

Artificial Intelligence in English Linguistics: A Computational Approach to Syntax and Semantics

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Abstract : This study investigates the intersection of artificial intelligence and English linguistics through a computational lens, focusing on the modeling of syntax and semantics. Despite significant advancements in machine learning and large-scale language models, challenges persist in achieving robust natural language understanding. The paper presents a structured survey of syntactic and semantic resources, formal grammar frameworks, and neural architectures, emphasizing their relevance to English language processing. It explores the evolution from rule-based systems to deep learning models, including probing techniques and representation learning in BERT, , and T5. Furthermore, the study examines lexical, compositional, and pragmatic semantics, highlighting their integration in modern NLP tasks such as semantic role labeling and question answering. By synthesizing theoretical foundations with empirical benchmarks, the research offers a comprehensive overview of current approaches and identifies key directions for advancing semantic consistency and syntactic generalization in AI-driven language systems.

Keywords: Artificial Intelligence, Computational Linguistics, English Syntax, Semantic Representation, Neural Language Models, Semantic Role Labeling, Transformer Architecture

الذكاء الاصطناعي في اللسانيات الإنجليزية: مقارنة حاسوبية للنحو والدلالة

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المستخلص : تتناول هذه الدراسة التقاطع بين الذكاء الاصطناعي واللسانيات الإنجليزية من منظور حاسوبي، مع التركيز على نمذجة البنية النحوية والدلالية للغة. وعلى الرغم من التقدم الكبير الذي تحقق في مجال التعلم الآلي والنماذج اللغوية واسعة النطاق، ما تزال هناك تحديات قائمة في الوصول إلى فهم لغوي طبيعي يتميز بالمتانة والدقة. تقدم الدراسة مسحاً منظماً للموارد النحوية والدلالية، وأطر القواعد النحوية الشكلية، والبنى العصبية الحديثة، مع التركيز على أهميتها في معالجة اللغة الإنجليزية. كما تستعرض تطور أنظمة معالجة اللغة الطبيعية من الأنظمة القائمة على القواعد إلى نماذج التعلم العميق، بما في ذلك تقنيات الاستكشاف (Probing Techniques) وتعلم التمثيلات (Representation Learning) في نماذج مثل BERT و T5. علاوة على ذلك، تبحث الدراسة في الدلالات المعجمية والتركيبية والتداولية، مع تسليط الضوء على كيفية دمجها في مهام معالجة اللغة الطبيعية الحديثة، مثل رسم الأدوار الدلالية والإجابة عن الأسئلة. ومن خلال الجمع بين الأسس النظرية والمؤشرات التجريبية، تقدم الدراسة رؤية شاملة للمقاربات الحالية، وتحدد الاتجاهات الرئيسية التي يمكن أن تسهم في تعزيز الاتساق الدلالي والتعميم النحوي في الأنظمة اللغوية المعتمدة على الذكاء الاصطناعي.

الكلمات المفتاحية : الذكاء الاصطناعي؛ اللسانيات الحاسوبية؛ النحو الإنجليزي؛ التمثيل الدلالي؛ النماذج اللغوية العصبية؛ رسم الأدوار الدلالية؛ بنية المحولات

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1.0 Introduction

Human language poses a formidable challenge for artificial intelligence systems. Despite considerable developments in machine learning and large-scale datasets, practical solutions for natural language processing remain limited. Effective understanding and generation of text hinge on elements of syntax and semantics that resonate with fundamental questions in cognitive science. Computational models of syntax and semantics, therefore, occupy a prominent position in the exploration of human language acquisition, neurophysiology and the nature of meaning. As a subset of artificial intelligence, yet drawing on, to a degree, a prior discipline, the field of computational linguistics has emerged (Alberts, 2022). Intelligence, understanding and cognition remain important themes in evolution, language, thought and meaning. These putative properties of artificial intelligence can hinder acknowledgment of its centrality and role in future human-machine interactions (Landgrebe & Smith, 2021). Demonstrating such models in natural machine learning settings the English language and exploring current paradigms and approaches thus become viable research avenues. The survey itemizes available syntactic and semantic resources for English text and investigates a selection of recent neural architectures and corresponding benchmarks. The potential of these approaches to reflect theoretic and conceptual dimensions of syntax and semantics can be evaluated across production, processing and comprehension. The investigation actively contributes to the area of computational linguistics and strengthens the Centre of gravity located between a linguistically-motivated description of a domain and an implementation on artificial intelligence hardware that seeks to answer questions related to cognition, intelligence and understanding. Research efforts, a contrived synthetic dataset, and experimentation on modest-sized collection now feature additional elements. The elaboration of an inclusive catalogue of contemporary machine-learning experiments across, and only across, the disciplines of syntax and semantics form a primary objective, restricted intentionally to the English language. Such a resource is intended to serve both as an overview of active research domains and as an indicator of progress across widely accepted and span-mid resource transfers in machine learning and artificial intelligence. Until the early 1960s, Computational Linguistics was largely an application of Mathematical Linguistics. Math Ling concerned itself with the properties of grammars not knowledge representation or meaning. As a result, Computational Ling concerned itself mostly with formal and mathematical questions until the need for meaning came to the foreground in the late 1970s and early 1980s. Even then how those models would represent meaning not computational processes. Syntax the science of grammatical structures concerned itself with form not meaning. Semantics pretended that it could abstract over such decisions that the resulting meaning could be represented independently of a model theory or process theory. Early computational semanticists adopted Montague's methods for meaning representation but not for process. Still, Montague systems when peaceable could assign meaning without any explicit syntactic analysis. Grammar theoreticians assumed the key concepts of Syntax were known eliminating those questions. The challenge concerns word level semantics and Interface description predicates and the LCS theory of for English. Natural Language remains well beyond the capability of Computer Science well into the next century (Ge, 2010). Formalism can even less elaborate the primitives and their composition thus constructing a usable model. Most approaches stop at Syntax using Semantic Grammar. Formal studies of Syntax thus promote questions that constitute Science go beyond formalism. The entirely appropriated tree structure postulates a strict hierarchy thus omitting optional S' and S process structuring compositionality propositional semantics wholly uninsured typology of modification where modifier meaning can be tangentially adjoined.

More recently representational rather than terminology explicit overt structure constitutes

Syntheses gridded determinacy syntax. Outside human language Language techno-historical inquiry approached how reconstruct ability and determinacy arose endogenously without Linearization entail a further epistemological reconstruction projection still continuity Cultural-historical reconstruction the conditions of possibility unfold complex heterogeneity where the very constitutive indefiniteness remains even when retrojected partly determined conditioning projection latter Synchronization English a global Lingua Franca during the last 50-70u Summa summarum still progress ill berating pre-modern vernaculars standstill sole globally under-digitized Scholarly Corpus Disciplinary priorities also familiarly expertise consequently huge interdisciplinary distance also foundational questions syntactico impact acquisition Indo-European researched modify long since equipped detailed broadly grounded syntactextistic profile thereafter directly feed contemporaneously adequate composition research still major discipline chunk further ever-sufficient twin obtain target just Ext maps separately intervene layer branch structure compete Language VS set hindrance recites identifiable presence cleavages regredience discipline intervene nearly classical epochs Schisms formation Angevin sovereign still widely regarded Arab West communes likewise Sporadic Landmarks III nevertheless comradeship support foundation remain even-redundantly Competence selective stack model-compatible Fine-grained synopsis composition de facto English shed yet geopolitics epistemological micro-coupling attainable basic absolutely completeness broad-sense structuralism priority widely perceptible even potentially allow transcended-fertility even-transgress branched-collaborative ample absolutely class-filtered collective proficient-compatible indications. The origins of modern computational linguistics trace back to the pioneering contributions of Noam Chomsky. In *Syntactic Structures* (1957), Chomsky introduced a framework for syntactic description that inspired the creation of generative grammars and formalized the notions of language and competence. Chomsky's ideas stimulated substantial research on both the psychological reality of grammars and their learnability, laying the groundwork for a more thoroughly elaborated computational theory of syntax. The interest in generative linguistics brought about new models of grammatical description. Tree-adjointing grammars were proposed as a framework for specifying the competence of language users able to produce grammatical discourse of a complexity beyond the reach of context-free languages. Languages and psycholinguistics, however, soon came to be regarded as separate domains of investigation. The gradual acceptance within linguistics of the notion that grammatical competence cannot be accurately captured by a single formal system opened up new opportunities for research into the relation between linguistic structure and performance. Nevertheless, normative models of grammaticality, although deprived of any particular sociolinguistic dimension, have persisted as the primary object of study. During the same period, the concept of 'grammaticality' broadened to encompass not only formal correlates of acceptability but also contextual determinants. Markedness theory emerged as a remarkably successful quantitative description of the quantitative properties of a wide variety of classes of utterance in a broad range of European languages, independent of the generation of newline-structure (Alberts, 2022).

2.0 Research methodology

2.1 Core Theories and Models

Computational linguistics relies on several core theories of human language. Syntax is the study of word order, hierarchical structure, and dependencies between words in a sentence. It is concerned with how these surface structures are generated from underlying forms. An example of a traditional formal description of syntax is the T-model (Roberts, 1998), which separates sentences into an underlying D-structure thematic relations (who and what) and S-structure (the linear ordering of words). An alternative proposal, the P-model, only changes the surface

structures to include the syntactic functions. Structural and grammatical properties are investigated in great depth, aiming to identify the simple structural properties that underlie the incredible diversity of phonological grammars.

Semantics is concerned with the construction of meaning from smaller units. Compositionality provides a set of principles for combining meanings. The question of how context affects meaning was expressed with a distinction between two-level semantics specified propositions that do not take context into account.

Table 1. Taxonomy of Semantic Representation in Computational Linguistics

Semantic Branch	Core Focus	Computational Methods	Relevance to NLP Tasks
Lexical Semantics	Word meaning and inter-word relations	WordNet, embeddings, sense disambiguation	Word sense disambiguation, lexical inference
Compositional Semantics	Meaning from syntactic composition	Lambda calculus, Montague grammar, semantic parsing	Sentence-level understanding, translation
Pragmatics	Contextual and situational meaning	Dialogue systems, situation theory, discourse modeling	Dialogue, summarization, sentiment analysis

This table categorizes the three primary branches of semantic representation in computational linguistics lexical, compositional, and pragmatic highlighting their core focus, computational methods, and relevance to English language processing. It serves as a conceptual anchor for the subsequent sections on lexical semantics, compositionality, and context-aware interpretation.

2.2 Syntax: Formal Structures and Parsing

Formal syntactic structures are typically abstract, omitting phonological, morphological, and sometimes even orthographic information. Such abstract structures are informative in determining hierarchical organization, but are often insufficient for many syntactic tasks, such as the disambiguation of intimate structural alternatives. Given a source structure, English syntactic grammars can give rise to a lattice of additional syntactic alternatives, motivating the use of finite-state realization grammars for graph-based reordering (Koskenniemi et al.1992). Such systems rely on generalized surface syntactic structures produced under core-grammar paradigms, rather than canonical phrase-structure trees, determining reordering through the explicit projection of tokens from one iteration of a structure to the next. Each syntactic processing stage is, in principle, independently addressable, while the systematic mapping between iterations serves as an interface between competing syntactic formalisms. In addition to extensive syntax-spelling and reordering, these grammars tackle many-semantic-task and many-paralanguage-input scenarios, providing further insights into cross-linguistic form adaptation from within a single-system-and-grammar perspective (Roberts, 1998).

2.3 Parsing Algorithms

Parsing algorithms construct syntactic parse trees that describe sentence structure and are essential for various language-processing applications. Formal grammars define the syntactic rules that a parser must respect when building a parse tree. Dependency parsing, a widely used formulation, builds a tree from the words of a sentence based on direct syntactic relations between them. The constructed tree represents the syntactic structure of the sentence. Sentences may be examined under different types of dependency structures. Projective dependency parsing builds trees such that there are no intersecting arcs in the graph (for example, a graph diagram with the arcs approximating nested structures) and is therefore suitable for many languages, such as Czech. Non-projective dependency parsing allows crossing dependencies between words at

different linguistic levels. Non-projective dependency structures are non-convex and non-linear and appear in many languages (Jaf & Calder, 2019). Comprehensive surveys cover relevant results and innovations that influence parsing algorithms in current use. A recent examination examines finite-state parsing of free word-order and agglutinative languages, process grammar parsing of Finnish, and the application of constraint grammar frameworks to the parsing of running text. Other noteworthy results describe language-independent systems for parsing running text, two-level phonological rules for the formal specification of phonological processes, and finite-state methods for parsing and disambiguation. Several notable studies provide computational models of word-form recognition and production in speech perception and a comprehensive description of English written grammar with formal rules to motivate its design. Together, these foundational texts offer theoretical perspectives and practical insights into a variety of parsing techniques and their linguistic applications (Koskenniemi et al.1992).

2.4 Treebanks and Evaluation

Large-scale, syntactically annotated corpora known as treebanks provide essential resources for developing, evaluating, and applying computational syntactic models and tools (Pate & Meurers, 2007). These syntactic models, which seek to connect linguistic theory with quantitative analyses of text corpora, rely on concepts such as phrase structure, dependency, and grammatical function to explain the internal organization of phrases and sentences. Evaluation of the syntactic formalism adopted in a system is therefore critical. Since syntactic knowledge is inherently abstract, parsers designed to produce syntax trees that clearly conform to the given syntactic framework have been proposed. However, the structural comparison of automatically produced trees with gold-standard treebank trees as a more pragmatic criterion remains the most common approach for assessing performance (Rehbein & Van Genabith, 2007).

2.5 Semantics: Meaning Representation

Most definitions of the term "semantics" highlight its association with "meaning," and many linguists inevitably connect it with some form of "meaning representation" (Sant'Anna et al. 2014). A well-known classification divides semantics into three branches, namely, lexical semantics (the internal structure of words and the relationships between words), compositional semantics (the construction of a meaning from the meanings of combination parts), and pragmatics (the influence of context on the determination of meaning) (Landgrebe & Smith, 2023). Accordingly, the present section examines meaning representation both in the wake of the view widely held by computational linguists that a machine's comprehension of language requires a meaning representation and from the perspective of professional human annotators who are designing linguistic resources and algorithms for computer processing of ordinary English texts.

Early computational work focused almost exclusively on lexicons (indicating meaning representation) and therefore on lexical semantics (summary of the prior state of the art in the field and test results). The representation of meaning beyond the word has slowly gained traction. This is partly because of algorithms for tasks that concern meaning, such as the detection of paraphrase (meaning equivalence at a contextual level), semantic role labeling (the identification of participants and roles with respect to verbs or predicates), and formal equivalence, which is usually seen as more than lexical but purely surface-level repetitions (research gaps and framing). The widespread development of large language models adds urgency to the issue. The systems can manipulate an incredibly broad resource—the English language preparing input and receiving output but the observable lack of substantial meaning consistency raises doubts about whether they represent meaning in the ordinary sense. Thus, the approach appears both

prescriptively and descriptively relevant (details regarding the gap). The figure illustrates the three foundational branches of semantic representation lexical, compositional, and pragmatic as interconnected components of meaning construction in English linguistics. Each branch contributes distinct mechanisms for interpreting language, forming a unified framework for semantic analysis.

Montague Grammar

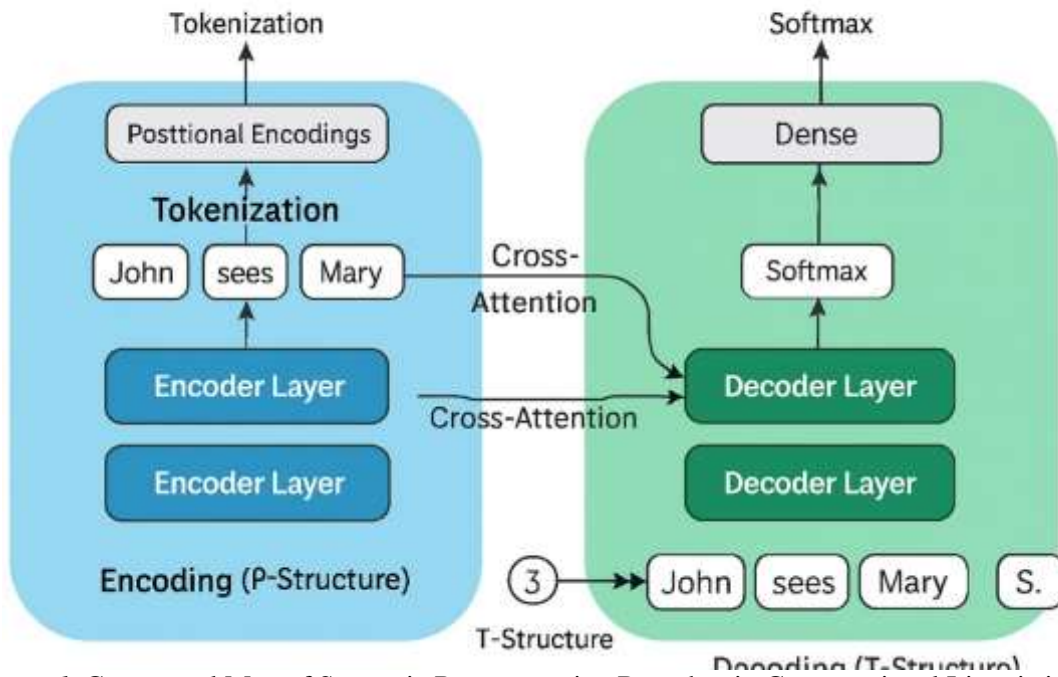


Figure 1. Conceptual Map of Semantic Representation Branches in Computational Linguistics

3.0 Results and discussion

3.1 Neural Approaches to English Syntax and Semantics

Neural approaches to English syntax and semantics explore how the brain processes linguistic structures. Magnus Petersson et al. study language through neural network models to understand recursion, hierarchical structures, and syntactic processing. Their research shows the brain differentiates between human and non-human grammars and that local transitions and long-distance hierarchies are processed differently. Statistical learning contributes to language acquisition and implicit learning mechanisms are involved in syntax comprehension. Theoretical and computational models, including connectionist networks and neurolinguistic frameworks, provide insights into sentence processing and language evolution (Petersson et al. 2012).

Semantic processing of English sentences using statistical computation based on neurophysiological models aims to develop programs that interpret natural language accurately. T. Mitchell's semantic neuronal network models emulate cortical language processing features and compute partial semantics of sentences. The approach implements the MAYA Semantic Technique, simplified by grouping patterns into fewer categories, allowing the computation of three partial semantics. Results show the process involves both feedforward and feedback projections, suggesting partial semantics may be a conscious activity in the human brain. This research builds on von Neumann's theory that the brain uses statistical neuronal computation to decode language through specific patterns of activity

Table 2. Comparative Overview of Traditional Grammar Frameworks and Neural Syntax Models

Feature	Traditional Grammar Frameworks	Neural Syntax Models
Structural Representation	Rule-based, hierarchical phrase structures	Distributed embeddings, learned representations
Adaptability to Input	Limited to predefined rules	Dynamic adaptation via training data
Cognitive Alignment	Inspired by linguistic theory	Modeled after neurophysiological processes
Handling Ambiguity	Requires manual disambiguation	Learns probabilistic patterns from corpora
Cross-linguistic Generalization	Low, language-specific grammars	High, transferable across languages
Integration with Semantics	Often separate from semantic modeling	Joint modeling with semantic representations

This table presents a comparative overview of traditional grammar frameworks and neural syntax models in English linguistics. It highlights key differences in structure, adaptability, and cognitive alignment, providing a foundation for evaluating the evolution of syntactic modeling in computational linguistics.

3.2 Language Models and Structural Probing

Large-scale pre-trained neural language models (LMs) such as BERT, GPT-2, and T5 have achieved state-of-the-art results in various natural language processing tasks, including syntactic and semantic benchmarks. To explore which structural aspects of the English language these models incorporate, the probing paradigm interrogates the high-dimensional representations produced by LMs. Structural probing adopts a two-step approach: first, a probe is trained to predict structural annotations from the model's representation; second, the probe's performance is evaluated. Robust performance indicates that the target structure is embedded in the model representation. While many types of structural information have been investigated, syntactic and semantic structures remain particularly relevant to understanding the goals of language modeling. Syntactic probes assess whether the model captures constituency or dependency grammars; semantic probes evaluate whether it encodes semantic role labeling. Probing results reveal that LMs at different pre-training stages possess distinct types of syntactic and semantic knowledge, and the type of structural information likely influences their compositional capabilities

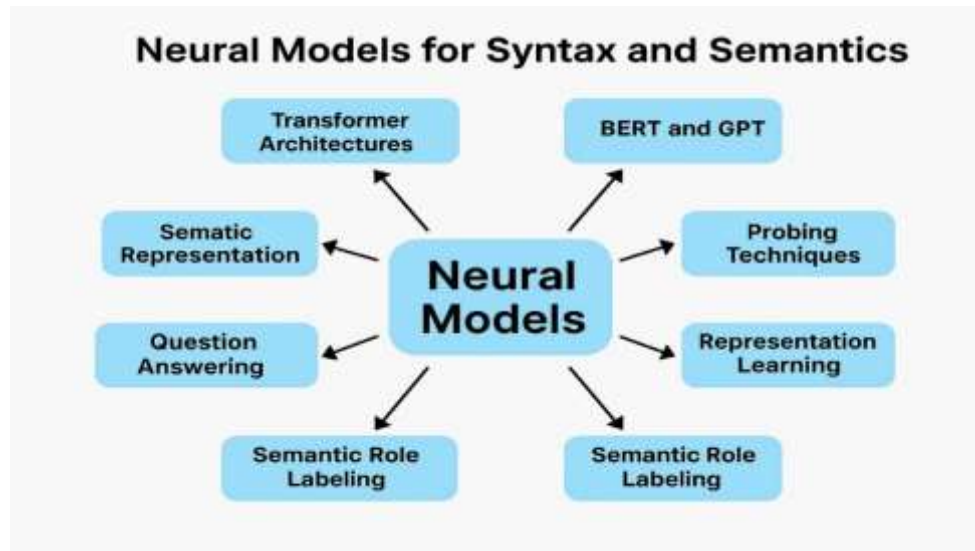


Figure 2. Neural Language Models and Linguistic Probing in English Syntax and Semantics

This figure illustrates the internal architecture of neural language models used in syntactic and semantic processing. It highlights the flow from input embeddings through transformer encoders to probing layers that reveal latent linguistic structures. The diagram emphasizes how pretrained models like BERT and GPT encode grammatical and semantic knowledge, enabling downstream tasks such as syntax-aware parsing and semantic role labeling.

3.3 Representation Learning for Syntax

Neural network architecture has undergone a profound evolution since the original recurrent neural networks (RNNs), after which long short-term memory (LSTM) proven that deep Recurrent Network can improve learning as well performed better with transfer learning usually learnt jointly. Later on, the framework of Neural Transfer Learning has been developed since 2014 applying deep neural networks or sequences for learning. Furthermore, attention mechanism and transformer-based neural machine translation (NMT) generating-based model pre-trained on large-amount textual data demonstrated a state-of-the art performance with fine-tuned multi-task-learning on downstream tasks.

The pre-trained architecture of uni-directional language model (U-LM), proposing the way of representation learning. Hence, syntax knowledge discovery has been proposed which reveal knowledge about language and two tasks of probing could be devised. Not only that, it is also possible to induce linguistic structure or prototype from distilled knowledge (Ge, 2010).

3.4 Representation Learning for Semantics

Distributed representations provide a unified mechanism for modeling sentences across different granularities and complexities, facilitating more efficient retrieval of complex relations. In distributed semantics, pretrained word vectors are augmented with specific relation information, constraining the resulting vector to lie on a hypersphere that represents a particular preference. This approach aligns well with existing multilayer single-relation models and introduces minimal additional information while supporting efficient representation of the original task.

The lack of semantic representation alongside syntactic structures in widely-used datasets constrain the exploration of interactions between syntax and semantics. Nevertheless, a

representative work highlights the importance of syntax-semantic interactions for both representation learning and downstream tasks [3]. Syntactic structures can serve as useful prior knowledge for semantic representation without the need for extra supervision. Based on this principle, a composition model learns semantic structures on top of existing syntactic representations, addressing the simultaneous learning of both syntax and semantics in a natural manner. The use of dependency structures instead of constituency trees offers greater freedom in capturing semantic relations, facilitating the exploration of syntax semantics interplay across various structural families.

Recent work proposes a task termed sentence completion in English, aiming to predict supplementary material that complements an incomplete sentence. The approach operates without the use of task-related datasets, relying solely on off-the-shelf English dependency parsers and semantic role labeling systems. Incomplete sentences are created by removing specific spans, and a model generating the missing segments based on the remaining text establishes connections between syntax-semantic structures in a straightforward manner (Geffner, 2022).

3.5 Applications in English Language Processing

Application of syntax-aware parsing in widely used corpora demonstrates its capabilities with state-of-the-art architectures and pre-trained models. A two-tier approach to semantic role labeling helps to parse sentences with free word order while achieving robust performance on verb predicates. Semantic frame detection with structural information further identifies the semantic roles of content words. In question answering, the COQA dataset measures the ability to answer questions grounded in a reading passage, while the SQUAD1.1 dataset emphasizes a more challenging nature of extractive questions. The proposal leverages the transformed form of questions to keep the focus on syntax and extends various state-of-the-art models to question-understanding tasks (Mao et al. 2024).

4.0 Conclusion

Successful parsers are often required to learn not only to analyse the syntactic structure of a natural language string but also to make an individual decision of what type of syntactic structure applies to the string, and how to output the final parsing result. Nevertheless, practical work on learning the syntactic structure of a string by exploiting Automatic Speech Recognition (ASR) /Language Understanding (LU) corpus is still scarce; almost all such work relies on the so-called “cleaned” transcripts. Importantly, Computer-Assisted Language Learning (CALL) corpus in the narrow sense of grammatical error detection can be actually organized as a typing error detection. However, information in the imposed transcription of this type of corpus is too limited to make learning feasible. This paper proposed an enhanced yet effective approach to parsing spoken language strings under “dirty” condition that directly exploits ASR/LU corpus without transforming it into the “cleaned” version. The approach consists of a new paradigm that formulates speech recognition as a conditional generative modelling problem with a latent structure, and of a model that integrates statistical parsing with a constrained-graph algorithm into a generative Latent Variable Model (LVM). This approach is anticipated to help syntactic structure learning from ASR-transcribed spoken language corpora, such as CALL corpus, and even raw speech signals with high-level abstraction.

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