the recognition and classification of definite entities such as names, dates, places; coreference (CO) resolution, the identification of identity relations between entities (including anaphoric references to them); template element (TE) construction, a fixed-format, database-like enumeration of organisations and persons; scenario template (ST) construction, the detection of specific relations holding between template elements relevant to a particular information need (in this case personnel joining and leaving companies) and construction of a fixed-format structure recording the entities and details of the relation. VIE is an integrated system that builds up a single, rich model of a text which is then used to produce outputs for all four of the MUC-6 tasks. Of course this model may also be used for other purposes aside from MUC-6 results generation, for example we currently generate natural language summaries of the MUC-6 scenario results.

5 Related work

MULTTEXT MULTTEXT (Ballim [5]; Thompson [25]) was an EC project, whose objective was to produce tools for multilingual corpus annotation and sample corpora marked-up according to the same standards used to drive the tool development. Annotation tools were to perform text segmentation, POS tagging, morphological analysis and parallel text alignment. The project defined an architecture centred on a model of the data passed between the various phases of processing implemented by the tools. Organisational problems have, unfortunately, led to an early termination of the project, but the tools and the architecture they run in should still be completed and distributed for research purposes.

The MULTTEXT architecture is based on a commitment to TEI-style (the Text Encoding Initiative) SGML encoding of information about text. The TEI defines standard tag sets for a range of purposes including many relevant to LE systems. Tools in a MULTTEXT system communicate via interfaces specified as SGML document type definitions (DTDs – essentially tag set descriptions), using character streams on pipes. A tool selects what information it requires from its input SGML stream and adds information as new SGML markup. An advantage here is a degree of data-structure independence: so long as the necessary information is present in its input, a tool can ignore changes to other markup that inhabits the same stream – unknown SGML is simply passed through unchanged. A disadvantage is that although graph-structured data may be expressed in SGML, doing so is complex (either via concurrent markup, the specification of multiple legal markup trees in the DTD, or by rather ugly nesting tricks to cope with overlapping, aka “milestone tags”). Graph-structured information might be present in the output of a parser, for example, representing competing analyses of areas of text.

Another feature of MULTTEXT is a set of abstract data types (ADTs) for all tool I/O supported by a single shared API (Application Programmers’ Interface) for access to the types. An executive (the tool shell) glues tools together in particular configurations according to user specifications. The shell may extract sub-trees from SGML documents to reduce the I/O load where tools only require a subset of a marked-up document. The ADT set forms an
object-oriented model\(^8\) of the data present in a marked-up document. Example classes include *Sentence*, *SentenceBlock* (sequence of sentences), *LexicalWord* (word plus definition from a lexicon). The ADT model reflects the type of processing available in the tool set – there is a type *TaggedSentence*, for example, but not a *ParsedSentence*. Finally, MULTEXT has developed some general support infrastructure for handling SGML and for parallelising tool pipelines. A query language for accessing components of SGML documents is defined and API in support of this language provided. For example a program might specify parts of a document by the pattern `DOC/*/s` which refers to all `<s>` objects under `<DOC>` tags – all SGML-marked sentences in the document. Additionally SGML-aware versions of various UNIX utilities are in development. Parallel execution may be supported at the level of single tools via a program that distributes pipelined operations over a set of networked machines.

**TIPSTER II** The TIPSTER programme in the US, currently in its second phase, has also produced a data-driven architecture for NLP systems. Like MULTEXT, TIPSTER addresses specific forms of language processing, in this case information extraction and document detection (or information retrieval – IR). As will become clear below, however, TIPSTER’s approach is not restricted to particular NL tasks.

Whereas in MULTEXT all information about a text is encoded in SGML, which is added by the tools, in TIPSTER a text remains unchanged while information is stored in a separate database in the form of *annotations*. Annotations associate portions of documents (identified by sets of start/end byte offsets or *spans*) with analysis information (*attributes*), e.g.: POS tags; textual unit type; template element. In this way the information built up about a text by NLP (or IR) modules is kept separate from the texts themselves. In place of an SGML DTD an *annotation type declaration* defines the information present in annotation sets, for example a set of values for MUC-style organisation template elements. Figure 2 shows an example from (Grishman [16]). SGML I/O is catered for by API calls to import and export SGML-encoded text.

| Id | Type     | Span Start | Span End | Attributes          |
|----|----------|------------|---------|---------------------|
| 1  | token    | 0          | 5       | pos=NP              |
| 2  | token    | 6          | 13      | pos=VBD             |
| 3  | token    | 14         | 17      | pos=DT              |
| 4  | token    | 18         | 22      | pos=NN              |
| 5  | token    | 22         | 23      |                     |
| 6  | name     | 0          | 5       | name_type=person    |
| 7  | sentence | 0          | 23      |                     |

**Figure 2.** TIPSTER annotations example

The definition of annotations in TIPSTER forms part of an object-oriented model that deals\(^8\) **OO in the sense of using inheritance and data encapsulation.**
with inter-textual information as well as single texts. Documents are grouped into collections, each with a database storing annotations and document attributes such as identifiers, headlines etc. Collections are the first-class entities in the architecture. The model also describes elements of IE and IR systems relating to their use, with classes representing queries and information needs.

Comparison of MULTTEXT and TIPSTER Both projects propose architectures appropriate for LE, but there are a number of significant differences. We discuss seven here, then note the possibility of complimentary interoperation of the two.

1. MULTTEXT adds new information to documents by augmenting an SGML stream; TIPSTER stores information remotely in a dedicated database. This has several implications. Firstly, TIPSTER can support documents on read-only media (e.g. CD-ROMs, which may be used for bulk storage by organisations with large archiving needs, even though access will then be slower than from hard disk; but note that a recent revision to the specification allows for writeable documents). Secondly, TIPSTER avoids the difficulties referred to earlier of representing graph-structured information in SGML. From the point of view of efficiency, the original MULTTEXT model of interposing SGML between all modules implies a generation and parsing overhead in each module. Later versions have replaced this model with a pre-parsed representation of SGML to reduce this overhead. This representation will presumably be stored in intermediate files, which implies an overhead from the I/O involved in continually reading and writing all the data associated with a document to file. There would seem no reason why these files should not be replaced by a database implementation, however, with potential performance benefits from the ability to do I/O on subsets of information about documents (and from the high level of optimisation present in modern database technology).

2. A related issue is storage overhead. TIPSTER is minimal in this respect, as there is no inherent need to duplicate the source text (which also means that it works naturally with read-only media like CD-ROMs). MULTTEXT potentially has to duplicate the source text at each intermediary stage, although this might be ameliorated by shifting to a database implementation.

3. TIPSTER’s data architecture is application-neutral – the objects in the model are generic to all information that is associated with definite ranges of text. (The more concrete aspects of the architecture to do with IE and IR model the objects involved in user interaction with such systems.) MULTTEXT’s model is tool-specific in that the classes of object that the model describes are those processed by the tools envisaged (although the underlying representation language, SGML, is information-neutral).

4. There is no easy way in an SGML-based system to differentiate sets of results (i.e. sets of markup) by e.g. the program or user that originated them. In general, storing information about the information present in an SGML system (or meta-information) is messy. This is a problem for MULTTEXT but not for TIPSTER. A related point is that TIPSTER can easily support multi-level access control via a database’s protection mechanisms – this is again not straightforward in SGML.

5. Distributed control is easy to implement in a database-centred system like TIPSTER – the DB can act as a blackboard, and implementations can take advantage of well-understood access control (locking) technology. How to do distributed control in MULTTEXT is not obvious.

6. TIPSTER provides no tools or databases, but many sites are already committed to TIPSTER-compatibility, so the set of modules available in the framework will grow over time. MULTTEXT is based around a set of tools and reference corpora annotated accordingly.
Interestingly, a TIPSTER system could function as a module in a MULTEXT system, or vice-versa. A TIPSTER storage system could write data in SGML for processing by MULTEXT tools, and convert the SGML results back into native format. Also, the extensive work done on SGML processing in MULTEXT could usefully fill a gap in the current TIPSTER model, in which SGML capability is not fully specified (plans are currently being formed in the US to address this problem – input from European experience would seem advisable). Integration of the results of both projects would seem to be the best of both worlds, and we hope to achieve this in GATE.

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