Learning Language from a Large (Unannotated) Corpus

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Abstract

A novel approach to the fully automated, unsupervised extraction of dependency grammars and associated syntax-to-semantic-relationship mappings from large text corpora is described. The suggested approach builds on the authors’ prior work with the Link Grammar, RelEx and OpenCog systems, as well as on a number of prior papers and approaches from the statistical language learning literature. If successful, this approach would enable the mining of all the information needed to power a natural language comprehension and generation system, directly from a large, unannotated corpus.

1 Introduction

Currently, the two primary methods of supplying natural language processing systems with "content" regarding specific languages are:

1. Explicit human-coded linguistic rules,

2. Supervised machine learning from human-annotated corpora.

Neither of these approaches is fully satisfactory, because both rely on substantial formalized coding by expert humans. Natural language is sufficiently complex and diverse that it eludes full formalization, either in the form of hand-coded rules, or in the form of annotation of corpora. Even if, in principle, some sufficiently large hand-coded rule-set or annotated corpus was enough to supply an NLP system with linguistic content, it leaves open the question of operating with the higher, more abstract structures that are the outcome of parsing: rule-sets do not address the issue of semantic content. Thus, in practice, these traditional approaches are unlikely to yield full success.

The goal here is to explore the alternative: the induction of grammar and semantics by means of unsupervised learning algorithms. Two approaches that have been discussed and attempted, to some extent, by the scientific community, are:

1. Machine learning from large, unannotated text corpora

2. Machine learning from (unannotated) data regarding spoken or textual language in non-linguistic contexts (e.g. texts together with pictures, or spoken language together with video and ambient audio).

Interesting ideas have been developed in both of these directions, but, so far, results have fallen far short of those obtained via the first two approaches.

The review of [KM04] provides a summary of the state of the art in automatic grammar induction (the third alternative listed above), as it stood a decade ago: it addresses a number of linguistic issues and difficulties that arise in actual implementations of algorithms. It is also notable in that it builds a bridge between phrase-structure grammars and dependency grammars, essentially pointing out that these are more or less equivalent, and that, in fact, significant progress can be achieved by taking on both points of view at once. Grammar induction has progressed somewhat since this review was written, and we will mention some of the more recent work below; but yet, it is fair to say that there has been no truly dramatic progress in this direction.
Here, we describe a novel approach to achieving the third alternative: automated grammar induction by machine learning of linguistic content from a large, unannotated text corpus. The methods described may also be useful for the fourth alternative (incorporation of extralinguistic data in the learning system’s inputs); and could make use of content created using hand-coded rules or machine learning from annotated corpora. However, our focus will be on learning linguistic content from a large, unannotated text corpus.

While the overall approach presented here is novel, the ideas are extensions and generalizations of the prior work of multiple authors, which will be referenced and in some cases discussed below. We believe the body of ideas needed to enable unsupervised learning of language from large corpora has been gradually emerging during the last decade. The approach given here has unique aspects, but also many aspects have already been validated by the work of others.

For sake of simplicity, we will deal here only with learning from written text. We believe that conceptually similar methods can be applied to spoken language as well, but that this brings extra complexities that we will avoid for the purposes of the present document. (In short: below, we represent syntactic and semantic learning as separate but similarly structured and closely coupled learning processes. To handle speech input thoroughly, we would suggest phonological learning as another separate, similarly structured and closely coupled learning process.)

Finally, we stress that the algorithms presented here are intended to be used in conjunction with a large corpus, and a large amount of processing power. Without a very large corpus, some of the feedback required for the learning process described would be unlikely to happen (e.g. the ability of syntactic and semantic learning to guide each other). We have not yet sought to estimate exactly how large a corpus would be required, but our informal estimate is that Wikipedia might or might not be large enough, and the Web is certainly more than enough.

2 Algorithmic Overview

The rest of this paper is devoted to fleshing out, providing detail, and mounting a theoretical defense of a rather simple, basic algorithm. Rather than getting lost in the details, it is important to keep a general notion of the algorithm in mind at all times. Thus, a crude sketch follows.

The algorithm is as follows: Step A) Define words to be ‘things’; Step B) Look for correlations between things; Step C) Cluster similar things together into classes; Step D) Define a new set of things as the clusters obtained from the last step and Step E) return to step B. By correlation, it will almost always be meant ‘mutual information’ or ‘mutual entropy’. This is a number capturing the strength of a relationship between ‘things’. The ‘relationship’ between things will be, in general, a graph or hypergraph. However, very early in the iteration of the algorithm, it will be very simple: if ‘things’ are words, then the ‘relationship’ is pairs of words, and one starts by measuring the mutual information of pairs of words.

The classification of step C is to be accomplished primarily using entropy maximization/minimization principles. To illustrate with pairs of words: consider words A, B and W. Then, word A and word B should be grouped together into a cluster C, if, for any word W, the total entropy of pair(word W, class C) + member(A in C) + member(B in C) is less than the total entropy of pair(word W, word A) + pair(word W, word B). If this inequality holds, then the cluster C should be formed; if not, then there is no advantage to having such a class, and it should be dissolved. (This example should not be taken literally, as, even for word pairings, the actual relationships that must be considered are more complex than this. Detailed inequalities for clustering are presented in an appendix).

The penultimate step D makes considerable demands on technology. In order to use ‘things’ observed in the environment, one must be able to recognize those things: and so, one needs to have a pattern recognizer. However, patterns do not sit all by themselves, but, in fact, they interconnect, and so one must have a way assembling them so that they match the observed input. This is the ‘parser’ of natural language processing. Here, in the abstract context of ‘patterns’ of ‘things’, its probably best to think of each pattern as a puzzle-piece. A collection of puzzle pieces must then be assembled into a complete, final picture that more or less matches the observed input. This is essentially a “constraint satisfaction problem”, which should conjure up the kinds of algorithms required, as well as the difficulties one may have in recognizing patterns in an input. For the general case, the best and most well-known algorithm for solving constraints is the DPLL algorithm, on which most SAT solvers and other systems are based. For language
learning, though, it does not seem that a jump to SAT is immediately required. Many patterns will be relatively simple, and have simple inter-dependencies, for which more basic algorithms should suffice. These include the backwards-forwards or the Viterbi algorithms, which should be fast, effective and sufficient. So, for example, in parsing a sentence, as each new word is ‘heard’, a set of different relationships with the surrounding words may be contemplated. After enough words have been heard in a row (say 5 or 7 or 10), their inter-relationship should become clear, and one can move on. This is essentially the Viterbi algorithm, which discards the unlikely combinations, keeping only the most likely candidate(s). A global, Boolean-SAT-style optimization is not required: what we hear now really should not affect the parse of a sentence we heard several minutes ago. However, this changes once the patterns become complex enough. So, for example, consider a set of large patterns, encoding meaning, that span multiple sentences or even paragraphs. These large patterns may not fit together in any simple way, and may require a good amount of wrestling to assemble together in a coherent, consistent fashion. This is where the full force of a strong constraint-satisfaction solver would be required.

Implicit in step D is also a layering or recursion of pattern complexity, and the application of ‘deep learning’ principles. The groupings of the previous step have a tendency to reduce the total number of rules or relationships needed to describe the corpus (entropy minimization); however, the complexity of the rules tends to increase. It is the sum of the (logarithm of) the number of rules, and the (logarithmic) complexity that provides the proper metric: an “Occam’s razor” to discover the least-complex and smallest set of rules possible. However, as confidence in a set of rules grows, and uncertainty diminishes, exceptions become more apparent. Such exceptions encode semantic information. So, for example, commonality between the phrases “the book has ...” and “the dog has ...” suggests that “book” and “dog” can be grouped into a class “noun”. The absence of phrases such as “the book barked at the squirrel” suggests that perhaps books and dogs differ, and can be sub-classified as inanimate and animate objects. This re-classification has the odd effect of strengthening the original conception of “noun”, by forcing out words that were incorrectly classified as nouns in the first place. This can be viewed as a form of “deep learning” at work: a higher, more abstract layer can serve to refine the correctness of a shallower, more concrete layer. Implicit in the algorithm is not just an inter-dependency of rules, but also a layering or hierarchy.

This, then, is the basic outline of the algorithm that is being proposed here. It should be clear, from this description, that it is capable of leveraging it’s way up from a lack of structure to a collection of complex patterns, and doing so without any ’training data’, in an unsupervised fashion. The remainder of this proposal is then devoted to justifying why this might be the right approach, as well as fleshing out in greater detail in how all this might work.

3 Assumed Linguistic Infrastructure

While the approach outlined here aims to learn the linguistic content of a language from textual data, it does not aim to learn the idea of language. Implicitly, we assume a model in which a learning system begins with a basic ”linguistic infrastructure” indicating the various parts of a natural language and how they generally interrelate; and it then learns the linguistic content characterizing a particular language. In principle, it would also be possible to have an AI system to learn the very concept of a language and build its own linguistic infrastructure. However, that is not the problem we address here; and we suspect such an approach would require drastically more computational resources.

The basic linguistic infrastructure assumed here includes:

• A formalism for expressing grammatical (dependency) rules is assumed.

  – The ideas given here are not tied to any specific grammatical formalism, but we find it convenient to make use of a formalism in the style of dependency grammar. Taking a mathematical perspective, different grammar formalisms can be translated into one-another, using relatively simple rules and algorithms. The primary difference between them is more a matter of taste, perceived linguistic ‘naturalness’, adaptability, and choice of parser algorithm. In particular, categorial grammars can be converted into link grammars in a straight-forward way, and

1 This is anchored on the psycho-linguistic observation that almost all dependencies are short, and rarely extend past the the first few nearest neighbors.
A comparison of dependency and phrase-structure parses, above and below. In general, one can be converted to the other (algorithmically); dependency parses tend to be easier understand and verify. In the dependency parse, an arrow points from the controlling word or head word to the dependent word. (Somewhat confusingly, the head of the arrow points at the dependent word; this means the tail of the arrow is attached to the head word). (Image taken from G. Schneider, “Learning to Disambiguate Syntactic Relations” Linguistik online 17, 5/03)

vice versa, but link grammars provide a more compact dictionary. Link grammars\cite{ST91} \cite{ST93} are a type of dependency grammar; these, in turn, can be converted to and from phrase-structure grammars. We believe that dependency grammars provide a more simple and natural description of linguistic phenomena. We also believe that dependency grammars have a more natural fit with maximum-entropy ideas, where a dependency relationship can be literally interpreted as the mutual information between word-pairs\cite{Yur98}. Dependency grammars also work well with Markov models; dependency parsers can be implemented as Viterbi decoders. Figure 1 illustrates two different formalisms.

- The discussion below assumes the use of a formalism similar that of Link Grammar. In this theory, each word is associated with a set of 'connector disjuncts', each connector disjunct controlling the possible linkages that the word may take part in. A disjunct can be thought of as a jig-saw puzzle-piece; valid syntactic word orders are those for which the puzzle-pieces can be validly connected. A single connector can be thought of as a single tab on a puzzle-piece (shown in figure 2). Connectors are thus 'types' $X$ with a + or - sign indicating that they connect to the left or right. For example, a typical verb disjunct might be $S- & O+$ indicating that a subject (a noun) is expected on the left, and an object (also a noun) is expected on the right.

- Some of the discussion below assumes aspects of (Dick Hudson’s) Word Grammar\cite{Hud84} \cite{Hud07}. This theory (implicitly) uses connectors similar to those of Link Grammar, but allows each connector to be marked as the head of a link or not. A link then becomes an arrow from a head word to the dependent word.

- Each word is associated with a “lexical entry”; in Link Grammar, this is the set of connector disjuncts for that word. It is usually the case that many words share a common lexical entry; for example, most common nouns are syntactically similar enough that they can all be grouped under a single lexical entry. Conversely, a single word is allowed to have multiple lexical entries; so, for example, “saw”, the noun, will have a different lexical entry from “saw”, the past tense of the verb “to see”. That is, lexical entries can loosely correspond to traditional dictionary entries. Whether or not a word has multiple lexical entries is a matter of convenience, rather than a
Figure 2: Link Grammar Connectors

An illustration of Link Grammar connectors and disjuncts. The connectors are the jigsaw-puzzle-shaped pieces; connectors are allowed to connect only when the tabs fit together. A disjunct is the entire (ordered) set of connectors for a word. As lexical entries appearing in a dictionary, the above would be written as

\[
\begin{align*}
\text{a the} & : D+; \\
\text{cat snake} & : D- \& (S+ \text{ or } O-); \\
\text{Mary} & : O- \text{ or } S+; \\
\text{ran} & : S-; \\
\text{chased} & : S- \& O+;
\end{align*}
\]

Note that although the symbols ‘\&’ and ‘or’ are used to write down disjuncts, these are not Boolean operators, and do not form a Boolean algebra. They do form a non-symmetric compact closed monoidal algebra. The diagram below illustrates puzzle pieces, assembled to form a parse:

The comparable ASCII-graphics parse, from a recent version of the parser, is:

\[
\begin{align*}
\text{the} & \quad \text{cat} \quad \text{chased} \quad \text{a} \quad \text{snake} \\
\text{D+D} & \quad \text{S+S} & \quad \text{O+O} \\
\text{the cat . n chased . v-d a snake . n}
\end{align*}
\]

The additional lower-case 's' shown here (e.g. $D$s) indicates that the link connects to a singular (not plural) noun. The words have also been decorated with parts of speech. (Images taken from [ST91].)
fundamental aspect. Curiously, a single Link Grammar connector disjunct can be viewed as a very fine-grained part-of-speech. For example, $S - & O+$ is the disjunct used for transitive verbs (verbs that take an object), while $S - & O+ & On+$ is the disjunct for ditransitive verbs (verbs that take two objects: a direct and indirect object). These fine-grained parts-of-speech correlate reasonably well with word senses (e.g. taken from WordNet) and can thus serve as a rough (and very rapid!) suggestion for word-sense disambiguation. In this way, disjuncts are a stepping stone to the semantic meaning of a word.

- A parser, for extracting syntactic structure from sentences, is assumed. What’s more, it is assumed that the parser is capable of using dynamic criteria, such as semantic relationships, to guide parsing.
  - The statement here is about the type of functionality needed from the parsing component. Traditional parsers presume a static, fixed lexis, and do not provide any mechanism by which parse ranking can be adjusted or steered, on-the-fly, by mechanisms outside of the domain of the parser itself (“deep learning”). Yet, such external influence seems centrally important to a realistic system.
  - A paradigmatic example of such a parser is the “Viterbi Link Parser”, currently under development for use with the Link Grammar. This parser is currently operational in a simple form. The name refers to its use of the general ideas of the Viterbi algorithm. This algorithm seems biologically plausible, in that it applies only a local analysis of sentence structure, of limited scope, as opposed to a global optimization, thus roughly emulating the process of human listening. The current set of legal parses of a sentence is pruned incrementally and probabilistically, based on flexible criteria. Although the core criteria are meant to be the traditional grammatical dependency rules taken from the lexis, they need not be limited to this. Thus, criteria that can sway parse likelihood potentially include the semantic classes and roles extracted from a partial parse obtained at a given point in time; such semantic relationships are typically not present in a traditional syntactic lexis. Dynamic likelihood criteria also allows for parsing to be guided by inter-sentence relationships, such as pronoun resolution, to disambiguate otherwise ambiguous sentences.
  - Inherent in parsing is assigning a likelihood or probability to a given parse. This probability is assembled from several sources, including an inherent strength of relationships (some disjuncts are inherently more appropriate than others), structural constraints (long range relationships and link-crossings are disfavored) as well as a combinatorial entropy of possible choices (“Sri Lanka” is a set phrase).

- A formalism for expressing semantic relationships is assumed.
  - A semantic relationship generalizes the notion of a lexical entry to allow for changes of word order, paraphrasing, tense, number, the presence or absence of modifiers, etc. An example of such a relationship would be $eat(X, Y)$ – indicating the eating of some entity $Y$ by some entity $X$. This abstracts into common form several different syntactic expressions: “Ben ate a cookie”, “A cookie will be eaten by Ben”, “Ben sat, eating cookies”.
  - Nothing particularly special is assumed here regarding semantic relationships, beyond a basic predicate-argument structure $WP-c$ $WP-a$. It is assumed that predicates can have arguments that are other predicates, and not just atomic terms; this has an explicit impact on how predicates and arguments are represented. A “semantic representation” of a sentence is a network of arrows (defining predicates and arguments), each arrow or a small subset of arrows defining a “semantic relationship”. However, the beginning or end of an arrow is not necessarily a single node, but may land on a subgraph. Because arrows may point from to to subgraphs, the resulting structure itself is no longer a graph in the proper sense, but a hypergraph.
  - Type constraints seem reasonable, but its not clear if these must be made explicit, or if they are the implicit result of learning. Thus, $eat(X, Y)$ requires that $X$ and $Y$ both be entities, and not, for example, actions or prepositions.

\[\text{Again, this is anchored on the observation that almost all dependencies are short, and rarely extend past the the first few nearest neighbors.}\]
• A formalism for expressing topics, themes and discourse structure is assumed.

- Topics, themes and general discourse structure are concepts that are probed at the more abstract levels of linguistic structure. A particularly appealing form of these, at least from the algorithmic, computer-science perspective, is Mel’čuk’s Meaning-Text Theory (MTT). [MPS71] [Kal03] The reason for this appeal is that the theory is based on a sequence of transformations on graphs (some of these apparently being ‘natural transformations’ in the category-theoretic sense), and thus amenable to precise formalization and an algorithmic treatment. A very short review of MTT is provided in an appendix.

- The formalism, insofar as it is ultimately graphical in nature, does not really extend much past that required for describing syntactic disjuncts or semantic relationships. Rather, the point here is that one can have not just 2-point relationships, such as eat(X, Y), but more generally, n-point relations which themselves may have some internal structure. Thus, one may write \( r(x_1, \ldots, x_n) \) for an n-point relation (or constraint) between objects, but also, specific relations may themselves have a hierarchical structure \( r(x_1, \ldots, r_k(y_1, \ldots, y_m), \ldots, x_n) \) encapsulating a required graphical sub-structure.

The above summarizes the basic software components and theoretical linguistic infrastructure that is presumed, entering into the exercise. To summarize the above from a computational or algorithmic viewpoint, it is presumed that linguistic relationships and dependencies can be captured in the form of relations \( r(x_1, \ldots, x_n) \), between items \( x_1, \ldots, x_n \), together with a parser (or pattern-matcher or constraint-solver) that can, given a lexicon of relations, and an input, can find a set of relations that, like puzzle-pieces, assemble to reproduce the input.

To be concrete, a Link Grammar connector \( S \) – can be more abstractly written as a relation \( r(w_1, w_\bullet, t = S) \) denoting that the current word \( w_\bullet \) must attach to a word \( w_l \) to the left, using a connector type \( S \). The Link Grammar constraint \& specifies that several connectors must be present and connected, and might be written as a relation \( r(c_1, c_2) \) where each \( c_k \) is a connector. The hierarchical nesting arises from the need to represent a Link Grammar disjunct. So, a transitive verb, normally expressed as \( S - & O+ \), might now be written as \( r(c(w_1, w_\bullet, t = S), c(w_\bullet, w_r, t = O)) \) indicating that the verb \( w_\bullet \) must have a subject \( w_l \) on the left and an object \( w_r \) on the right. However, in the abstract, such a relationship is not fundamentally different from one such as \( r(X, Y, s = eat) \) for the semantic relation \( eat(X, Y) \), or the relation \( r(f = magnitude, \text{noun} = \text{rain}, \text{modifier} = \text{torrential}) \) for the lexical function that associates magnitude modifiers with the object being modified.

The role of the parser is to take input at one abstraction level, and generate an output at the next abstraction level. At the lowest level, parsing consists of taking a string of words, and generating a set of dependency relationships. At the next level, parsing consists of taking a set of dependency relationships, and extracting semantic relationships. In either case, the only allowed parses are those that fulfill the constraints imposed by the (currently known) relationships. These constraints include structural relations (e.g. being to the left of) as well as type relations (e.g. being a noun).

The point here is that, although we listed the assumed infrastructure in linguistic terminology, the actual required infrastructure is not inherently linguistic: rather, it is a system of constraints, each enforced with some probability or strength, used to analyze an input, and discover the (graphical, typed relationship) structure within it. We believe that this generic infrastructure can be applied to domains outside of linguistics, but will not dwell further on this point here.

## 4 Linguistic Content To Be Learned

Given the above linguistic infrastructure, what remains for a language learning system to learn is the **linguistic content** that characterizes a particular language. Specifically, given the assumed framework, key items to be learned are listed below. These are listed roughly in order of sophistication and complexity, with the earlier elements being easier to learn, and being learnt earlier, than the later items.

Although the previous section concluded with an abstract view of the infrastructure, of being merely a collection of structural relationships, we revert back to a set of concrete tasks to be achieved. Thus we have the following:
• A list of 'link types' that will be used to form 'disjuncts' must be learned.

  – An example of a link type is the 'subject' link $S$. This link typically connects the subject of a sentence to the head verb. Given the normal English subject-verb word order, nouns will typically have an $S+$connector, indicating that an $S$ link may be formed only when the noun appears to the left of a word bearing an $S-$ connector. Likewise, verbs will typically be associated with $S-$ connectors. The current Link Grammar contains roughly one hundred different link-types, with additional optional subtypes that are used to further constrain syntactic structure. This number of different link types seems required simply because there are many relationships between words: there is not just a subject-verb or verb-object relationship, but also rather fine distinctions, such as those needed to form grammatical time, date, money, and measurement expressions, punctuation use, including street-addresses, cardinal and ordinal relationships, proper (given) names, titles and suffixes, and other highly constrained grammatical constructions. This is in addition to the usual linguistic territory of needing to indicate dependent clauses, comparatives, subject-verb inversion, and so on. It is expected that a comparable number of link types will need to be learned.

  – Some link types are rather strict, such as those that connect verb subjects and objects, while other types are considerably more ambiguous, such as those involving prepositions. This reflects the structure of English, where subject-verb-object order is fairly rigorously enforced, but the ordering and use of prepositions is considerably looser. When considering the looser cases, it becomes clear that there is no single, inherent 'right answer' for the creation and assignment of link types, and that several different, yet linguistically plausible linkage assignments may be made.

  – The definition of a good link-type is one that leads the parser – applied across the whole corpus – to allow parsing to be successful for almost all sentences, and yet not to be so broad as to enable parsing of word-salads. Significant pressure must be applied to prevent excess proliferation of link types, yet no so much as to over-simplify things, and provide valid parses for unobserved, ungrammatical sentences.

• Lexical entries for different words must be learned.

  – Typically, multiple connectors are needed to define how a word can link syntactically to others. Thus, for example, many verbs have the disjunct $S-\&O+$ indicating that they need a subject noun to the left, and an object to the right. All words have at least a handful of valid disjuncts that they can be used with, and sometimes hundreds or even more. Thus, a “lexical entry” must be learned for each word, the lexical entry being a set of disjuncts that can be used with that word.

  – Many words are syntactically similar; most common nouns can share a single lexical entry. Yet, there are many exceptions. Thus, during learning, there is a back-and forth process of grouping and ungrouping words; clustering them so that they share lexical entries, but also splitting apart clusters when its realized that some words behave differently. Thus for example, the words “sing” and “apologize” are both verbs, and thus share some linguistic structure, but one cannot say “I apologized a song to Vicky” because apologize is not a ditransitive verb; if these two verbs were initially grouped together into a common lexical entry, they must later be split apart.

  – The definition of a good lexical entry is much the same as that for a good link type: observed sentences must be parsable; random sentences mostly must not be, and excessive proliferation and complexity must be prevented.

We pause here to observe that the distinction between purely syntactic relations, and those with semantic overtones, can be blurry. Basic semantic content can be derived from exceptions to over-generalized syntactic rules, or from a narrowing of the applicability of such rules to finer classes. Thus, for example, “the book chased a squirrel” is not likely to be observed during a scan of a large corpus. This can be dealt with at the lexical level: it is a mistake to place “book” into a class of “nouns”; rather, it belongs to a class of “inanimate nouns”. Likewise, “chase” is not merely some transitive verb, but a verb that can only attach to animate subjects. With sufficient parsimony pressure, it seems reasonable that such finer semantic distinctions could be learned at what naively appears to be a purely syntactic level. The extent to which this might take place
depends heavily on the metaphoric content of the input corpus: a literary review might contain a sentence “the book chased an absurd premise” suggesting naively that books perhaps are animate. Again, semantic content can appear as exceptions to generalized rules.

- Semantic relationships must be learned.
  - The semantic relationship $eat(X,Y)$ is prototypical. Foundationally, such a semantic relationship may be represented as a set whose elements consist of syntactico-semantic subgraphs. For the relation $eat(X,Y)$, a subgraph may be as simple as a single (syntactic) disjunct $S - & O+$ for the normal word order “Ben ate a cookie”, but it may also be a more complex set needed to represent the inverted word order “a cookie was eaten by Ben”.
  - The task here is then to learn synonymous re-phrasings: not just sets of words that are synonyms, but phrases. These need not be centered on a verb, so that “Wyoming borders on Colorado” is synonymous to “Colorado is a neighbor of Wyoming”, and both are captured by a prepositional relation “next_to(Colorado, Wyoming)”. Such re-phrasings are at a different abstraction level from the syntactic parse level.
  - The set of all of these different subgraphs defines the semantic relationship. The subgraphs themselves may be syntactic (as in the examples above), or they may be other semantic relationships, or a mixture thereof.
  - Not all re-phrasings are semantically equivalent. “Mr. Smith is late” has a rather different meaning from “The late Mr. Smith.”
  - In general, place-holders like X and Y may be words or category labels. In early stages of learning, it is expected that X and Y are each just sets of words. At some point, though, it should become clear that these sets are not specific to this one relationship, but can appropriately take part in many relationships. In the above example, X and Y must be entities (physical objects), and, as such, can participate in (most) any other relationships where entities are called for. More narrowly, X is presumably a person or animal, while Y is a foodstuff. Furthermore, as entities, it might be inferred when these refer to the same physical object (see the section ‘reference resolution’ below).
  - Categories can be understood as sets of synonyms, including hyponyms (thus, “grub” is a synonym for “food”, while “cookie” is a hyponym.

- Idioms and set phrases must be learned.
  - English has a large number of idiomatic expressions whose meanings cannot be inferred from the constituent words (such as “to pull one’s leg”). In this way, idioms present a challenge: their sometimes complex syntactic constructions belies their often simpler semantic content. On the other hand, idioms have a very rigid word-choice and word order, and are highly invariant. Set phrases take a middle ground: word-choice is not quite as fixed as for idioms, but, none-the-less, there is a conventional word order that is usually employed. Note that the manually-constructed Link Grammar dictionaries contain thousands of lexical entries for idiomatic constructions. In essence, these are multi-word constructions that are treated as if they were a single word.

Each of the above tasks have already been accomplished and described in the literature; for example, automated learning of synonymous words and phrases has been described by Lin [LP01] and Poon & Domingos [PD09]. However, Lin and Poon & Domingos each assume the pre-existence of a syntactic dependency parser, rather than starting from ground zero. The authors are not aware of any attempts to learn all of these, together, in one go, rather than presuming the pre-existence of dependent layers.

Furthermore, no previous work has attempted to attack language learning in a fully abstract structural setting, although in some sense, work within the framework of Markov Logic Networks (MLN), such as that of Poon & Domingos, comes close. Taken at an abstract level, MLN combines several distinct components: the notion of a network or graph (and thus similar to the notion of a Bayesian network; the term “Markovian” referring to a certain independence assumption), the idea that a network can express first-order logic (or, more generally, the internal language of category theory), and finally, that unknowns must be distributed uniformly in probability space (by applying a maximum entropy principle). One difficulty with MLN is
common to all maximum-entropy (ME) approaches, and that is that solving for the Lagrange variables of the ME equations is an NP-hard problem: the potential function can be riddled with local maxima; hill-climbing may be slow and converge to an inappropriate solution. Thus, while in principle, it is useful to express fealty to the notion of evenly distributing unknowns, in practice, the algorithms can be slow to converge. As a result of this, another commonly successful approach is that of Bayesian networks (such as Hidden Markov Models). Here, probabilities are assigned by a different algorithm (following from a naïve application of Bayes theorem) that is usually far faster. However, the application of naïve Bayes almost immediately breaks down due to the need for independence assumptions. So, for example, while “Sri Lanka” is, formally, two distinct words, these cannot be treated independently of one another: it is nearly impossible, in English, to use the one word without the other, and so, from the combinatorial viewpoint, these must really count as only one word. Bayesian approaches typically have difficulty with counting. Thus, neither Bayesian nor MLN approaches are entirely satisfactory; a different algorithmic approach is sought, while keeping in place the fundamental concept of a network of relations.

Thus, to return to the abstract setting outlined at the end of the previous section: we wish to learn a lexis of relations \( r(x_1, \ldots, x_n) \). Treated as relations, these can be viewed as forming a “network”. Insofar as they are constraints with variables, they can be viewed as a form of “logic”, although the constraints are not those of first-order logic (as is amply clear from the Link Grammar operators & and “or”: these do not form a Boolean algebra, but rather a certain closed monoid). So here, we keep the general notion of a “network”, and recognize that the problem to be solved is to discover the relations, and to uniformly, fairly assign probabilities to each relation. The algorithm for discovering the relations, and to assigning appropriate probabilities and metrics, is discussed in the next section. But first, we continue expanding the linguistic horizon slightly.

### 4.1 Deep Comprehension

While the learning of syntactic and semantic relations is the primary focus of the discussion here, the search for semantic structure must not end there; more is possible. In particular, natural language generation has a vital need for lexical functions, so that appropriate word-choices can be made when vocalizing ideas. In order to truly understand text, one also needs, as a minimum, to discern referential structure, and sophisticated understanding requires discerning topics and themes. Discerning such structure seems to be a bare minimum for what it means to truly “comprehend” language. The aspects discussed here are taken from Meaning-Text Theory (MTT), briefly summarized in the appendix. Because these more abstract structures can again be viewed as graphical relations, and as transformations on the structure of graphs, then these too seem to be amenable to automated discovery.

A list of linguistic aspects that seem approachable are listed below. We believe automated, unsupervised learning of these aspects is attainable, building on top of the ‘simpler’ language language structures described above. We are not aware of any prior work aimed at automatically learning these, aside from relatively simple, unsophisticated (bag-of-words style) efforts at topic categorization. Learning these may prove to be extremely challenging, as the layered, recursive approach requires that the earlier syntactic and semantic levels be relatively “noise-free” in order for more complex, more abstract structures to be discerned. It is not yet clear that the earlier stages can achieve enough accuracy to allow these later stages to proceed. What’s more, two of these aspects is where linguistics meets the reality of the external world, and are arguably where “understanding” takes over from “semantics”. This is discussed further below.

So:

- Lexical functions should be learned.
  
  - Lexical functions are (named) classes of predicate-argument relationships. Thus, for example, the lexical function \( \text{MAGN}_1() \) specifies a list of appropriate words for expressing magnitude. One then has \( \text{MAGN}(\text{rain}) == \text{torrential—hard} \), \( \text{MAGN}(\text{wind}) == \text{strong} \) and \( \text{MAGN}(\text{emotion}) == \text{hot} \). Similarly, the subject lexical function \( S_1() \) indicates authorship, so \( S_1(\text{crime}) == \text{perpetrator}, S_1(\text{book}) == \text{author} \). Lists of synonyms and antonyms are also examples of lexical functions. In theories of semantics, such as Meaning-Text Theory, dozens of lexical functions are known and well-defined [MP87, Kah03, Mil06]; there may be more, but parsimony suggests that there cannot be thousands.
• Referential structure should be learned.

  – References may be pronouns, or references to external objects. For example, in “Patricia went to the store. She bought a dress.”, the word “she” refers to Patricia. In fact, the words “dress” may also refer to a specific object in the observer’s environment; however, such a reference cannot be obtained by purely corpus-linguistic methods. That said, in a prolonged discussion about a dress, it should be possible to infer, without external cues, that the entire discussion is about the same, singular dress, as opposed to a different dress every time the word appears.

  – Referential structure requires a model of the external world, a model of “other” and possibly a model of “self”. That is, in order to understand that the word “dress” always refers to the same object requires that there be a model of the world in which there is one distinctive dress which can be the object of discussion. Likewise many pronomial constructions require models of other actors, and also a model of self as an actor, in order to be properly understood.

• Topic themes/communicative intent should be learned.

  – Semantic-communicative structure captures the communicative intent; it partitions a semantic structure graph into two parts: the ‘theme’ (what is being talked about) and the ‘rheme’ (what is being said about the theme). A semantic structure is just a graph of the semantic relationships extracted from a sentence. Consider the (rather sophisticated) sentence: “The senator harshly criticized the Government for its decision to increase income taxes”. This graph will contain semantic relations such as criticize(X,Y,Z), which is to be understood as ‘X criticizes Y for Z’; this relation has three arrows from ‘criticize’ to X, Y and Z. Other arrows link these in turn, to form a directed graph. One partitioning of this graph is to take “Government’s decision to increase income taxes” as the theme, and “the senator’s harsh criticism” as the rheme. This partitioning is appropriate when entire paragraphs are devoted to the Government’s decision; the Senator’s criticism is but one statement that pops up.

  – Note that the above partitioning presumes that a rather sophisticated referential structure has already been extracted: the theme should appear in multiple sentences, and even in multiple paragraphs, and should already have been identified as ‘one and the same thing’ across these various appearances.

  – This partitioning is not unique. One can also take “the Senator” as the theme, and “criticism of government policy” as the rheme. Such a partitioning would be appropriate when reading the Senator’s biography. In other words, topics and themes cannot be discerned from single sentences alone, but only become apparent from relationships across many paragraphs.

The point here is that there are deeper structures in text, and that these seem like they might be discernible in a mechanistic fashion. This belief is built on the observation that these structures also take the form of graphical relations. Whether the lower syntactic and semantic relations are clean and coherent enough for these more abstract structures to be discerned is unclear.

At any rate, the referential structure is where language meets reality. Natural language understanding, at this point, requires that a model of the external world be accessible, so that referents can be attached to the objects to which they might refer. This is again an act of “parsing”, of joining the unattached ends of referential connectors to the parts of the external world to which they might plausibly refer to, and then checking the entire structure, by means of transitive reasoning, for consistency. We use the word “transitive” here in the same sense that one defines the “transitive closure” of a relation: so, for example, if John says he was bitten by an animal, and our model of the external world indicates that a dog was present, one may then conclude that the “animal” refers to that particular dog, by the application of a single joining relation: a dog is an animal. At any rate, these observations should make clear that this is where learning stops being about language, and instead turns into something else. The something else is different and harder: it requires models of the external world, and it requires reasoning, so that the model of the external world can be manipulated to align with the topic of conversation.

This also implies that the order of learning proposed here is reversed from the normal direction in humans: children first construct models of the external world based on visual inputs; these models are then adorned
with associated sounds, which eventually resolve into words, due to their regularity. The regularity of syntax is the last to be discerned, not the first. Doing the same in a disembodied context is far, far harder: how does one discern that the external world consists of persistent objects that have names (nouns) and are in changing relationships to one-another (verbs)? Because of this reversed order, it is quite possible that the learning proposed here will founder shortly after the syntactic stage, falling far short of creating a sensory perception model. At any rate, the proposal here entirely omits any mechanism for constructing a model of the external world, and correlating language with it.

5 A Methodology for Unsupervised Language Learning from a Large Corpus

The language learning approach presented here is novel in its overall nature. Each part of it, however, draws on prior experimental and theoretical research by others on particular aspects of language learning, as well as on our own previous work building computational linguistic systems. The goal is to assemble a system out of parts that are already known to work well in isolation.

Prior published research, from a multitude of authors over the last few decades, has already demonstrated how many of the items listed above can be learnt in an unsupervised setting (see e.g. [Yur98, KM04, LP01, CS10, PD09, SM07, KSPC13] for relevant background). All of the previously demonstrated results, however, were obtained in isolation, via research that assumed the pre-existence of surrounding infrastructure far beyond what we assume above. The approach proposed here may be understood as a combination, generalization and refinement these techniques, to create a system that can learn, more or less ab initio from a large corpus, with a final result of a working, usable natural language comprehension system.

Thus, in some sense, the approach advocated here can be considered to be a mash-up of techniques. However, a concomitant task is to formalize the underlying mathematics of the undertaking, so that it becomes clear what approximations are being taken, and what avenues remain unexplored. Some fairly specific directions in this regard suggest themselves, not the least of which is the need to write down appropriate formulations for the distribution of probabilities, and the inequalities that must hold in order for a learning event to occur.

Much of the prior research alluded to above makes use of probabilistic arguments, usually with the implicit desire of treating unknowns fairly and evenly. In Bayesian arguments, this amounts to a statement about priors and assumptions about independence. In maximum-entropy methods, the goal is to explicitly distribute unknown probabilities as evenly as possible. Quite often, an approach is ad hoc, with some arbitrary but plausible metric providing a utility function that can be maximized or minimized. Each approach has its pros and cons: independence assumptions get Bayesian methods into trouble; the complexity of the entropic partition function can sometimes make maximum entropy methods intractable, while the ad hoc nature of ad hoc approaches stymie a broader theoretical vision for the correct generalization of a phenomenon.

The approach advocated below takes a pragmatic stance. That is, while maximum entropy principles would seem to provide the correct theoretical framework, they also require that it be clearly understood what is being counted (so that the entropy can be correctly measured). Thus, there is room for applying more traditional probabilistic reasoning, and even ad hoc simplifications and short-cuts. As in most scientific disciplines, progress here is best achieved by coupling experimental exploration to theoretical and mathematical development.

5.1 A High Level Perspective on Language Learning

On an abstract conceptual level, the approach proposed here depicts language learning as an instance of a general learning loop such as:

1. Observe structural relationships between linguistic entities (such as words, or other entities described in previous sections). Find frequently occurring and novel relationships: this can be done by means of mutual information (for example), which adjusts for the novelty of a (conditional) relationship by properly weighting it by the occurrence frequency of the conditions in other contexts. That is, mutual information is one good way to pluck novel relationships out of a sea of white noise.
2. Give each structural relationship a (unique) name. The name is required so that it can be counted and held and worked with.

3. Treat each structure relationship as a constraint: relations that are not seen are assumed to be prohibited. That is, there is no corpus of grammatically incorrect sentences; rather, incorrectness is inferred from silence. New inputs are grammatically “parsable” insofar as they are consistent with the relationships (constraints) that have been observed before.

4. Group together similar structural relationships. This is the application of the law of parsimony, or of “Occam’s razor”: simply making a list of all possible observed relationships, as suggested by steps 1 and 2, can result in very long lists; a shorter description is desired. That is, one valid way of specifying a language is to provide an infinite list of grammatically correct sentences. Such a list is not at all compact; one wishes to group together similar sentences. Steps 1 and 2 suggest how to find the patterns about which one should group; there remains the actual task of grouping, which is this step. Grouping can be done using ad hoc distance metrics, to discover similar things. Grouping can also be done by entropy minimization (not maximization!) methods: cutting a list down to $N$ items from $2^N$ items by grouping reduces the entropy by $\log 2 = \log 2^N - \log N$.

5. For each such grouping make a category label, and add it to the lexis of expected relations.

6. Return to Step 1, and restart observations, but this time, doing so in terms of the known, expected relations. So, for example, if the previous round of observations lead to the discovery of groupings such as nouns and determiners, and the fact that these occur in immediate proximity to one-another, then this should be taken as a “known” aspect of language. Armed with this relationship, perhaps other relationships can now become clear, such as that nouns can sometimes be subjects, and sometimes objects of verbs. With each iteration, new relationships presumably emerge; however, they cannot become visible or clear until all “known” aspects are already accounted for. Learning a set of constraints sets a new baseline; deviations from the new baseline, if they are strong enough, are candidates for new relations. Thus the iterative nature of the algorithm.

It stands to reason that the result of this sort of learning loop, if successful, will be a hierarchically composed collection linguistic relationships possessing the following **Linguistic Coherence Property**: Linguistic entities are reasonably well characterizable in terms of the compactly describable patterns observable in their relationship with with other linguistic entities.

This sort of property has observed to hold for many linguistic entities, an observation dating back at least to Saussure [1977] and the start of structuralist linguistics. It is basically a fancier way of saying that the meanings of words and other linguistic constructs, may be found via their relationships to other words and linguistic constructs. We are not committed to structuralism as a theoretical paradigm, and we have considerable respect for the aid that non-linguistic information – such as the sensorimotor data that comes from embodiment – can add to language, as stressed in prior publications [Goehl08]. However, the potential utility of non-linguistic information for language learning does not imply the impossibility or infeasibility of learning language from corpus data alone. It is inarguable that non-linguistic relationships comprise a significant portion of the everyday meaning of linguistic entities; but yet, redundancy is prevalent in natural systems, and we believe that purely linguistic relationships may well provide sufficient data for learning of natural languages. If there are some aspects of natural language that cannot be learned via corpus analysis, it seems difficult to identify what these aspects are via armchair theorizing, and likely that they will only be accurately identified via pushing corpus linguistics as far as it can go.

This generic learning process is a special case of the general process of symbolization, described in [Goehl94] and elsewhere as a key aspect of general intelligence. In this process, a system finds patterns in itself and its environment, and then symbolizes these patterns via simple tokens or symbols that become part of the system’s native knowledge representation scheme (and hence parts of its “metalanguage” for describing things to itself). Having represented a complex pattern as a simple symbolic token, it can then easily look at other patterns involving this patterns as a component.

Note that in its generic format as stated above, the “language learning loop” is not restricted to corpus based analysis, but may also include extralinguistic aspects of usage patterns, such as gestures, tones of voice,
and the physical and social context of linguistic communication. Linguistic and extra-linguistic factors may
come together to comprise "usage patterns." However, the restriction to corpus data does not necessarily
denude the language learning loop of its power; it merely restricts one to particular classes of usage patterns,
whose informativeness must be empirically determined.

In principle, one might be able to create a functional language learning system based only on a very
generic implementation of the above learning loops. In practice, however, biases toward particular sorts of
usage patterns can be very valuable in guiding language learning. In a computational language learning
context, it may be worthwhile to break down the language learning process into multiple instances of the
basic language learning loops, each focused on different sorts of usage patterns, and coupled with each other
in specific ways. This is in fact what we will propose here.

Specifically, the language learning process proposed here involves:

• One language learning loop for learning purely syntactic linguistic relationships (such as link types and
  lexical entries, described above), which are then used to provide input to a syntax parser.

• One language learning loop for learning higher-level "syntactico-semantic" linguistic relationships (such
  as semantic relationships, idioms, and lexical functions, described above), which are extracted from
  the output of the syntax parser.

• One language learning loop for associating the resulting syntactico-semantic relationships to a model
  of the external world.

These three loops are not independent of one-another; the second loop can provide feedback to the first,
regarding the correctness of the extracted structures; then as the first loop produces more correct, confident
results, the second loop can in turn become more confident in it’s output. Likewise, the third loop selects
proper interpretations for the output of the second loop. In this sense, the three loops attack the same sort
of slow-convergence issues that 'deep learning' tackles in neural-net training.

The syntax parser itself, in this context, is used to extract directed acyclic graphs (dags), usually trees,
from the graph of syntactic relationships associated with a sentence. These dags represent parses of the
sentence. So the overall scope of the learning process proposed here is to learn a system of relationships
that displays appropriate coherence and that, when applied by an appropriate parser to the
inputs from the previous layer, will yield parse trees that reflect the information content in
the input. The sensory input at the lowest layer is raw text; the output is parse trees, which are then fed
as input to the next layer. The process is repeated, until a sufficiently abstract form is obtained, such that
it can be correlated with model of the external world.

5.2 Learning Syntax

The process of learning syntax from a corpus may be understood fairly directly in terms of entropy max-
imization. As a simple example, consider the measurement of the entropy of the arrangement of words in
a sentence. To a fair degree, this can be approximated by the sum of the mutual entropy between pairs
of words. Yuret showed that by searching for and maximizing this sum of entropies, one obtains a tree
structure that closely resembles that of a dependency parse\textsuperscript{[Yur98]}. That is, the word pairs with the highest
mutual entropy are more or less the same as the arrows in a dependency parse, such as that shown in figure
1. Thus, an initial task is to create a catalog of word-pairs with a large mutual entropy (mutual information,
or MI) between them. This catalog can then be used to approximate the most-likely dependency parse of a
sentence.

The link-types of such an unlabeled parse tree should be taken as unique to each word-pair; that is, there
is a unique link type to connect any two (connectable) words. For a typical modern language, this implies
many millions of distinct link types; from the syntactic viewpoint, this is intolerable, its an overly complex
description of language. The immediately obvious course of action is to somehow group together different
link types, reducing their number. But if different words share a common link type, then perhaps the words
should also be grouped together into common classes. The result of such grouping presumably results in the
automated discovery of something similar to part-of-speech groupings. So, for example, the computation of
word-pair MI is likely to reveal the following high-MI word pairs: "big car", "fast car", "expensive car", "red
car". (Such word pairs have been previously observed in earlier MI experiments.) It is intuitively obvious
that one may group together the words big, expensive, fast and red into a single category, interpreted as modifiers to car. But how might the correctness of such a grouping be automatically verified? The answer is relatively straight-forward: the same modifier grouping can be observed acting on other nouns: e.g. “big bicycle”, “fast bicycle”, etc. Two effects are at play here: a reinforcement of the correctness of the original grouping of modifiers, but also the suggestion that perhaps cars and bicycles should be grouped together. Superficially, it appears that one can discover two classes of words from this example: modifiers and nouns; crudely put, parts of speech.

More importantly, the discovery comes about through a reduction in the total number of syntax rules at play: rather than having to “remember” (log, record) millions of unique word pairs, it is sufficient to remember a smaller number of word classes, and a smaller number of link types to connect them. Entropy is defined as the logarithm in the total number of states; complexity may be defined as the entropy in a set of rules; such clustering is a reduction of the total complexity of the syntactic description. This is biologically plausible: the human mind does not maintain millions of syntactic relations, but an apparently much smaller set, possibly in the hundreds, or less.

There is an interesting mathematical foundation for understanding the role of link types; it comes from categorial grammar [KSPC13]. The link between two word classes carries a type; the type of that link is defined by these two classes. In this example, a link between a modifier and a noun would be a type denoted as M,N in categorial grammar, M denoting the class of modifiers, and N the class of nouns. In Link Grammar, this type name is replaced by a shorter link name, without a slash, but is the same thing. (So, for this example, the existing Link Grammar dictionaries use the A link for the M,N type, with A meant to conjure up ‘adjective’ as a mnemonic.) The short link name is a boon for readability, as categorial grammars usually have very complex-looking link-type names: e.g. (NP|S)/NP for the simplest transitive verbs. The point being made here is that typing and type theory [Pro13] provide a good foundation for dealing with the difficulty of ‘naming things’ discovered through classification and clustering. The contents of a cluster is, in a certain sense, ad hoc, and based on what the texts that have been ingested. The relations between clusters, however, are not: not only are they dictated by language, but also come with an algebra describing how they combine: this is type theory. In that sense, typing seems to be an inherent part of language; type theory appears to provide the correct formalization for discussing it.

The Link Grammar dictionaries contain lists of disjuncts, not lists of word-pairs. The last step of learning a workable grammar is then to discover the disjuncts. This may be done by performing a minimum-spanning-tree (MST) parse of input text [MPRH05, MLP06], driven entirely by the mutual information obtained between word-pairs. Given that each link is implicitly labeled by the two words it joins, the word connectors are trivially extracted as the link type, together with a direction indicator. A disjunct is then simply the ordered list of all of the connector that land on a given word. Thus, disjuncts can be extracted on a sentence-by-sentence basis after a pass through an MST parser. This then sets the stage for the next step of pattern recognition.

Given a single word, appearing in many different sentences, one should presumably find that this word only makes use of a relatively small, limited set of disjuncts. It is then a counting exercise to determine which disjuncts occur the most often for this word, and more, what the disjuncts mutual information should be. The set of these disjuncts then form this word’s lexical entry. Similar to the discovery of high-MI word pairs, this devolves into another ”counting exercise”. Because the structures being discovered are now subgraphs, instead of word pairs, this is sometimes called “frequent subgraph mining”. This term is somewhat misleading: it is not the absolute frequency of occurrence of the subgraph that is important, but its relative (conditional) frequency, conditioned on the frequency of the other parts of the graph that it connects to. The logarithm of the conditional probability is called the relative entropy, or mutual information, and so the counting exercise has again devolved into the computation of MI of structures extracted from a corpus. An appendix gives formulas to make these words precise; it is given because a proper definition appears to be rare in the linguistic literature.

At this point, a second clustering step may be applied: its presumably noticeable that many words use more-or-less the same disjuncts in syntactic constructions. These can then be grouped into a common lexical entry. Given that a different set of word groupings (into parts of speech) was previously generated, one may ask: how does that grouping compare to this grouping? Is it close, or can the groupings be refined? If the groupings cannot be harmonized, then perhaps there is a certain level of detail that was previously missed: perhaps one of the groups should be split into several parts. Conversely, perhaps one of the groupings
was incomplete, and should be expanded to include more words. Thus, there is a certain back-and-forth feedback between these different learning steps, with later steps reinforcing or refining earlier steps, forcing a new revision of the later steps. The precise refinement of how this is to be done awaits experimental trials.

5.2.1 Loose language

A recognized difficulty with the direct application of Yuret’s observation (that the high-MI word-pair tree is essentially identical to the dependency parse tree) is the flexibility of the preposition in the English language [KMD1]. The preposition is so widely used, in such a large variety of situations and contexts, that the mutual information between it, and any other word or word-set, is rather low (is uniformly distributed, and thus carries little information). The two-point, pair-wise mutual entropy provides a poor approximation to what the English language is doing in this particular case. It appears that the situation can be rescued with the use of a three-point mutual information (a special case of interaction information [Bel03]).

The discovery and use of such constructs is described in [PD09]. A similar, related issue can be termed “the richness of the MV link type in Link Grammar”. This one link type, describing verb modifiers (which includes prepositions) can be applied in a very large class of situations; as a result, discovering this link type, while at the same time limiting its deployment to only grammatical sentences, may prove to be a bit of a challenge. Even in the manually maintained Link Grammar dictionaries, it can present a parsing challenge because so many narrower cases can often be treated with an MV link. In summary, some constructions in English are so flexible that it can be difficult to discern a uniform set of rules for describing them; certainly, pair-wise mutual information seems insufficient to elucidate these cases.

Curiously, these more challenging situations occur primarily with more complex sentence constructions. Perhaps the flexibility is associated with the difficulty that humans have with composing complex sentences; short sentences are almost 'set phrases', while longer sentences can be a semi-grammatical jumble. In any case, some of the trouble might be avoided by limiting the corpus to smaller, easier sentences at first, perhaps by working with children’s literature at first.

5.2.2 Elaboration of the Syntactic Learning Loop

We now reiterate the syntactic learning process described above in a more systematic way. By getting more concrete, we also make certain assumptions, and restrictions, some of which may end up getting changed or lifted in the course of implementation and detailed exploration of the overall approach proposed here. What is discussed in this section is merely one simple, initial approach to concretizing the core language learning loop we envision in a syntactic context.

Syntax, as we consider it here, involves the following basic entities:

- words
- categories of words
- ”co-occurrence links”, each one defined as (in the simplest case) an ordered pair or triple of words, labeled with frequency counts and mutual information
- ”syntactic link types”, each one defined by the two sets of words that are connected
- ”disjuncts”, each one associated with a particular word \( w \), and consisting of an ordered set of link types that connect to the word \( w \). That is, each of these links contains at least one word-pair containing \( w \) as first or second argument. (This nomenclature here comes from Link Grammar; each disjunct is a conjunction of link types. A word is associated with a set of disjuncts. In the course of parsing, one must choose between the multiple disjuncts associated with a word, to fulfill the constraints required of an appropriate parse structure.)

An elementary version of the basic syntactic language learning loop described above would take the form.

1. Search for high-MI word pairs. Define an initial set of word-pair link types as the given co-occurrence links.

2. Cluster words into categories based on the similarity of their associated usage links
Note that this will likely be a tricky instance of clustering, and classical clustering algorithms may not perform well. One interesting, less standard approach would be to use OpenCog’s MOSES algorithm to learn an array of program trees, each one serving as a recognizer for a single cluster.

3. Define initial syntactic link types from categories that are joined by large bundles of usage links

That is, if the words in category $C_1$ have a lot of usage links to the words in category $C_2$, then create a syntactic link type whose elements are $(w_1, w_2)$, for all $w_1 \in C_1, w_2 \in C_2$. Remove the word-pair link types associated with $(w_1, w_2)$, as these are now all subsumed by the new link type.

4. Associate each word with an extended set of usage links, consisting of: its existing usage links, plus the syntactic links that one can infer for it based on the categories the word belongs to. These are the “disjuncts” of Link Grammar. Typically, determiners and adjectives have just one link (linking to the modified noun), nouns have one or two links (one to an adjective, one to a verb) while verbs typically have three or four links (one to a subject, one to an object, possibly a link to a particle or preposition or other adverb, and one to the head).

For example, suppose $cat \in C_1$ and $C_1$ has syntactic link $L_1$. Suppose $(cat, eat)$ and $(dog, run)$ are both in $L_1$. Then if there is a sentence ”The cat likes to run”, the link $L_1$ lets one infer the syntactic link $cat \xrightarrow{L_1} run$. The corpus is re-scanned to obtain the frequency of this syntactic link, as well as its mutual information (logarithm of the conditional probability).

Given the sentence ”The cat likes to run in the park,” a chain of syntactic links such as $cat \xrightarrow{L_1} run \xrightarrow{L_2} park$ may be constructed.

5. Look for commonality between disjuncts. This may indicate clusterings of words or link-types that were previously missed; alternately, these may indicate that previous clusterings were excessively aggressive.

6. Return to Step 2, but using the extended set of usage links produced in Step 4, with the goal of refining clusters, the set of link types, and the set of disjuncts for accuracy. Initially, all categories contain one word each, and there is a unique link type for each pair of categories. This is an inefficient representation of language, and so the goal of clustering is to have a relatively small set of clusters and link types, with many words/word-pairs assigned to each. This can be done by maximizing the sum of the logarithms of the sizes of the clusters and link types; that is, by maximizing entropy. Since the category assignments depend on the link types, and vice versa, a (very?) large number of iterations of the loop are likely to be required. Based on the current Link Grammar English dictionaries, one expects to discover hundreds of link types (or more, depending on how subtypes are counted), and perhaps a thousand word clusters (most of these corresponding to irregular verbs and idiomatic phrases).

Many variants of this same sort of process are conceivable, and it’s currently unclear what sort of variant will work best. But this kind of process is what one obtains when one implements the basic language learning loop described above on a purely syntactic level.

How might one integrate semantic understanding into this syntactic learning loop? Once one has semantic relationships associated with a word, one uses them to generate new ”usage links” for the word, and includes these usage links in the algorithm from Step 1 onwards. This may be done in a variety of different ways, and one may give different weightings to syntactic versus semantic usage links, resulting in the learning of different links.

The above process would produce a large set of syntactic links between words. We then find a further series of steps. These may be carried out concurrently with the above steps, as soon as Step 4 has been reached for the first time.

1. Given the set of disjuncts, one carries out parsing using a process such as link parsing or word grammar parsing, thus arriving at a set of parses for the sentences in one’s reference corpus. Alternative parses may be ranked according to the total mutual information, summed over all disjuncts. Each parse may be viewed as a directed acyclic graph (dag), usually a tree, with words at the nodes and syntactic-link type labels on the links.
2. This allows a different set of statistics to be gathered for each disjunct: how often it proves actually useful during (link-typed) parsing. That is, the initial probabilities and entropies for the disjuncts essentially followed from how often they are employed by an MST parser, which generates a spanning tree essentially without regard to the link types. Re-parsing, this time with actual link type agreement enforced, will presumably give similar parses, but presumably more accurate ones. In addition, the usage probabilities will change as a result.

   In particular, forcing link type agreement might cause some words to be missed in the parse. For an MST parse, this is not an issue: one simply hunts for some high-MI connection, and attaches to that. With link types, there may be no valid linkage at all. This suggests the existence of a problem with the current link type and disjunct assignments: these are somehow incomplete, if they fail to link all the words in the sentence. In essence, link parsing is stricter than MST parsing; the strictness is a source of feedback for validating the grammar.

3. One can now return to Step 2 using the new probabilities, which should suggest new and refined clusters.

Several subtleties have been ignored in the above, such as the proper discovery and treatment of idiomatic phrases, the discovery of sentence boundaries, the handling of embedded data (price quotes, lists, chapter titles, etc.) as well as the potential speed bump that are prepositions. Fleshing out the details of this loop into a workable, efficient design is the primary engineering challenge. This will take significant time and effort.

5.3 Learning Semantics

Syntactic relationships provide only the shallowest interpretation of language; semantics comes next. One may view semantic relationships (including semantic relationships close to the syntax level, which we may call "syntactico-semantic" relationships) as ensuing from syntactic relationships, via a similar but separate learning process to the one proposed above. Just as our approach to syntax learning is heavily influenced by our work with Link Grammar, our approach to semantics is heavily influenced by our work on the RelEx system \cite{RVG05, LGE10, GPPG06, LGK12}, which maps the output of the Link Grammar parser into a more abstract, semantic form. Prototype systems \cite{GPA10, LGK12} have also been written mapping the output of RelEx into even more abstract semantic form, consistent with the semantics of the Probabilistic Logic Networks \cite{CGH08} formalism as implemented in the OpenCog \cite{HG08} framework. These systems are largely based on hand-coded rules, and thus not in the spirit of language learning pursued in this proposal. However, they display the same structure that we assume here: the difference being that here we specify a mechanism for learning the linguistic content that fills in the structure via unsupervised corpus learning, obviating the need for hand-coding.

Specifically, we suggest that discovery of semantic relations can proceed in a manner similar to the unsupervised discovery of synonyms, such as that described in \cite{LP01}, or it’s generalization from 2-point relations to 3-point and N-point relations, as described in \cite{PD09}. These mechanisms allow the automatic, unsupervised recognition of synonymous phrases, such as “Texas borders on Mexico” and “Mexico is Texas neighbor”, to extract the general semantic relation $\text{next}_\text{to}(X,Y)$, and the fact that this relation can be expressed in one of several different ways.

Simplistically stated, the idea is that semantic learning can proceed by scanning the corpus for sentences that use similar or the same words, yet employ them in a different order, or have point substitutions of single words, or of small phrases. Sentences which are very similar, or identical, save for one word, offer up candidates for synonyms, or sometimes antonyms. Sentences which use the same words, but in seemingly different syntactic constructions, are candidates for synonymous sentences. These may be used to extract semantic relations: the recognition of sets of different syntactic constructions that carry the same meaning. In practice, the comparisons and search for similarity is not made on the raw text strings, but on the parsed forms of the sentences, so as to avoid issues of word alignment during comparison. Parsing establishes a graph that provides a context for differences in subgraphs.

In essence, similar parse structures must be recognized, and then word and parse-tree differences between other-wise similar parse graphs are compared. There are two primary challenges: how to recognize similar
graphs, and how to assign probabilities.

The work of [PD09] articulates solutions to both challenges. For the first, it describes a general framework in which relations such as \textit{next-to}(X,Y) can be understood as lambda-expressions $\lambda x \lambda y. \text{next-to}(x,y)$, so that one can employ first-order logic constructions in place of graphical representations. This is partly a notational trick; it just shows how to split up input syntactic constructions into atoms and terms, forming a term algebra with signature \textit{BN99} [Hor97]. For the second challenge, they show how probabilities can be assigned to the atoms and terms, by making explicit use of the notions of conditional random fields (or rather, a certain special case, termed Markov Logic Networks). Conditional random fields, or Markov networks, are a mathematical formalism that describes how entropy can be uniformly distributed across a graphical network where edges and vertices may both be typed, and range over a domain of values. As such, this generalizes a basic, fundamental theorem from information theory, that the probability distribution that most evenly distributes unknowns or priors is the same as the probability distribution that maximizes the entropy \textit{Ash95}. Unfortunately, the general theory has several drawbacks: it is quite abstract and dense, and algorithmically, it falls into the NP-hard class of problems.

The procedures described in [LP01] thus provide a much simpler, easier-to-understand introduction to how semantic information can be extracted. With that simplicity comes two faults: a lack of proper mathematical grounding means that it is not clear how to generalize the work to sub-graphs of arbitrary shape (which is provided by Poon & Domingos), nor is the generalized probabilistic framework articulated. Instead, Lin gets by with a number of \textit{ad hoc} metrics used to measure semantic similarity. This may be a reasonable approach: the \textit{ad hoc} similarity metrics have the side effect of taking the NP-hard maximum entropy algorithm and replacing it with a simpler, more rapidly convergent method.

The above can be used to extract synonymous constructions, and, in this way, semantic relations. However, neither of the above references deal with distinguishing different meanings for a given word. That is, while \textit{eats}(X,Y) might be a learnable semantic relation, the sentence \textit{He ate it} does not necessarily justify its use. Of course: \textit{He ate it} is an idiomatic expression meaning \textit{he crashed}, which should be associated with the semantic relation \textit{crash}(X), not \textit{eats}(X,Y). There are global textual clues that this may be the case: trouble resolving the reference \textit{“it”}, and a lack of mention of foodstuffs in neighboring sentences. A viable yet simple algorithm for the disambiguation of meaning is offered by the Mihalcea algorithm \textit{Mih05} [SM07]. This is an application of the (Google) PageRank algorithm to word senses, taken across words appearing in multiple sentences. The premise is that the correct word-sense is the one that is most strongly supported by senses of nearby words; a graph between word senses is drawn, and then solved as a Markov chain. In the original formulation, word senses are defined by appealing to WordNet, and affinity between word-senses is obtained via one of several similarity measures. Neither of these can be applied in learning a language \textit{de novo} (one has neither a WordNet for the language, nor any similarity measures). Instead, these must both be deduced by clustering and splitting, again. So, for example, it is known that word senses correlate fairly strongly with disjuncts (based on authors unpublished experiments)\textsuperscript{3} and thus, a reasonable first cut is to presume that every different disjunct in a lexical entry conveys a different meaning, until proved otherwise. The above-described discovery of synonymous phrases can then be used to group different disjuncts into a single \textit{“word sense”}. Disjuncts that remain ungrouped after this process are already considered to have distinct senses, and so can be used as distinct senses in the Mihalcea network.

Sense similarity measures can then be developed by using the above-discovered senses, and measuring how well they correlate across different texts. That is, if the word \textit{“bell”} occurs multiple times in a sequence of paragraphs, it is reasonable to assume that each of these occurrences are associated with the same meaning. Thus, each distinct disjunct for the word \textit{“bell”} can then be presumed to still convey the same sense. One now asks, what words co-occur with the word \textit{“bell”?} The frequent appearance of \textit{“chime”} and \textit{“ring”} can and should be noted. In essence, one is once-again computing word-pair mutual information, except that now, instead of limiting word-pairs to be words that are near each other, they can instead involve far-away

\textsuperscript{3}This can be understood in a simple, intuitive fashion. Traditional dictionary entries are grouped according to the part of speech of a word: different parts of speech are associated with different word senses. The Link Grammar disjunct is like an extremely fine-grained part of speech: it distinguishes not only between noun and verb, but also between the contexts in which it is used (transitive, ditransitive, with or without modifiers, quantifiers, determiners, particles, etc.) That word senses might correlate with this fine-grained part of speech should come as no surprise. Such correlation is not unique to Link Grammar; it should be directly observable in any dependency grammar. The correlation might be harder to detect in phrase-structure grammars, since lexical entries are not words, but phrase structures, and thus its not obvious how to correlate word senses to phrase structures.
words, several sentences apart. One can then expand the word sense of “bell” to include a list of co-occurring
words (and indeed, this is the slippery slope leading to set phrases and eventually idioms).

Failures of co-occurrences can also further strengthen distinct meanings. Consider “he chimed in” and
“the bell chimed”.

In both cases, chime is a verb. In the first sentence, chime carries the disjunct S- & K+ (here, K+ is the standard Link Grammar connector to particles) while the second has only the simpler
S-. Thus, based on disjunct usage alone, one already suspects that these two have a different
meaning. This is strengthened by the lack of occurrence of words such as “bell” or “ring” in the first case,
with a frequent observation of words pertaining to talking.

There is one final trick that must be applied in order to get reasonably rapid learning; this can be loosely
thought of as “the sigmoid function trick of neural networks”, though it may also be manifested in other
ways not utilizing specific neural net mathematics. The key point is that semantics intrinsically involves a
variety of uncertain, probabilistic and fuzzy relationships; but in order to learn a robust hierarchy of semantic
structures, one needs to iteratively crispen these fuzzy relationships into strict ones.

In much of the above, there is a recurring need to categorize, classify and discover similarity. The naivest
means of doing so is by counting, and applying basic probability (Bayesian, Markovian) to the resulting
counts to deduce likelihoods. Unfortunately, such formulas distribute probabilities in essentially linear ways
(i.e. form a linear algebra), and thus have a rather poor ability to discriminate or distinguish (in the sense
of receiver operating characteristics, of discriminating signal from noise). Consider the last example: the
list of words co-occurring with chime, over the space of a few paragraphs, is likely to be tremendous. Most
of this is surely noise. There is a trick to over-coming this that is deeply embedded in the theory of neural
networks, and yet completely ignored in probabilistic (Bayesian, Markovian) networks: the sigmoid function.
The sigmoid function serves to focus attention on a single stimulus, and elevate its importance, and, at the
same time, strongly suppress all other stimuli. In essence, the sigmoid function looks at two probabilities,
say 0.55 and 0.45, and says “let’s pretend the first one is 0.9 and the second one is 0.1, and move forward
from there”. It builds in a strong discrimination to all inputs. In standard, text-book probability theory,
such discrimination is utterly unwarranted; it runs counter to probability theory. However, applying strong
discrimination to learning can help speed learning by converting certain vague impressions into certainties.
These certainties may be correct or incorrect; it is the task of learning to distinguish the two. The point
here is that this non-linear behavior provides a kind of amplification, which allows vague impressions to be
converted into certainties that can then be built upon to obtain additional certainties.

Thus, in all of the above efforts to gauge the similarity between different things, it is useful to have a sharp
yes/no answer, rather than a vague muddling with likelihoods. In some of the above-described algorithms,
this sharpness is already built in: so, Yuret approximates the mutual information of an entire sentence as the
sum of mutual information between word pairs: the smaller, unlikely corrections are discarded. Clearly, they
must also be revived in order to handle prepositions. Something similar must also be done in the extraction
of synonymous phrases, semantic relations, and meaning: the domain is that much likelier to be noisy, and
thus, the need to discriminate signal from noise that much more important.

5.3.1 Elaboration of the Semantic Learning Loop

We now provide a more detailed elaboration of a simple version of the general semantic learning process
described above. The same caveat applies here as in our elaborated description of syntactic learning above:
the specific algorithmic approach outlined here is a simple instantiation of the general approach we have
in mind, which may well require refinement based on lessons learned during experimentation and further
theoretical analysis.

One way to do semantic learning, according to the approach outlined above, is as follows:

1. An initial semantic corpus is posited, whose elements are parse graphs produced by the syntactic
process described earlier.

2. A semantic relationship set (or rel-set) is computed from the semantic corpus, via calculating the
frequent (or otherwise statistically informative, i.e. high MI) subgraphs occurring in the elements of
the corpus. Each node of such a subgraph may contain a word, a category or a variable; each node may
be typed by the list of connections it is allowed to make. The links of the subgraph are labeled with
(syntactic, or semantic) link types. Each parse graph is annotated with the semantic graphs associated
with the words it contains (explicitly: each word in a parse graph may be linked via a ReferenceLink to each variable or literal with a semantic graph that corresponds to that word in the context of the sentence underlying the parse graph.)

- For instance, the link combination $v_1 \xrightarrow{S} v_2 \xrightarrow{O} v_3$ may commonly occur (representing the standard Subject-Verb-Object (SVO) structure).
- For this example, the sentence “the rock broke the window” would result in links of the form rock $\xrightarrow{ReferenceLink} v_1$ connecting the word-instance nodes (the “rock” node) in the parse structure with variable nodes (such as $v_1$) in this associated semantic subgraph.

3. Rel-sets are divided into categories based on the similarities of their associated semantic graphs.

- This division into categories manifests the sigmoid-function-style crispening mentioned above. Each rel-set will have similarities to other rel-sets, to varying fuzzy degrees. Defining specific categories turns a fuzzy web of similarities into crisp categorial boundaries; which involves some loss of information, but also creates a simpler platform for further steps of learning.
- Two semantic graphs may be called ”associated” if they have a nonempty intersection. The intersection determines the type of association involved. Similarity assessment between graphs $G_1$ and $G_2$ may involve estimation of which graphs $G_1$ and $G_2$ are associated with in which ways. Intersection is done by finding the largest common subgraph.
- For instance, ”The cat ate the dog” and ”The frog was eaten by the walrus” both represent the semantic structure $eat(cat,dog)$ in two different ways. In link parser terminology, they do so respectively via the subgraphs $G_1 = v_1 \xrightarrow{S} v_2 \xrightarrow{O} v_3$ and $G_2 = v_1 \xrightarrow{S} v_2 \xrightarrow{P} v_3 \xrightarrow{MV} v_4 \xrightarrow{J} v_5$. These two semantic graphs will have a lot of the same associations. For instance, in our corpus we may have ”The big cat ate the dog in the morning” (including big $\xrightarrow{A} cat$) and also ”The big frog was eaten by the walrus in the morning” (including big $\xrightarrow{A} frog$), meaning that big $\xrightarrow{A} v_3$ is a subgraph commonly associated with both $G_1$ and $G_2$. Due to having many commonly associated graphs like this, $G_1$ and $G_2$ are likely to be associated to a common cluster.
- As in syntactic parsing, a reasonable metric for clustering can be obtained by applying pressure to reduce the overall complexity of the system. Overall complexity is obtained by counting: summing the total number of rules, relations, classes and class sizes needed to capture the content of the language. Insofar as the logarithm of a count is the entropy, this is an exercise in entropy minimization. The goal is to prune away relations which never occur (because they are semantic nonsense: “colorless green ideas”), leaving behind only those which can be used to express legitimate facts.

4. Nodes referring to these categories are added to the parse graphs in the semantic corpus. Most simply, a category node $C$ is assigned a link of type $L$ pointing to another node $x$, if any element of $C$ has a link of type $L$ pointing to $x$. (More sophisticated methods of assigning links to category nodes may also be worth exploring.)

- If $G_1$ and $G_2$ have been assigned to a common category $C$, then ”I believe the pig ate the horse” and ”I believe the law was invalidated by the revolution” will both appear as instantiations of the graph $G_3 = v_1 \xrightarrow{S} \text{believe} \xrightarrow{CV} C$. This $G_3$ is compact because of the recognition of $C$ as a cluster, leading to its representation as a single symbol. The recognition of $G_3$ will occur in Step 2 the next time around the learning loop.

5. Return to Step 2, with the newly enriched semantic corpus.

As noted earlier, these semantic relationships may be used in the syntactic phase of language understanding in two ways:

- Semantic graphs associated with words may be considered as ”usage links” and thus included as part of the data used for syntactic category formation.
• During the parsing process, full or partial parses leading to higher-probability semantic graphs may be favored.

6 The Importance of Incremental Learning

Note that the above sequence of learning steps vaguely resembles the layering of “deep learning”, or of hierarchical modeling. That is, learning must occur at several levels at once, each reinforcing, and making use of results from another. Link types cannot be identified until word clusters are found, and word clusters cannot be found until word-pair relationships are discovered. However, once link-types are known, these can be then used to refine clusters and the selected word-pair relations.

The learning process described here builds up complex syntactic and semantic structures from simpler ones. To start it, all one needs are basic before and after relationships derived from a corpus. Everything else is built up from there, given the assumption of appropriate syntactic and semantic formalisms and a semantics-guided syntax parser.

However, for this bootstrapping learning to work well, one will likely need to begin with simple language, so that the semantic relationships embodied in the text are not that far removed from the simple before/after relationships. The complexity of the texts may then be ramped up gradually. For instance, the needed effect might be achieved via sorting a very large corpus in order of increasing reading level.

7 Conclusion

We propose a general algorithm through which syntax and semantics can be induced from a large text corpus. The algorithm builds on established ideas and demonstrated algorithms from the linguistic and machine learning fields; the primary novelty proposed here is that these are mature enough to be able to be hooked together, so that the results from induction at a lower layer can be used to provide input to a higher layer, and that, conversely, higher layers can be used to guide learning in the lower layers.

The ordering of the layers proposed here is reversed from the ordering one might expect in embodied cognition, where one might first seek to associate single words with non-verbal sensory inputs, eventually building a model of the external world labeled with nouns for persistent objects, and verbs for actions. Such labeling provides the foundation for semantics in embodied cognition; syntax is learned only later, to encode semantics that single words alone cannot capture. Here, we reverse the process, attempting to learn syntax first, and only later the semantics, and possible a world-model. Whether this is feasible is remains unclear: neither form of learning, in one direction, or the other, has ever been demonstrated. There are certainly any number of traps and pitfalls in the descriptions given above. Nonetheless, we believe that the state of the art in both mathematical theory, and in the power of computer systems is sufficiently advanced that this can be attempted.

Initial experiments to test some of these hypothesis have been performed by the authors over the last number of years. Work has begun to implement the ideas proposed here. The work is slow, as it is understaffed; the project described here is large, requiring man-years to demonstrate even a vague prototype, and possibly dozens or hundreds to develop a polished system, with a fully developed theory supported by detailed published experiments.

Current work can be found in the OpenCog codebase: http://github.com/opencog/opencog/ most specifically, in the opencog/nlp/learn subdirectory, with supporting code in other directories. The overall OpenCog project is primarily focused on embodied cognition, and so both directions are being explored: learning language via embodied models of the external world, as well as learning language from corpus analysis, as described here.

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Appendix A: Meaning-Text Theory

The most comprehensive theory of meaning, and its conversion to text is Meaning-Text Theory (MTT) [MP87, Kahl03, Mil106, Ste90]. Although the theory itself is primarily oriented towards the generation of text from meaning, I believe that its representation of meaning is ideal for extracting meaning from text. MTT is not only compatible with dependency grammar, it can be thought of as an extension to it; it provides rules for converting meaning into dependency graphs. These rules are quite specific, and thus lend themselves to an algorithmic implementation: this is another strength of MTT. Possibly the most important contribution of MTT to linguistics is the discovery of “lexical functions”, which map concepts to words.

At its core, MTT captures meaning with a “semantic representation” (SemR). A semantic representation is a network of predicate-argument relations (in the sense of a linguistic predicate [WP-e] and linguistic argument [WP-a]). An example of such a network is shown in figure 3. Each arrow in the figure is a semantic dependency, that is, a predicate-argument relationship (arguments are also called ‘semantic actants’ in the theory). The arrows are labeled with numbers corresponding to the valency or number of arguments that a node may have. Thus, for example, the verb “criticize” has a valency of three: “X criticizes Y for Z”.

Nodes in the graph may be primitive or atomic, in which case they are called ‘semes’, although they may also have structure and are thus called ‘semantemes’. Note that semantemes are highly lexicalized: that is, the definition of a semanteme specifies the number of actants, and their roles. In essence, semantemes correspond to dictionary entries (a ‘lexis’ is a dictionary).

More properly, the network described above is a ‘SemS’ (semantic structure); it is but one part, although a core part, of a SemR. The network captures the propositional/situational meaning at the core. The other three parts of SemR are termed Sem-CommS, RhetS and RefS. The Sem-CommS (semantic-communicative structure) captures the communicative intent; the ‘theme’ (what is being talked about) and the ‘rheme’ (what is being said about the theme). For example, in figure 3 the topic is ‘media’, and the rheme is what the media is talking about (a raise in taxes). There is no unique assignment of themes and rhemes to a network, thus, for example, in figure 4 the theme is the raise in taxes, and the rheme is what is being said about it: the media is criticizing it. The Sem-CommS also has several other parts, the most important of which is distinguishing what is new information from what is given; that is, differentiating what is asserted from background pre-suppositions. A general axiom of MTT is that meaning is invariant under paraphrasing: thus, for example, “The media harshly criticized the Government for its decision to increase income taxes” and “The Government’s decision to increase income taxes was severely criticized by the media” are roughly synonymous; thus the network underlying the two figures 3 and 4 is the same. Tightening down the distinction between new and pre-supposed information breaks synonymy; it narrows the range of sentences that can be considered synonymous, of saying the same thing. Thus, MTT can capture the finer points of a speech-writer’s art: the careful crafting of sentences to convey a very specific meaning.

The other parts of SemR are RhetS and RefS. RhetS specifies the rhetorical style used in converting a semantic network to text (such as headline-news, where sentences are clipped (“Thieves rob Bank”); informal speech with lots of lulz, typos, ikr, smh and smiley winks ;-¿, or proper newspaper-English.) The RefS captures the referential structure: the references to concrete objects in the (model of the) external environment (“the ball rolled under the sofa” refers to a specific ball and sofa) or anaphora (the pronoun ‘she’ in ‘she waved goodbye’ refers to a specific person).

MTT distinguishes between several different forms or levels of representation: the above described is SemiR, the semantic representation. There is also a SyntR, the syntactic representation, roughly corresponding to a dependency parse, as well as MorphR, a morphological representation, where not only has the
word-order been chosen, but so have verb tenses, inflections of nouns and the like. A PhonR representation
gives the spoken, phonemic form of a sentence. Each of these levels has additional structures that capture
important information (such as verb tense, choice of adjective or adverb modifiers and the like). Between
each of these levels are a set of correspondence rules that translate structures at one level to those in another.
Roughly speaking, correspondence rules can be thought of as functors that map networks at one level to
those of another. MTT attempts to treat these rules as mechanically as possible, with an eye to algorithmic
implementation.

Perhaps the most important contribution of MTT to linguistics is the discovery of 'lexical functions' (LF’s); these appear in the correspondence rules. Lexical functions bind a meaning to a lexeme. For
example, the LF $\text{MAGN}()$ is a function that specifies a list of appropriate words for expressing magnitude.
One then has $\text{MAGN}(\text{rain}) == \text{torrential—hard}$, $\text{MAGN}(\text{wind}) == \text{strong}$ and $\text{MAGN}(\text{emotion}) == \text{hot}$. The
point here is that in each case, a magnitude is being expressed; yet, it is context-specific: one would not
normally say 'hot rain', 'hard wind' or 'torrential emotion'; the LF specifies the allowable modifiers for a
given noun. The LF $\text{MAGN}()$ is broad in scope, applying to nouns in general; not all LF’s are universal in
this way. Some can have a very narrow scope: for example, 'leap' only applies to 'year'. Another example
is the subject LF $\text{S}_1()$ that indicates authorship: $\text{S}_1(\text{crime}) == \text{perpetrator}$, $\text{S}_1(\text{book}) == \text{author}$. A third
example is the quasi-subject function that gives noun-equivalents for verbs: $\text{QS}_0(\text{criticize}) == \text{criticism}$. MTT defines many different lexical functions; a sampling of these for the verb 'criticize', taken from [Mil06], are:

- $\text{QSYN}$: attack, disapprove, reproach
- $\text{QANTI}$: praise, congratulate
- $\text{QS}_0$: criticism
- $\text{S}_1$: critic
- $\text{A}_1$: critical [of N]
- $\text{MAGN}$: bitterly, harshly, seriously, severely, strongly
- $\text{MAGN}_{\text{Quant}}$: all the time, relentlessly, without stopping
- $\text{ANTI MAGN}$: half-heartedly, mildly
- $\text{ANTI VER}$: unjustly, without reason

As should be apparent from the above, lexical functions provide all of the relations that can be found
in resources like WordNet (viz, a machine-readable catalog of word-senses, their synonyms, antonyms and
hyponyms), while providing a more comprehensive view of the nature of these relations. Similarly, the
predicate-argument lexical entries of MTT resemble the frames of FrameNet. Unlike FrameNet, however,
MTT describes the mechanisms by which these semantic frames become connected to syntactic representa-
tions. It provides a more comprehensive description of how frames interact with other aspects of grammar.

To recap: meaning is captured by referential structures, obtained from semantic structures built of
lexical functions. The goal of learning language is to ascend through a hierarchy of structures, from raw
text, through dependency grammars, up to referential disambiguation of a world-model. To make sure that
learning takes place at a reasonable pace, deep-learning style reinforcement must happen at each layer, so
that the simpler, shallower layers (the syntactic layers) are somewhat developed before the semantic layers
are attacked; yet the deeper layers can also guide correct learning at the shallower layers. MTT, as
opposed to some other theory or framework, seems appropriate for providing a basic framework of what
must be learned. This is in part because MTT seems to be the most comprehensive theory describing not
only the various layers, but also algorithmic mechanisms of transforming one layer into another.

The language learning system must learn lexical functions on its own; it must learn how to pick out
predicate-argument structures; these are not pre-supposed. Rather, MTT provides a viewpoint by which the
success of the learning system might be judged: instead of treating learning as a black-box, one might expect
being able to examine what is being learned, and one might reasonably expect it to resemble the outlines of
MTT.
Appendix B: Mutual Information

This appendix provides some gymnastics for working with probabilities associated with structures and relations. It is provided only because such discussions are rare in the literature. Only the very simplest cases is worked here: the mutual information between a pair of words. Hopefully, generalizations then become obvious.

Let \( P(R(w_l, w_r)) \) represent the probability (frequency) of observing two words, \( w_l \) and \( w_r \) in some relationship or pattern \( R \). Typically, in Link Grammar, it would be a linkage of type \( t \) connecting word \( w_l \) on the left to word \( w_r \) on the right; however, the relation \( R \) can be more general than that.

The simplest model has only one type \( t \), the ANY type, and assigns equal probabilities to all words. But we know all words are not equi-probable, so let \( P(w) \) be the probability of observing word \( w \). We know from experience this is a Zipfian distribution. We are then interested in the conditional probability \( P(R(w_l, w_r)|w_l, w_r) \) of observing the two words \( w_l \) and \( w_r \) in a relation \( R = R(w_l, w_r) \), given that the two individual words were observed. From the definition of conditional probabilities, one has that

\[
P(R) = P(R|w_l, w_r)P(w_l)P(w_r)
\]

or, equivalently, that

\[
P(R|w_l, w_r) = \frac{P(R)}{P(w_l)P(w_r)}
\]

Here, the relation \( R \) encompasses several facts: that one word is to the left of the other, and that they are connected by a certain link-type, as well as capturing other ‘ambient’ information, perhaps such as other nearby words.

It is important here to harmonize this with the notation used by Yuret\cite{Yur98} and commonly employed in the MST parser literature. There, a probability \( P(w_l, w_r) \) is defined of seeing the ordered pair; that is, the relation \( R \) is implicit. To make it explicit, we should write: \( P(w_l, w_r) = P(R(w_l, w_r)) \) to indicate the relation explicitly, and to note that the order of the positions in the relation matter. Yuret also uses the notation \( P(w_l, \ast) \) and \( P(\ast, w_r) \) for wild-card summations, defined as

\[
P(w_l, \ast) = \sum_{w_r} P(w_l, w_r) \quad \text{and} \quad P(\ast, w_r) = \sum_{w_l} P(w_l, w_r)
\]

In practical use, one quickly observes that \( P(w_l, \ast) \) is almost equal to \( P(w_l) \) but not quite, since \( P(w_l, \ast) \) is the probability of seeing \( w_l \) within the certain relationship or pattern, which must be less than the prior probability of observing \( w_l \) in general. Thus, one has \( P(w_l, \ast) \leq P(w_l) \) which can be viewed as a conditional probability:

\[
P(w_l, \ast) = P(R(w_l, \ast)) = P(R(w_l, \ast)|w_l)P(w_l)
\]

In practice, then, for word-pairs, one has that \( P(R|w_l) \) is almost equal to 1, but not quite. Inserting this into the above gives

\[
P(R(w_l, w_r)|w_l, w_r) = \frac{P(R(w_l, w_r))}{P(w_l, \ast)P(\ast, w_r)} P(R(w_l, \ast)|w_l) P(R(\ast, w_r)|w_r)
\]

Re-ordering this gives

\[
\frac{P(R(w_l, w_r)|w_l, w_r)}{P(R(w_l, \ast)|w_l) P(R(\ast, w_r)|w_r)} = \frac{P(w_l, w_r)}{P(w_l, \ast)P(\ast, w_r)}
\]

The right hand side above is recognizable from Yuret’s work; he defines the mutual information as

\[
\text{MI}(w_l, w_r) = \log_2 \frac{P(w_l, w_r)}{P(w_l, \ast)P(\ast, w_r)}
\]

so that large positive MI is associated with words that occur together only with themselves (e.g. “Northern Ireland”, from his examples.) So, on the right, we have that \( P(w_l, w_r) \) is usually very small, and that \( P(w, \ast) \approx P(\ast, w) \approx P(w) \) subject to the inequality given before.

The LHS of equation (1) shows how to properly normalize conditional probabilities for general structures when performing “frequent subgraph mining”. First, we have observationally seen that \( P(R(w_l, \ast)|w_l) \approx
\[ P(R(*,w_r)|w_r) \approx 1, \] and thus must conclude that \( P(R(w_l,w_r)|w_l,w_r) \) is 'large'; much larger than (unconditional) word-pair frequencies.

The LHS of equation (1) then demonstrates how to obtain conditional entropies in general. Thus, given an \( n \)-point relation \( R(x_1,x_2,\cdots,x_n) \) one computes first the unconditional probability \( P(R(x_1,x_2,\cdots,x_n)) \).

The conditional probability is then obtained as usual:

\[
P(R(x_1,x_2,\cdots,x_n)|x_1,x_2,\cdots,x_n) = \frac{P(R(x_1,x_2,\cdots,x_n))}{P(x_1)P(x_2)\cdots P(x_n)}
\]

The entropy is then build recursively by normalizing by the probability of wild-card relations:

\[
MI(R(x_1,x_2,\cdots,x_n)|x_1,x_2,\cdots,x_n) = \log_2 \frac{P(R(x_1,x_2,\cdots,x_n)|x_1,x_2,\cdots,x_n)}{P(R(*,x_2,\cdots,x_n)|x_2,\cdots,x_n)P(R(x_1,*\cdots,x_n)|x_1,x_3,\cdots,x_n)\cdots}
\]

The point of this derivation is to provide a simpler practical formulation for working with structural relations in language. Most presentations of conditional mutual information obscure the structural relationships, by hiding the wild-card summations in a different notation that makes it hard to discern their presence; see, for example [WP-c] for a demonstration of an equivalent but more opaque notation. Do observe that the RHS above is a special case, though, where the \( x_k \) appearing in the relation are identical to those appearing in the condition. When these are not the same, then a summation is required, as usual:

\[
I(R(X_1,X_2,\cdots,X_n|Z)) = \sum_{z \in Z} P(z) \sum_{x_k \in X_k} P(R(x_1,x_2,\cdots,x_n)|Z)) \log_2 \frac{P(R(x_1,x_2,\cdots,x_n)|Z)}{P(R(*,x_2,\cdots,x_n)|Z)\cdots}
\]

The difference between this and the previous equation is that, when the \( X_k = \{x_k\} \) are all singleton sets, and \( Z = \{z = (x_1,x_2,\cdots,x_n)\} \) is likewise a singleton set, then the summations disappear. One is left with a mutual information, scaled by the (unconditioned) probability of seeing the particular pattern. Because the pattern may in fact be very rare, this is not as useful in practical experimentation than the renormalized mutual information.
Figure 3: A Semantic Representation

An example of a semantic representation (SemR) from Meaning-Text Theory. This network of predicate-argument arrows captures the meaning of the sentence “The media harshly criticized the Government for its decision to increase income taxes.” Here, “media” is the topic or theme, and what the media is saying is the rheme. Compare this to figure 4. Figure taken from [Mil06]

Figure 4: Alternative Semantic Topic

An alternative partitioning of a semantic network into theme and rheme. In this case, the topic is “the Government’s decision to raise taxes”, and what is being said about this topic is that the media is sharply critical of it. In words, one could say that “The Government’s decision to increase income taxes was severely criticized by the media.” Note that this sentence is more-or-less synonymous with that given in figure 3. Figure taken from [Mil06]