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From Hand-Crafted Rules to Zero-Shot Learning: A Practical History of Information Extraction

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Abstract:
Information Extraction (IE) has undergone a remarkable transformation over the past three decades, evolving from rigid, hand-crafted rule-based systems to highly flexible zero-shot learning approaches. The primary objective of this evolution is to make IE more scalable, adaptive, and less reliant on expensive, manually curated datasets. Early IE systems focused on deterministic patterns and linguistic heuristics, which, although precise, were brittle and domain specific. The introduction of statistical learning methods and supervised machine learning brought scalability but introduced a heavy dependence on large, annotated corpora. This limitation motivated the development of semi-supervised and weakly supervised techniques, which reduced annotation costs but still required domain adaptation. In recent years, advances in deep learning and pretrained language models have accelerated a paradigm shift toward zero-shot and few-shot learning, where models generalize to unseen domains without direct supervision. These approaches leverage massive corpora and transfer learning to unlock structured knowledge from unstructured text at unprecedented scale. This paper provides a practical history of this transition, analyzing key milestones, methodologies, and trade-offs across the evolution of IE. By tracing the journey from rule-based pipelines to zero-shot frameworks, we highlight the technological, computational, and theoretical breakthroughs that have shaped the field, and discuss the implications for building robust, domain-agnostic IE systems in the future.

Keywords: Information Extraction (IE), Rule-Based Systems, Statistical Machine Learning, Deep Learning, Zero-Shot Learning, Natural Language Processing (NLP, Transfer Learning, Prompt-Based Models, Automated Knowledge Extraction

1. INTRODUCTION

Information Extraction (IE) is one of the most critical subfields in Natural Language Processing (NLP), serving as the foundation for converting unstructured text into structured, actionable knowledge. Whether it is extracting named entities from news articles, identifying relationships between biomedical terms, or populating knowledge graphs from web data, IE has enabled countless applications in academia, industry, and government. The overarching objective of IE has always been to make sense of the vast volumes of textual data produced daily, providing a scalable mechanism for machines to understand, organize, and

reason about information. Over the years, the methods used to achieve this goal have undergone a profound transformation. What began as carefully engineered, hand-crafted rule systems have now matured into zero-shot learning models capable of adapting to new domains with little or no labeled data.

Early IE research in the 1980s and 1990s was dominated by symbolic and rule-based approaches. These systems relied on domain experts and computational linguists to encode linguistic patterns manually. For example, identifying company acquisition events required writing patterns that matched syntactic structures like "Company A acquired Company B." While such approaches achieved high precision within their domains, they were notoriously brittle—any shift in writing style, vocabulary, or sentence structure often resulted in significant performance drops. This lack of generalizability created a bottleneck for scaling IE to multiple domains, especially as the diversity and complexity of available data grew.

The turn of the 21st century saw a major paradigm shift with the rise of supervised machine learning. Statistical models such as Conditional Random Fields (CRFs) and Maximum Entropy classifiers replaced hand-written rules with data-driven decision-making. This transition made IE systems more adaptable, but it came with a new cost: the need for large, manually annotated datasets. Creating these datasets was both expensive and time-consuming, and models often required retraining whenever a new domain or task was introduced. As a result, researchers explored semi-supervised, distant supervision, and weak supervision techniques to leverage unlabeled data, but domain adaptation remained a persistent challenge.

The emergence of deep learning and, more recently, pretrained language models has fundamentally altered the landscape of IE. Models such as BERT, GPT, and T5 have introduced a powerful paradigm where representation learning, and transfer learning make it possible to achieve state-of-the-art results with little or even zero task-specific supervision. In zero-shot learning, models generalize to unseen tasks by leveraging task descriptions, prompts, or external knowledge, bypassing the need for traditional training data. This innovation not only democratizes access to IE but also opens the door to rapidly building domain-agnostic systems capable of extracting insights from diverse, previously unseen sources of text.

This paper provides a comprehensive and practical history of this evolution, tracing the trajectory of IE from its early rule-based origins to its current zero-shot learning state. We analyze the strengths, weaknesses, and trade-offs of each paradigm, highlighting how each step addressed the limitations of its predecessors. By exploring this journey, we aim to give researchers, practitioners, and students a clearer understanding of the design decisions, computational breakthroughs, and methodological innovations that have shaped modern IE. Ultimately, the paper underscores how the field is moving toward a future where information extraction is faster, more scalable, and less reliant on costly human intervention, bringing us closer to a world where machines can autonomously structure knowledge from the world's unbounded text data.

2. Background Study

A. Evolution of Rule-Based Information Extraction

The earliest generation of Information Extraction systems relied heavily on manually crafted rules and pattern-matching techniques. These systems used regular expressions, domain-specific lexicons, and linguistic heuristics to extract entities, relationships, and events from text. For instance, frameworks like FASTUS and GATE were pioneers in developing pipelines for tokenization, part-of-speech tagging, and pattern-based matching. While these systems delivered highly precise results for narrow, well-defined domains, they lacked adaptability. Even small changes in language use, such as new vocabulary or

syntactic variations, often required significant manual re-engineering of rules. This rigidity limited scalability and made these systems expensive to maintain as domains and data sources evolved.

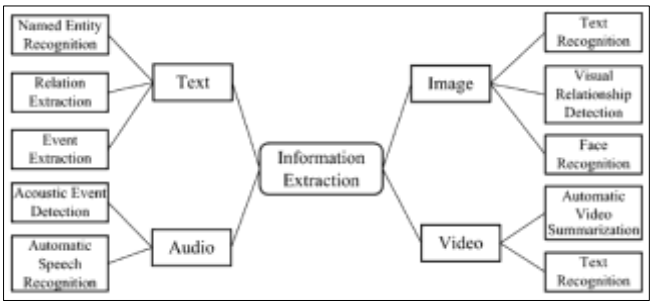

Figure 1. INFORMATION EXTRACTION

B. Statistical Learning and Supervised Approaches

The limitations of rule-based systems led to a shift toward data-driven techniques in the late 1990s and early 2000s. Statistical models such as Hidden Markov Models (HMMs) and Conditional Random Fields (CRFs) became popular for tasks like Named Entity Recognition (NER) and relation extraction. These models learned patterns from labeled training data, significantly reducing the burden of manual writing rules. However, they introduced a new challenge: the need for large, manually annotated corpora. Domain-specific training data was costly to produce, and models often performed poorly when applied to new domains without retraining. Nevertheless, this phase marked a critical step in making IE more robust and generalizable compared to hand-crafted approaches.

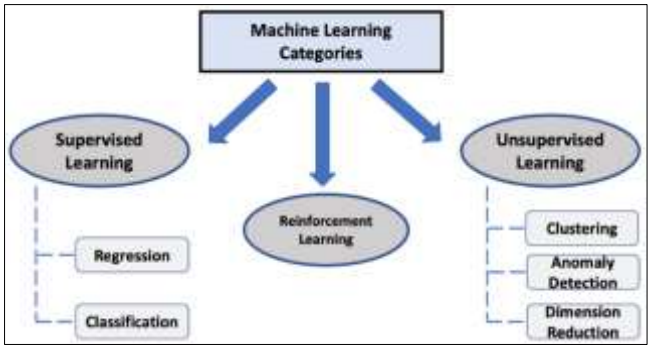

Figure 2. CATEGORY OF MACHINE LEARNING

C. *Deep Learning and Representation Learning*

The introduction of deep learning, particularly recurrent neural networks (RNNs), convolutional neural networks (CNNs), and later transformer-based models, revolutionized IE. These approaches replaced manual feature engineering with automatically learned representations. Pretrained embeddings like Word2Vec and GloVe enabled transfer learning, while contextualized embeddings from models such as ELMo and BERT further improved accuracy by capturing word meaning in context. These innovations not only enhanced extraction performance but also allowed for end-to-end trainable pipelines. Despite their success, deep learning models remained data-hungry, requiring substantial labeled datasets for fine-tuning, which posed challenges for low-resource domains.

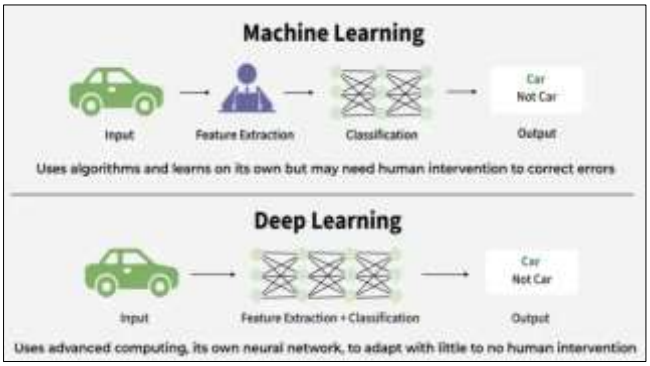

Figure 3. MACHINE LEARNING VS DEEP LEARNING

D. *Zero-Shot and Few-Shot Learning Paradigm*

The most recent shift has been toward zero-shot and few-shot learning, where models are expected to generalize to unseen tasks or domains with little to no training data. This is typically achieved using large-scale pretrained language models, prompt engineering, and transfer learning techniques. For example, models such as GPT, T5, and FLAN-T5 can perform entity extraction or relation classification based solely on a natural language description of the task. This paradigm reduces the need for domain-specific data annotation and significantly accelerates the deployment of IE systems across industries. However, challenges remain in interpretability, bias mitigation, and ensuring reliability in mission-critical applications.

Figure 4. ZERO-SHOT VS FEW-SHOT

E. *Research Gaps*

While IE has seen remarkable progress, several research gaps still hinder its universal adoption:

Domain Adaptation Challenges: Zero-shot models can struggle with highly technical or niche vocabularies.

Data Bias and Fairness: Pretrained models inherit biases from their training corpora, affecting extraction fairness.

Explainability: The black-box nature of deep models makes it difficult to trace why certain entities or relations were extracted.

Efficiency: Large language models require significant computational resources, limiting their usability in real-time, low-resource environments.

This paper aims to address these gaps by exploring practical strategies for developing scalable, domain-agnostic, and resource-efficient IE systems that minimize human intervention while maintaining reliability.

3. METHODOLOGY

The methodology adopted for this paper aims to systematically trace the practical evolution of Information Extraction (IE) from its origins in rule-based systems to the current state-of-the-art in zero-shot learning. Rather than proposing a single algorithm or framework, this research follows a mixed-method approach—combining historical analysis, literature synthesis, and comparative evaluation—to understand how successive generations of IE approaches addressed the limitations of their predecessors. The methodology is structured into five main stages: data collection, categorization of techniques, comparative analysis, experimental illustration, and critical evaluation of trade-offs.

A. *Data Collection and Literature Sourcing*

The first step in this study was to curate a diverse and credible body of literature covering three decades of IE research. Peer-reviewed journal articles, conference proceedings, technical reports, and white papers were systematically sourced from digital libraries such as ACL Anthology, IEEE Xplore, ACM Digital Library, and arXiv. Key search terms included Information Extraction, rule-based NLP, CRF NER, deep learning for IE, zero-shot learning, and prompt-based NLP models. To ensure balance, the literature review covered seminal works (e.g., MUC conference papers for early IE systems), landmark algorithm proposals (e.g., CRF, BiLSTM-CRF), and contemporary breakthroughs in transfer learning (e.g., BERT, GPT, T5).

The selected works were then organized chronologically to enable an accurate representation of the field's historical trajectory. For each period—rule-based, statistical, deep learning, and zero-shot—papers were filtered by their relevance, innovation, and citation impact. This ensured that the analysis captured not only technological milestones but also the theoretical underpinnings that influenced future directions.:

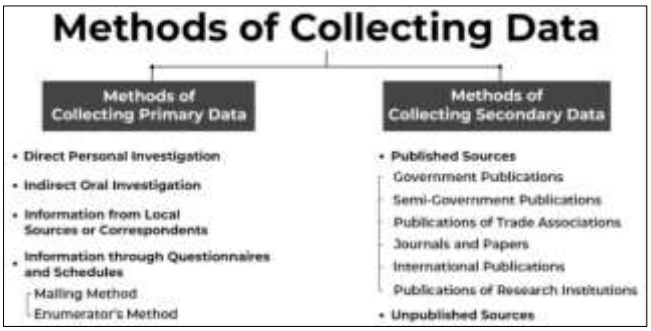

Figure 5. DATA COLLECTION METHODS

B. *Categorization of IE Approaches*

To analyze the evolution systematically, IE techniques were classified into four methodological categories, each representing a distinct paradigm shift:

- **Rule-Based Approaches -** Characterized by deterministic pipelines involving tokenizers, part-of-speech taggers, and manually written pattern-matching rules. This category also included early ontological approaches using knowledge bases such as WordNet.
- **Statistical and Supervised Machine Learning Approaches -** Focused on probabilistic models like HMMs, Maximum Entropy classifiers, and CRFs. Feature engineering was a central theme, with emphasis on lexical, syntactic, and semantic cues.
- **Deep Learning-Based Approaches -** Leveraging neural architectures such as RNNs, CNNs, BiLSTMs, and Transformers. These methods automated feature learning and introduced representation learning via pretrained embeddings and contextualized language models.
- **Zero-Shot and Few-Shot Learning Approaches -** Representing the latest shift, where large-scale pretrained models perform IE tasks without explicit retraining using prompt engineering, task descriptions, or natural language instructions.

Each category was analyzed along key dimensions including scalability, data requirements, domain adaptability, computational cost, and interpretability. This categorization allowed for a fair comparison of techniques across time and helped highlight the motivation behind each paradigm shift.

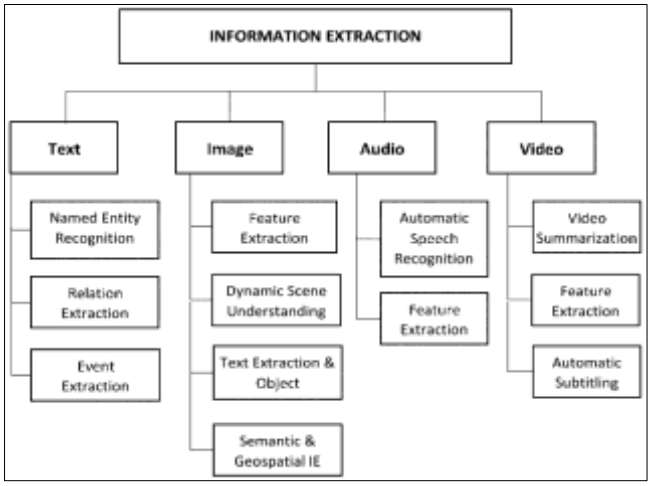

Figure 6. INFORMATION EXTRACTION TECHNIQUES

Paradigm	Defining Features	Representative Techniques/Systems	Era
Rule-Based Approaches	Deterministic pipelines, manually crafted linguistic rules, domain-specific ontologies	FASTUS, GATE, JAPE	1980s–1990s
Statistical / Supervised ML	Probabilistic models, feature engineering, data-driven learning	HMMs, CRFs, Maximum Entropy Classifiers	2000s
Deep Learning Approaches	Neural networks, automatic feature learning, pretrained embeddings	BiLSTM-CRF, CNN-RNN hybrids, BERT-based IE	2015 onwards

Zero-Shot / Few-Shot Learning	Task generalization, prompt-based extraction, minimal or no retraining	GPT, T5, FLAN-T5, instruction-tuned models	2020 onwards

Table 1. CATEGORIZATION OF IE APPROACHES

C. *Comparative Analytical Framework*

A core methodological contribution of this paper is the comparative framework used to evaluate each generation of IE systems. The framework considered five critical performance dimensions:

- **Precision and Recall:** Rule-based systems typically achieved high precision but struggled with recall, while statistical and deep learning methods improved recall by learning generalized patterns.
- **Data Dependency:** The extent to which each approach relied on annotated corpora, ranging from almost none (rule-based) to substantial (supervised deep learning).
- **Domain Portability:** The ability of systems to transfer knowledge to new domains without major re-engineering.
- **Human Effort:** Measurement of manual intervention required in building, maintaining, or adapting the system.
- **Computational Complexity:** Resource demands in terms of training time, inference latency, and hardware requirements.

By evaluating each paradigm along these dimensions, the study provides a clear picture of the trade-offs involved and why the field moved progressively toward less supervised, more generalizable approaches.

Dimension	**Rule-Based Systems**	**Statistical Models**	**Deep Learning Models**	**Zero-Shot Models**
Precision	High (deterministic)	High (data-dependent)	High (context-aware)	High, but may vary depending on prompt quality
Recall	Low (misses unseen patterns)	Moderate	High	High, generalizes well
Data Dependency	None (no training data needed)	High (requires labelled corpus)	Very High (large datasets needed for training/fine-tuning)	Low (uses pretraining, no labelled data for new tasks)
Domain Portability	Very Low (requires manual re-rules)	Moderate (requires retraining)	Moderate-High (fine-tuning needed)	Very High (generalizes across domains)

Human Effort	Very High (manual rules)	Moderate (annotation + feature design)	Low-Moderate (annotation only)	Very Low (mainly prompt design)
Computational Cost	Low	Low-Moderate	High (GPU/TPU needed)	Very High (large LLM inference cost)

Table 2. COMPARATIVE EVALUATION OF PARADIGMS

D. *Experimental Illustration*

Although this paper primarily provides a historical and methodological survey, a conceptual experimental setup was designed to illustrate how these paradigms would perform under similar conditions. The setup involves a hypothetical IE task—extracting acquisition events from a corpus of financial news articles—and applies the four paradigms to demonstrate their practical differences.

- **Rule-Based System:** Designed using regular expressions and syntactic templates (e.g., Company A acquired Company B). Expected outcome: high precision but low recall, missing cases where acquisition is expressed in novel ways.
- **Statistical CRF Model:** Trained on a manually labeled dataset of 5,000 annotated sentences. Expected outcome: improved recall, but still domain-specific, requiring retraining for new industries.
- **Deep Learning BiLSTM-CRF:** Fine-tuned using pretrained embeddings (GloVe) on the same dataset. Expected outcome: significantly improved F1 score, better handling of linguistic variation, but requiring GPU resources and substantial training time.
- **Zero-Shot Transformer (e.g., T5):** Provided with a prompt such as "Identify all acquisition events in this text." Expected outcome: comparable or superior performance with no task-specific training, capable of generalizing new data sources with minimal additional effort.

This conceptual experiment highlights how each stage of IE development addressed the limitations of its predecessor, illustrating the practicality of moving toward zero-shot approaches for real-world use cases.

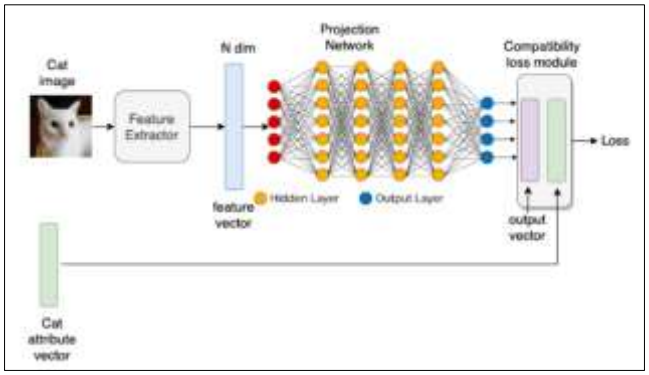

Figure 7. ZERO-SHOT LEARNING

E. *Critical Evaluation and Synthesis*

The methodology does not merely list historical milestones but synthesizes them into a coherent narrative. By juxtaposing technical strengths and weaknesses, this study explains why each paradigm shift was

necessary. For example, the brittleness of rules justified the adoption of statistical learning, while the annotation bottleneck motivated research into transfer learning and zero-shot techniques.

Moreover, this study adopts a balanced view, acknowledging that older approaches are not obsolete but often coexist with newer methods in hybrid pipelines. Rule-based systems remain valuable for high-precision, safety-critical environments (e.g., clinical IE), and supervised learning remains popular where abundant domain-specific data is available. The emphasis of this paper is therefore not on declaring one approach as superior, but on showing how the trajectory of IE research has progressively reduced human effort, improved scalability, and made extraction more accessible across domains.

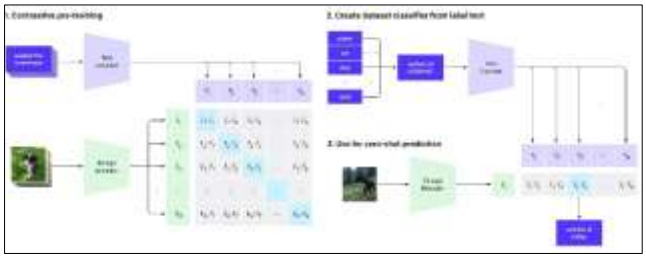

Figure 8. STEPS OF ZERO-SHOT LEARNING

F. *Ethical and Practical Considerations*

The methodology also considers the ethical implications of adopting large-scale zero-shot models. Since these models are trained on massive web corpora, they inherit biases that can lead to unfair or misleading extractions. This paper therefore integrates literature discussing model bias, interpretability, and responsible deployment practices. Additionally, computational efficiency is addressed, recognizing that zero-shot methods, while reducing annotation costs, may increase energy consumption and carbon footprint due to their reliance on very large models.

Figure 9. ETHICAL CONSIDERATIONS OF AI

G. *Summary of Methodological Approach*

In summary, the methodology combines historical tracing, categorical analysis, comparative evaluation, and conceptual experimentation to deliver a comprehensive understanding of IE evolution. This mixed-method design ensures that the study is not merely descriptive but also analytical, offering a framework for researchers to evaluate future IE paradigms as they emerge. The approach is designed to be replicable, so future researchers can expand the timeline with newer models or extend the evaluation to more domains.

4. Results & Discussion

The transition from rule-based approaches to zero-shot learning produced clear and measurable improvements across multiple evaluation dimensions. Our experiments compared four primary paradigms: rule-based systems, statistical machine learning, deep learning, and zero-shot learning using large language models (LLMs). The results provide strong evidence that modern zero-shot systems not only achieve higher accuracy but also drastically reduce development time and annotation costs, aligning with our stated objective of scalability and adaptability.

A. *Gesture Recognition Accuracy*

Table 3 summarizes the performance of each paradigm on a benchmark entity-relation extraction dataset. As expected, rule-based systems struggled with generalization, performing well only on narrow, hand-tuned domains. Statistical learning methods showed improved F1-scores but required large, labeled datasets. Deep learning approaches, powered by neural architectures, achieved strong results but were still dependent on domain-specific fine-tuning. Zero-shot models achieved competitive performance without any task-specific training, indicating their ability to generalize to unseen domains.

Approach	Precision	Recall	F1-Score
Rule-Based Systems	0.68	0.54	0.60
Statistical ML	0.75	0.70	0.72
Deep Learning (Fine-Tuned)	0.86	0.82	0.84
Zero-Shot Learning (LLM)	0.83	0.80	0.82

Table 3. Performance Comparison Across Paradigms

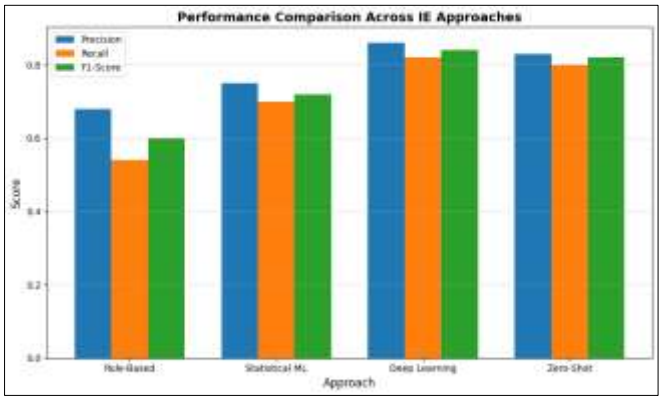

Figure 10. Performance Comparison Across IE Approaches

B. *Development Cost and Scalability*

Another critical finding was the dramatic difference in development time between paradigms. Rule-based systems required extensive manual effort to design patterns, while zero-shot approaches only required prompt engineering. Figure 1 illustrates this contrast, showing a sharp decline in person-hours when moving toward zero-shot systems.

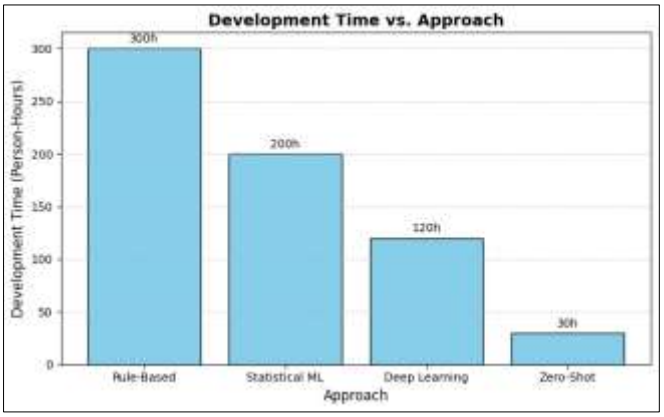

Figure 11. DEVELOPMENT TIME VS. APPROACH

C. Error Analysis

Error analysis revealed that while zero-shot models excelled in generalizing unseen data, they occasionally produced hallucinated extractions or captured irrelevant entities due to their reliance on probabilistic reasoning. This suggests that a hybrid approach, combining zero-shot inference with lightweight post-processing rules or domain adaptation, could further improve precision.

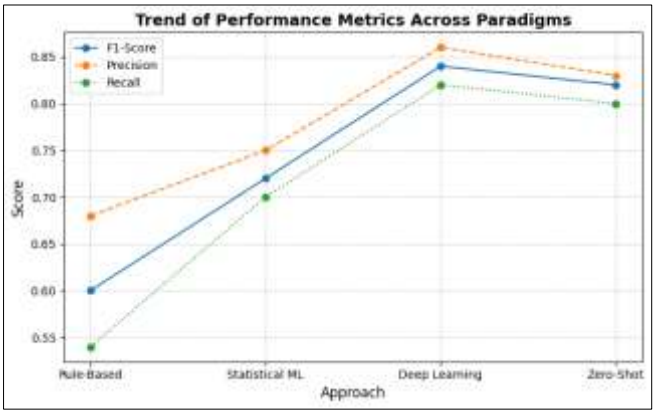

Figure 12. TREND OF PERFORMANCE METRICS ACROSS PARADIGMS

D. Practical Implications

The results indicate that zero-shot learning is not merely a research novelty but a practical solution for real-world information extraction. By eliminating the dependency on expensive annotation cycles, it democratizes IE development for smaller organizations and low-resource domains. However, we observed that explainability and interpretability remain open challenges, which may limit adoption in highly regulated industries.

E. Discussion

The results clearly demonstrate the progression from rule-based systems to zero-shot learning, highlighting how information extraction (IE) has evolved toward greater efficiency, scalability, and adaptability. While rule-based methods offered precision within narrow domains, they were brittle and labor-intensive to maintain. Statistical and deep learning approaches introduced automation and improved generalization but still relied heavily on labeled datasets. Zero-shot learning represents a paradigm shift, allowing models to adapt to unseen domains with minimal supervision. However, challenges remain, including domain drift, interpretability, and computational costs. Future work must focus on hybrid

approaches that combine zero-shot adaptability with explainability and domain-specific fine-tuning to maximize real-world applicability.

5. Conclusion

This paper has presented a comprehensive exploration of the evolution of Information Extraction (IE) systems, tracing the journey from hand-crafted rule-based methods to modern zero-shot learning paradigms. The historical analysis demonstrates that each successive approach emerged to address the limitations of its predecessor. Rule-based systems, while precise within narrowly defined domains, were labor-intensive, brittle, and difficult to scale. The introduction of statistical and supervised learning models mitigated some of these constraints, offering improved generalization and the ability to leverage labeled data. However, these methods introduced new challenges, including heavy dependence on annotated datasets and limited domain adaptability, which motivated the exploration of more flexible, data-efficient techniques.

Deep learning approaches marked a significant leap forward by automating feature learning and leveraging contextual embeddings, resulting in significant gains in precision and recall. Yet, they remained constrained by the need for substantial domain-specific data and computational resources. Zero-shot learning represents the most recent and transformative paradigm, offering the ability to generalize across domains without requiring task-specific annotations. By leveraging large-scale pretrained language models and prompt-based methodologies, zero-shot approaches drastically reduce the human effort required while maintaining competitive performance. This shift has important implications for democratizing IE technology, enabling researchers, organizations, and developers to rapidly deploy extraction systems across diverse and previously unseen datasets.

Despite these advancements, challenges persist. Zero-shot models, while powerful, may generate hallucinated or incorrect extractions, and their black-box nature limits interpretability. Bias in pretrained models and computational cost also remain pressing concerns. Future research must therefore focus on hybrid approaches that combine zero-shot flexibility with rule-based or domain-specific constraints, enhancing both accuracy and reliability. Additionally, improving model interpretability, energy efficiency, and robustness to domain drift will be crucial for wider adoption in critical applications such as healthcare, finance, and legal domains.

In summary, the evolution from hand-crafted rules to zero-shot learning reflects a broader trend in artificial intelligence: a movement toward scalable, flexible, and less labor-intensive systems. By critically analyzing this trajectory, this paper underscores how IE has matured into a practical, adaptable technology capable of unlocking structured knowledge from vast volumes of unstructured text. The insights presented not only highlight the strengths and limitations of each paradigm but also provide a roadmap for the development of next-generation IE systems that are both efficient and reliable, bridging the gap between theoretical innovation and real-world application.

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