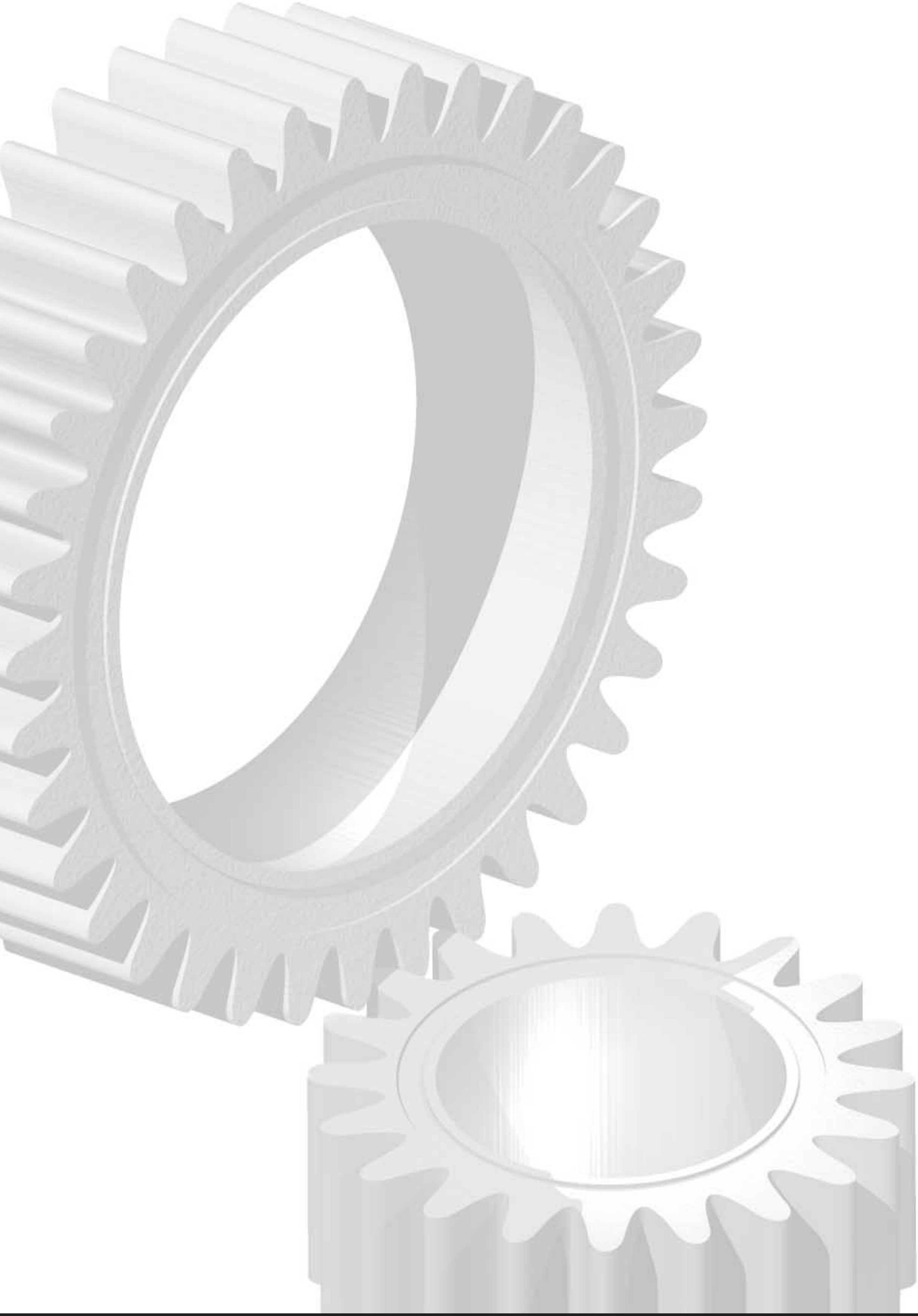
Technology White Paper



Autonomy®

www.autonomy.com

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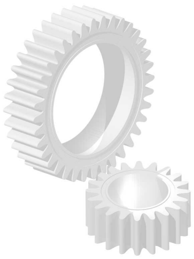

Autonomy Fundamentals

1.1 Introduction

The challenge is significant. In stark contrast to business practices of a few years ago, the modern enterprise is increasingly reliant on the efficient processing of unstructured information. Whether e-mails, Web pages or word processing documents, the content of unstructured information forms a critical link in virtually every value chain process and hence, business operation. It is increasingly apparent that the efficient management of such information is directly linked to the bottom line.

By automating a set of key tasks that are performed every day on unstructured information such as categorization, linking, personalization and delivery, Autonomy's technology enables the automation of business operations that were previously performed manually. This offers significant savings for every type of organization and industry. Indeed, given that analysts now estimate that unstructured information is doubling in quantity every three months, few businesses can afford not to choose to automate these tasks if they expect to remain competitive.

Autonomy employs a unique combination of technologies that enables computers to form an understanding of text, Web pages, e-mails, voice, documents and people and hence, automate key operations upon them. Able to power any application dependent upon unstructured information including: e-commerce, customer relationship management, knowledge management, enterprise information portals and online publishing, Autonomy provides the infrastructure technology.

Autonomy has already penetrated a diversity of vertical markets and has been achieved principally because every market sector needs to address the challenge of unstructured information.

Autonomy's unique combination of technology, provides:

- **Accuracy**
- **Speed and performance**
- **Scalability**
- **Security**
- **Language Independence**
- **Easy integration**
- **Support for any content format**

Autonomy is therefore able to power any application dependent upon unstructured information including:

- *Business Intelligence*
- *Content Publishing*
- *E-Commerce*
- *Electronic Customer Relationship Management*
- *Email Routing*
- *Enterprise information portals*
- *Internet Portal*
- *Knowledge Management*
- *Online Publishing, etc.*

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Intellectual Foundations

Autonomy's strength lies in a unique combination of technologies that employs advanced pattern matching techniques (non-linear adaptive digital signal processing), utilizing Bayesian Inference and Claude Shannon's principles of information theory. Autonomy software identifies the patterns that naturally occur in text, based on the usage and frequency of words or terms that correspond to specific ideas or concepts. Based on the preponderance of one pattern over another in a piece of unstructured information, Autonomy enables computers to understand that there is X% of probability that a document in question is about a specific subject. In this way, Autonomy is able to extract a document's digital essence, encode the unique "signature" of the key concepts, then enable a host of operations to be performed on that text, automatically.

The innovative high-performance pattern-matching algorithms that provide the sophisticated contextual analysis and concept extraction, automate the categorization and cross-referencing of information, thereby dynamically improving the efficiency of information retrieval and enabling the dynamic personalization of digital content. For the first time, computers can now be enabled to automatically form an understanding of a page of text, web pages, e-mails, voice, documents and people, and automate operations dependant upon them.

2.1 Bayesian Inference

The theoretical underpinnings for Autonomy's approach can be traced back to Thomas Bayes, an 18th century English cleric whose works on mathematical probability were not published until after his death ("Philosophical Transactions of the Royal Society of London", 1763). Bayes' work centered on calculating the probabilistic relationship between multiple variables and determining the extent to which one variable impacts on another.

A typical problem is to judge how relevant a document is to a given query or agent profile. Bayesian theory aids in this calculation by relating this judgement to details that we already know, such as the model of an agent. More formally, the resulting, "a posteriori" distribution $p(\theta|x)$, which is applicable in judging relevance, can be given as a function of the known, "a priori" models and likelihood

$$p(\theta|x) = \frac{p(x|\theta).p(\theta)}{\sum_{\theta' \in \Theta} p(x|\theta').p(\theta')}$$

Extensions of the theory go further than relevance information for a given query against a text. Adaptive probabilistic concept modeling (APCM) analyzes correlation between features found in documents relevant to an agent profile, finding new concepts and documents. Concepts important to sets of documents can be determined, allowing new documents to be accurately classified.

A traditional statistical argument is that if a coin is tossed 100 times and comes up heads every time, it still has an evens chance of coming up tails on the next throw. An alternative, Bayesian approach, is to say that 100 consecutive heads are evidence that the coin is not fair, or perhaps has heads on both sides. In a similar manner knowledge about the documents deemed relevant by a user to an agent's profile can be used in judging the relevance of future documents. APCM allows this information to be "back propagated"; in other words agents can be improved by retraining.

Although no one knows for certain what Bayes' original goal was, Bayes' Theorem has become a central tenet of modern statistical probability modeling. By applying Contemporary computational power to the concepts pioneered by Bayes, it is now feasible to calculate the relationships between many variables quickly and efficiently, allowing software to manipulate concepts.

2.2 Shannon's Information Theory

Information Theory is the mathematical foundation for all digital communications systems.

Claude Shannon's innovation as described in his "Mathematical Theory of Communication" (1949) was to discover that "information" could be treated as a quantifiable value in communications.

Consider the basic case where the units of communication (for example, words or phrases) are independent of each other. If p_i is the probability of the i^{th} unit of communication, the average quantity of information conveyed by a unit, Shannon's entropy or measure of uncertainty is:

$$H=-\sum p_i.\log_2(p_i)$$

This formula reaches its maximum when the probabilities are all equal; in this case the resulting text would be random. If this is not the case the information conveyed by the text will be less than this maximum; in other words there is some redundancy. This result is then extended, by more sophisticated mathematical arguments, to when units are related.

Natural languages contain a high degree of redundancy. A conversation in a noisy room can be understood even when some of the words cannot be heard; the essence of a news article can be obtained by skimming over the text. Information theory provides a framework for extracting the concepts from the redundancy.

Autonomy's approach to concept modeling relies on Shannon's theory that the less frequently a unit of communication occurs, the more information it conveys. Therefore, ideas, which are more rare within the context of a communication, tend to be more indicative of its meaning. It is this theory which enables Autonomy's software to determine the most important (or informative) concepts within a document.

3 The Dynamic Reasoning Engine™ (DRE™)

At the heart of Autonomy's software is the Dynamic Reasoning Engine (DRE™). The DRE™ is based on advanced pattern-matching technology that exploits high-performance probabilistic modeling techniques. The DRE™ performs the core information operations:

- **Concept matching**: The DRE™ accepts a piece of content* or reference (identifier) as an input and returns references to conceptually related documents ranked by relevance, or contextual distance. This is used to generate automatic hyperlinks between pieces of content.
- **Agent creation**: The DRE™ accepts a piece of content* and returns an encoded representation of the concepts, including each concept's specific underlying patterns of terms and associated probabilistic ratings.
- **Agent retraining**: The DRE™ accepts an agent and a piece of content* and adapts the agent using the content.
- **Agent Matching**: The DRE™ accepts an agent and returns similar agents ranked by conceptual similarity. This is used to discover users with similar interests, or find experts in a field.
- **Agent Alerting**: The DRE™ accepts a piece of content and returns similar agents ranked by conceptual similarity. This is used to discover users who are interested in the content, or find experts in a field.
- **Categorization**: The DRE™ accepts a piece of content and returns categories ranked by conceptual similarity. This is used to discover which categories the content is most appropriate for, allowing subsequent tagging, routing or filing.
- **Summarization**: The DRE™ accepts a piece of content and returns a summary of the information containing the most salient concepts of the content. In addition, summaries can be generated that relate to the context of the original inquiry - allowing the most applicable dynamic summary to be provided in the results of a given inquiry.
- **Clustering**: The DRE™, in conjunction with the Clusterizer module, can organize large volumes of content or large numbers of profiles into self-consistent clusters. Clustering is an automatic agglomerative technique which partitions a corpus by grouping together information containing similar concepts.
- **Active Matching**: The DRE™ can accept textual information describing the current user task and returns a list of documents ordered by contextual relevance to the active task.
- **Retrieval**: The DRE™ accepts natural language queries and returns a list of documents containing the concepts looked for, ordered by contextual relevance to the query. The DRE™ also supports Boolean queries.

*piece of content refers to a sentence, paragraph or page of text, the body of an e-mail, a record containing human readable information, or the derived contextual information of an audio or speech snippet.

Benefits of Autonomy's technology

4.1 Automation

Autonomy's technology addresses a fundamental set of operations that demands to be continuously performed on a wide range of information management and processing tasks across all unstructured information formats in every digital domain. Given that such tasks have previously been performed by expensive, inaccurate - and always slow - manual labor, Autonomy's technology offers the radical automated solution for countless numbers of business operations and with it, a direct link to significant bottom line savings.

Virtually every market sector and industry has invested to some degree in Autonomy, automating the processing and management of unstructured information. Given the uninterrupted growth of unstructured information which is doubling every three months (Gartner), efficient processes that manage and extract value from such information are solely dependant on the ability to automate the tasks that previously, have been performed with manual labor.

4.2 Infrastructure

Autonomy's technology is not an application but rather, a fundamental piece of infrastructure technology that can fuel the automation of business critical operations across the entire enterprise or process a raft of operations within any application dependant upon unstructured information.

In addition, the Autonomy Content Infrastructure™ (ACI™) is a new technology specification that enables automated and compatible business-to-business and peer-to-peer infrastructure. By using the ACI™ to operate on unstructured information, all types of software providers will be able to deliver the scalability, operating efficiencies and immediate responsiveness that drive today's e-business. ACI™ does not require complex programming, extensive integration, business rules, or middleware. It also does not require information to be manually tagged, linked or categorized. ACI-compliant applications are immediately compatible through their common understanding of unstructured information.

More than 30 leading software companies are already incorporating Autonomy's technology into the next version of their enterprise applications, whether for customer relationship management, e-business, customer care, e-mail routing and security, content delivery, or client-server systems. Vendors delivering ACI-compliant applications include OpenMarket, Oracle, Octane, Delano, Nexor and Intraspect.

4.3 Accuracy

Profiling and personalization are meaningless words to most people because most software applications use inaccurate key word or linguistic based technologies to attempt profiling and personalization emulation with, in most cases, hopeless and disappointing results. In contrast, Autonomy's technology provides highly accurate analysis of a users' information requirements utilizing both implicit and - where required – explicit techniques to establish dynamic, real time, results that go far beyond users experiences and in many cases, expectations.

4.4 Speed

Autonomy's technology is deployed to solve mission critical business problems, with a wide variety of capacity and performance requirements. With the ever-increasing volumes of users and data, and 365 by 24 operation, the importance of immediate results, and rapid and unpredictable increases in content and usage impose rigorous requirements on Autonomy's underlying technology. Real-world examples and internal benchmarks prove Autonomy more than satisfies those requirements for fast, accurate search and categorization.

4.5 Scalability

Because our product architecture is designed to be completely modular, multi-threaded and use multiplexing sockets, Autonomy's infrastructure technology provides high performance, a high capacity and scalable platform for content exploitation.

4.6 Security

Whether your company is implementing a knowledge management solution, publishing content, selling goods and services through electronic channels or providing application software products, a key consideration is security.

Autonomy's unique combination of sophisticated mathematical algorithms and software automate the processing and conceptual analysis of large volumes of both content and users, to provide highly personalized, content exploitation solutions without sacrificing the security issues described above.

Autonomy provides three basic forms of security. These are as follows:

1. **Authentication**: This governs who is able to log in to the system.
2. **Entitlement**: This governs which items in the results list can be seen by the user.
3. **Authorization**: This governs who is able to view documents having clicked on the links in the results list and is not required with entitlement.

4.7 Language Independence

It is very important for global companies today to be able to provide the right information to the right people regardless of the language the content is represented in. Autonomy's technology is completely language independent. It does not rely on any intimate knowledge of English grammatical structure or that of any particular language. It treats words as abstract symbols of meaning, deriving its understanding through the context of their occurrence rather than a rigid definition of grammar. Autonomy's software supports over 22 languages, including English, German, French, Italian, Chinese, Japanese...

4.8 Easy integration

Autonomy Application Builder™ has been designed to help companies and partners to integrate Autonomy's technology to create their own customized applications. The provision of APIs in C, JAVA and HTTP means you can integrate with a wide variety of development languages and Web scripting technologies.

4.9 Support for any format

Autonomy's technology aggregates content from any data sources. Autonomy supports over 200 file formats, and can access repositories such as LotusNotes, Oracle, Exchange, etc.

5 Alternative approaches

Many companies claim to have solutions that solve the challenge of managing unstructured information or have promised technologies to deliver personalized information services. However, most of these systems and approaches have severe limitations particularly where scalability and cost are concerned. For example:

5.1 Keyword Searching or Boolean Query

The most common approach to information management is through traditional keyword search. This simple method involves asking a user to enter some terms into a text field. It then searches through a list of documents to return with a list of those containing the search terms.

5.1.1 Limitations

- **No context**

  The most common attempts to manage unstructured data employ keyword search. Search methods often exacerbate information overload. Although they can identify documents in which a search term appears, they cannot tell how relevant the document is to the subject being researched. They simply look for the occurrence of keywords and are unable to decipher whether the concept represented by a search term is related to the main idea of a document.

  In addition, keyword-based approaches sometimes make the mistake of assuming that the more often a term is mentioned in a document, the more relevant the document is to the search. This is not always the case. Consider the following phrase: “I was walking down the street the other night. It was a long street, a dark street... and at the end of the street I was attacked by a mugger.” Although the word “street” is mentioned several times, the phrase is really about a crime.

- **Inaccurate**

  Reliance on inefficient computer linguistics, keyword definitions and tags produces inaccurate results and is normally costly to implement and maintain. It is not scalable nor deployable as a solution to the challenges that unstructured information presents in every market sector.

- **Manual**

  Keyword engines do nothing more complex than look for a few words, which is very manually intensive at the back end, requiring humans to continually manage and update keyword associations or “topics”.

- **Intensive user participation**

  Keyword methodologies rely heavily on the sophistication of the end user to be able to author queries in fairly complex and specific language (also known as Boolean form) i.e. CD AND (NOT (financial OR money OR invest*) AND music.”

- **Do not learn**

  Keyword search engines cannot “learn” through use, or be exposed to queries on the word dog and learn that when dog is input, it is the four legged, furry kind of sheepdog for which information is being sought without user intervention.

  It is also very difficult for keyword search systems to find things by being shown an example. Typically a “more like this...” function will simply increase the number of keywords in the query based on what terms appear most frequently in the example document. This will often result in more documents instead of less, which is what the user really wants.

5.1.2 Autonomy’s approach

Autonomy’s concept matching technology avoids these problems by matching concepts instead of simple keywords, although it does have the ability to perform standard Boolean text queries as well. Autonomy takes into account the context in which terms appear. This eliminates many false hits while also catching documents that may not contain the specific term, but do include the concept.

5.2 Collaborative Filtering or Social Agents

Collaborative Filtering is an attempt to allow computers to make personal recommendations to users based on their similarity to other users. The basic principle is quite simple: by getting a large number of users to give information about their preferences (usually by filling out forms and checking boxes) the system endeavors to make recommendations.

An example serves to clarify the basic principle. Imagine three users: Mick, Bud, and Brad have been asked to give their three favorite musicians.

Mick's favorite musicians:	*Elvis*	*Buddy Holly*	*Little Richard*
Bud's favorite musicians:	*Jimi Hendrix*	*James Brown*	*Aretha Franklin*
Brad's favorite musicians:	*Elvis*	*Jerry Lee Lewis*	*Little Richard*

In collaborative filtering the computer compares the results, finds that Mick and Brad are similar and so swaps each other's suggestions: "Mick, you may like Jerry Lee Lewis"; "Brad, you may like Buddy Holly".

5.2.1 Limitations

- **Limited use**
  Collaborative filtering works well only for a closed set of items (e.g. music, books). It will not work well for online services seeking to recommend relevant news stories or articles for purchase because the number of possible "subjects "is too large and diverse. It is also difficult to infer value from user rankings beyond the immediate set of items being ranked. Does indicating a preference for Elvis and Buddy Holly correlate with drinking Pepsi rather than Coke?
- **Not personalized**
  In the example above, the system assumes similar people act in similar ways. However, even for music, users tastes are complex. John may like Buddy Holly and Jerry Lee Lewis, hate Elvis, but like Mozart. The technology cannot take personal idiosyncrasies into account.
- **Intensive user participation**
  Collaborative filtering also requires tedious active participation from users. They must continuously fill out questionnaires or set ratings and grades for each object, a process which soon loses its novelty value.
- **Not scalable**
  This approach has inherent scalability problems for large numbers of users due to the multidimensional comparisons over all users. It is for these reasons that Forrester Research concluded in its May 1997 report "Personalize or Perish" that collaborative filtering is useful in only a very small percentage of applications.

- **Cannot handle new information**
  The day one problem: On day one of a service there are no questionnaires for the system to work from.

Collaborative filtering cannot deal very well with new information. In an e-commerce environment, the system cannot recommend users who would be interested in a new product because nobody has purchased it before. For example, when the Spice Girls first came to prominence there were no existing questionnaires mentioning them.

5.2.2 Autonomy's approach

Autonomy's technology understands users' interests or employee expertise by extracting key ideas from the information a user reads. It is then building a profile that can be used for personalizing information or serve targeted advertising messages. Because these services are based on a user's actual interests, they do not require him to fill out lengthy questionnaires or rate his likes and dislikes.

These profiles can be kept completely anonymous and do not require the user to provide any private demographic information. However, profiles can be combined with any known demographic information to further personalize the services provided.

As an individual reads additional articles online, publishes material on the corporate Intranet or submits documents to the knowledge management system, the system updates the profile by recalculating interest levels in the different ideas. Concepts that once occurred frequently but no longer are important are replaced over time. In this way, the system keeps pace with an individual's changing interests. This is in contrast to an explicit preference setting, which users must remember to adjust as their interests evolve.

5.3 Parsing and Natural Language Analysis

For the last twenty years much effort has been put into an obvious approach to deal with unstructured information called parsing (also semantic or lexical analysis). Rules of grammar and lexicons are applied to try to explicitly understand textual information.

Example:

The cat sat patiently on the mat. = (The cat = subject) (sat = verb) (patiently = adverb)
(on = preposition) (the mat = object).

5.3.1 Limitations

- **No context**

  In spite of more than 20 years of research into parsing approaches, parsing is rarely used in real applications because of its poor performance for real world problems. The following cases illustrate the limitations of this approach, namely, parsing's inability to handle ambiguity.

  Example 1:

  ”The dog came into the room, it was white.”

  It is unclear from the sentence whether it is the room or the dog that is white. On the other hand, a human being would have little problem deciphering the following examples because of his or her familiarity with both rooms and dogs:

  “The dog came into the room, it was furry.”
  “The dog came into the room, it was full of furniture.”

  The computer, however, would still be stumped. It lacks the understanding to solve such ambiguities. Some advanced systems will allow the construction of a set of rules for the machine to follow to resolve these uncertainties. However, the instruction set would be incredibly cumbersome and difficult to maintain, AND WOULD significantly degrade the system's performance.

  Example 2:

  “The fly, it's clear to me, can fly faster than the bee.”

  First, the computer may be confused by the word “fly,” which is used in this sentence as both a subject and a verb. But that is an easy problem to solve. What about the word “it”? How does one parse a word that refers to abstract thought? These problems are exacerbated when a computer attempts to extract meaning by parsing full paragraphs.

  Example 3:

  “The president arrived by car to meet the Chinese premier.”

  Like keyword-based approaches, parsing cannot determine the relative importance of ideas. In other words, the computer will assign an equal level of importance to the President, his mode of transportation and the leader he is meeting with. Parsing at best can only handle a few sentences. A strict parsing mechanism has great difficulty extracting meaning from a full paragraph.

- **Not reliable**

  Because parsing is based on a true/false decision-tree structure, one incorrect decision can derail the entire analysis.

- **Language dependent**

  The approach is language specific, and the reliance on the grammar of a given language is vulnerable to slang or grammatically incorrect constructions. Because linguistic approaches base their understanding of ‘foreign ’content using a thesaurus, they cannot scale easily. This makes the deployment of multi-language or region specific applications and offerings very complicated and time-consuming.

- **Manual**

  Another approach championed by search vendors involves the linguistic processing of a question or command such as “Open a Word Processor”or “Where will I find this?” While this can be appropriate for one sentence questions, or questions which concern a known universe of information, the language model simply breaks down when employed on large documents containing a large number of concepts. It is recognized however, that this approach is useful to the market but it is a smaller market by definition and requires a significant amount of manual labor at the back-end.

5.3.2 Autonomy’s approach

Autonomy’s software avoids these problems because its pattern-matching technology uses predictable statistical word patterns to represent concepts and functions independently of any given language.

5.4 Manual Tagging

With an upswing in enterprise portal, creating taxonomies that address various information types (including documents, structured data, HTML, XML, and multimedia) is imperative. Manual tagging schemes are becoming an increasingly popular method of labeling digital material. However, there are significant barriers to ensuring that it increases the efficiency of managing information: the costs!

5.4.1 Limitations

- **Descriptive inconsistency**
  One example of the effect of human behavior and the inherent limitations of manually describing information – albeit from existing descriptions - is illustrated by the results of a US Department of Defense edict, mandating that internal users responsible for authoring documents also create an appropriate description of the content of the document. At first glance, a seemingly sensible and pragmatic decision. However, after many months of activity, it was discovered that the vast majority of documents had been loosely described and tagged as ‘general ’. Whilst tagging schemes, and particularly XML, attempts to break away from such generalist terms, it remains dependant upon the same shortcomings of human behavior that manifest themselves as ‘inconsistency’. An individual’s ability to describe information is dependant upon their personal experience, knowledge and opinions. Such ‘intangibles’ vary from person to person and are also dependant upon circumstance, dramatically reducing the effectiveness of the results.

Further complications arise when subjects incorporate multiple themes. Should an article about 'technology development in Russia within the context of changing foreign policy' be classified as (i) Russian technology (ii) Russian foreign policy, or (iii) Russian economics? The decision process is both complex and time consuming and introduces yet more inconsistency, particularly when the sheer number of options available to a user is considered. For example, over 800 tags for general newspaper subjects make the task of choosing a potentially basic subject description in a reasonable time-scale, an even more challenging process.

- **Idea Distancing**
  Tags also fail to highlight the relationships between subjects. Termed 'idea distancing', there are often vital relationships between seemingly separately tagged subjects such as wing design/low drag/and /aerofoil/efficiency/. The first category may contain information about the way the wings are designed to achieve low air resistance. The latter category discusses ways in which efficient aerofoils are made. Obviously, there will be a degree of overlap between these categories and because of this, a user may be interested in the contents of both. However, without understanding the meanings of the category names, there is no clear correlation between the two.
- **Not scalable**
  In order to be very specific in retrieval and processing of tagged-based documents, the number of tags will need to be very high. For example, tag numbers in a company such as Reuters run into the tens of thousands. However, as the number of tags increases, so does both the effort and the likelihood of misclassification.
- **High labor costs**
  Taxonomy creation and tagging is still a predominantly manual effort requiring input from librarians, users, and IT staff. This means large labor costs involved in making sense of information.

5.4.2 Autonomy's approach

Autonomy addresses the inefficiencies introduced by many of the manual issues associated with creating tags by adding a layer of intelligence to the management of XML: understanding the content and purpose of either the tag itself, or related information, or both.

Conclusion

By understanding concepts as expressed within a particular context, Autonomy's technology represents a significant advance beyond simple text searching, collaborative filtering, parsing or manual tagging. As the amount of unstructured text available to users explodes, companies are in greater need of an intelligent infrastructure that can automate the management, personalization and delivery of information while reducing the level of manual effort required to get the right information to the right people at the right time.

Computers need to be smarter. They need to understand more about the information being communicated, and less about where and how information is stored.

Autonomy looks forward to continuing progress in enabling computers to better understand the meaning of digital information in any form.

7 Further Reading

- "Interactive Technology Strategies - Personalize or Perish?" The Forrester Report; Volume Two, Number Three, May 1997
- "Bayesian Methods Applied to Neural Networks" by Radford Neal, *Springer Verlag*
- "Bayesian Forecasting" by Mike West, *Springer Verlag*
- "Applied Bayesian Forecasting and Times Series Analysis" by Pole, West & Harrison, *Chapman & Hall*
- "Bayesian Statistics" by P. Lee, *John Wiley & Sons*
- "Numerical Bayesian Methods Applied to Signal Processing" by O-Ruinadah and W.J. Fitzgerald, *Springer Verlag*

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