

Novelty Assessment Report

Paper: Language Identification in the Limit with Computational Trace

PDF URL: <https://openreview.net/pdf?id=1OAGf7ntSE>

Venue: ICLR 2026 Conference Submission

Year: 2026

Report Generated: 2025-12-29

Abstract

Training on Chain-of-Thought (CoT) traces has empirically shown to dramatically improve the capabilities of Large Language Models (LLMs), yet a formal understanding of its power remains limited. In this work, we investigate the role of training on such computational traces from the perspective of language learnability. We introduce a new learning model, identification in the limit with trace, which augments Gold's classic paradigm [Gold'67] by providing the learner not only with examples from a target language but also with computational traces from the machine that accepts them. Our results reveal that access to these traces dramatically enhances the power of the learner. We first prove that with perfect computational traces, the class of all computable languages (those recognizable by Turing Machines) becomes identifiable in the limit. This stands in sharp contrast to Gold's famous impossibility result, which holds even for the simple class of languages that are recognizable by deterministic finite automata. We then analyze the more challenging scenario where the learner has only partial information regarding the computational traces, which are also subject to adversarial corruptions. In this setting, we establish a set of trichotomic results on the amount of error that can be tolerated for the successful identification of language classes across the Chomsky hierarchy.

Disclaimer

This report is **AI-GENERATED** using Large Language Models and WisPaper (a scholar search engine). It analyzes academic papers' tasks and contributions against retrieved prior work. While this system identifies **POTENTIAL** overlaps and novel directions, **ITS COVERAGE IS NOT EXHAUSTIVE AND JUDGMENTS ARE APPROXIMATE**. These results are intended to assist human reviewers and **SHOULD NOT** be relied upon as a definitive verdict on novelty.

Note that some papers exist in multiple, slightly different versions (e.g., with different titles or URLs). The system may retrieve several versions of the same underlying work. The current automated pipeline does not reliably align or distinguish these cases, so human reviewers will need to disambiguate them manually.

If you have any questions, please contact: mingzhang23@m.fudan.edu.cn

Core Task Landscape

This paper addresses: **Language Identification in the Limit with Computational Traces**

A total of **24 papers** were analyzed and organized into a taxonomy with **13 categories**.

Taxonomy Overview

The research landscape has been organized into the following main categories:

- **Theoretical Foundations of Language Learnability**
- **Applied Language Identification Systems**

Complete Taxonomy Tree

- Language Identification in the Limit with Computational Traces Survey Taxonomy
- Theoretical Foundations of Language Learnability
 - Classical Language Identification in the Limit (2 papers)
 - [4] Language identification in the limit (E Mark Gold, 1967) [View paper](#)
 - [15] Language identification in the limit (E Mark Gold, 1967) [View paper](#)
 - Extended Identification Models (2 papers)
 - [6] A Characterization of List Language Identification in the Limit (Charikar, 2025) [View paper](#)
 - [16] Computational limits on team identification of languages (Sanjay Jain, 1996) [View paper](#)
 - Computational Trace-Augmented Learning ★ (1 papers)
 - [0] Language Identification in the Limit with Computational Trace (Anon et al., 2026) [View paper](#)
- Applied Language Identification Systems
 - Spoken Language Identification
 - Neural Architectures for Speech-Based Identification (4 papers)
 - [3] Language Identification in Short Utterances Using Long Short-Term Memory (LSTM) Recurrent Neural Networks (Ruben Zazo, 2016) [View paper](#)
 - [17] Spoken Language Identification Using Deep Learning. (Christian Anthony Julius, 2021) [View paper](#)
 - [18] Is Attention always needed? A Case Study on Language Identification from Speech (Atanu Mandal, 2021) [View paper](#)
 - [19] Spoken Language Identification using ConvNets (Sarthak, 2019) [View paper](#)
 - Acoustic Feature Extraction and Representation (3 papers)
 - [5] Identification of Indian Languages using Ghost-VLAD pooling (N, 2022) [View paper](#)
 - [7] Exploring Residual Cepstral Features for Spoken Language Identification (Baveet Singh Hora, 2023) [View paper](#)
 - [10] An automatic language identification system (M. Savic, 1991) [View paper](#)
 - Self-Supervised and Transfer Learning for Speech (2 papers)
 - [13] Improved Language Identification Through Cross-Lingual Self-Supervised Learning (Andros Tjandra, 2021) [View paper](#)
 - [21] BERT-LID: Leveraging BERT to Improve Spoken Language Identification (Yuting Nie, 2022) [View paper](#)
 - Open-Set and Robust Spoken Identification (1 papers)
 - [14] Robust Open-Set Spoken Language Identification and the CU MultiLang Dataset (Eyceoz, 2023) [View paper](#)
 - Regional and Low-Resource Spoken Language Studies (1 papers)
 - [2] Towards audio-based identification of Ethio-Semitic languages using recurrent neural network. (Amlakie Aschale Alemu, 2023) [View paper](#)
 - Written Language Identification

- Script-Agnostic and Multilingual Text Identification (3 papers)
 - [8] Script-Agnostic Language Identification (Agarwal, 2024) [View paper](#)
 - [9] LIMIT: Language Identification, Misidentification, and Translation using Hierarchical Models in 350+ Languages (Agarwal, 2023) [View paper](#)
 - [22] The WiLI benchmark dataset for written language identification (Thoma, 2018) [View paper](#)
- Character and Hierarchical Representation Models (2 papers)
 - [20] Open-Set Language Identification (Sherwin Malmasi, 2017) [View paper](#)
 - [23] Hierarchical Character-Word Models for Language Identification (Aaron Jaech, 2016) [View paper](#)
- Script-Specific and Regional Text Identification (2 papers)
 - [1] Language Identification of Philippine Creole Spanish: Discriminating Chavacano From Related Languages (Aileen Joan Vicente, 2024) [View paper](#)
 - [12] Language Identification of Devanagari Poems (Priyankit Acharya, 2020) [View paper](#)
- Cross-Lingual Influence and Translation Studies (1 papers)
 - [24] Profiling source language traces in contemporary literary translations (Lynch, n.d.) [View paper](#)
- Optimization and Human-Computer Interaction Applications (1 papers)
 - [11] Enhancing human computer interaction with coot optimization and deep learning for multi language identification. (Elvir Akhmetshin, 2024) [View paper](#)

Narrative

Core task: language identification in the limit with computational traces. This field sits at the intersection of formal learning theory and practical language recognition, exploring how learners can identify languages from infinite sequences of examples when augmented with computational information. The taxonomy divides into two main branches: Theoretical Foundations of Language Learnability, which examines formal models of inductive inference and the conditions under which language classes become learnable, and Applied Language Identification Systems, which encompasses practical methods for recognizing languages from text or speech data. The theoretical branch traces back to foundational work such as Limit Identification[4] and extends through team-based and hierarchical learning models like LIMIT Hierarchical[9] and Team Computational Limits[16], while the applied branch spans diverse approaches from classical acoustic features to modern deep learning architectures like BERT-LID[21] and ConvNets Spoken[19], addressing challenges across written text, spoken utterances, and low-resource scenarios.

Within the theoretical foundations, a particularly active line explores how computational traces—auxiliary information about the learning process itself—can enhance learnability beyond classical Gold-style identification. Computational Trace[0] contributes to this direction by investigating how such traces enable learners to identify language classes that would otherwise remain unlearnable, positioning itself within the Computational Trace-Augmented Learning cluster alongside works examining related augmentation strategies like List Language Characterization[6] and Source Traces Profiling[24]. This contrasts with purely limit-based approaches that rely solely on positive examples, and differs from applied systems like LSTM Short Utterances[3] or Ghost-VLAD Indian[5], which focus on engineering effective features for practical recognition tasks rather than exploring the formal boundaries of what becomes learnable when computational side-information is available. The central question remains how much and what kind of trace information suffices to expand the frontier of identifiable language classes.

Related Works in Same Category

No sibling papers were found in the same taxonomy leaf. A taxonomy-subtopic-level comparison will be produced instead.

Taxonomy-Level Summary

The original leaf focuses on augmenting language identification with computational traces from accepting machines, including adversarial scenarios. Its siblings cover classical Gold-style identification without traces and theoretical extensions like list/team/probabilistic identification. All three subtopics address formal learnability within the identification in the limit framework, but differ in their augmentation mechanisms.

Similarities: - All three subtopics operate within the formal framework of language identification in the limit - All address theoretical characterizations of identifiable language classes - All concern learning from positive data or structured presentations of languages

Differences: - Computational Trace-Augmented Learning uniquely incorporates computational traces from accepting machines as additional information, while Classical focuses on text presentations alone - Extended Identification Models explores alternative success criteria (list, team) and probabilistic variants, whereas Computational Trace-Augmented Learning maintains standard identification but adds trace information - The original leaf explicitly addresses adversarial corruption scenarios with traces, a robustness dimension not mentioned in the sibling categories - Classical Language Identification serves as the foundational baseline, while the other two represent orthogonal extension directions (trace augmentation vs. identification paradigm variants)

Suggested Search Directions: - Hybrid models combining computational traces with team or list identification - Robustness and adversarial learning in extended identification models beyond trace-based approaches - Computational complexity of learners in trace-augmented versus classical settings

Sibling Subtopics

- **Classical Language Identification in the Limit** (leaves: 1, papers: 2)
 - Scope: Foundational work on Gold's paradigm and characterizations of identifiable language classes without computational traces.
 - Exclude: Excludes extensions with computational traces or team-based models; those belong under respective sibling categories.
- **Extended Identification Models** (leaves: 1, papers: 2)
 - Scope: Theoretical extensions including list identification, team identification, and probabilistic variants of language learning.
 - Exclude: Excludes computational trace-based models; those belong under Computational Trace-Augmented Learning.

Contributions Analysis

Overall novelty summary. The paper introduces a formal learning model that augments Gold's classical identification in the limit paradigm with computational traces from accepting machines. It occupies the 'Computational Trace-Augmented Learning' leaf within the theoretical foundations branch, where it appears as the sole paper in this specific category. This positioning suggests the work addresses a relatively sparse research direction within formal language learnability theory, distinct from the more populated classical identification models and their probabilistic or team-based extensions found in sibling categories.

The taxonomy reveals neighboring work in 'Classical Language Identification in the Limit' and 'Extended Identification Models', which explore foundational learnability results and variants like list or team identification without computational traces. The paper diverges from these by explicitly incorporating trace information as an augmentation mechanism. It also stands apart from the extensive applied systems branch covering spoken and written language identification, which focuses on empirical recognition tasks rather than formal characterizations of what becomes learnable under different information regimes.

Among the three contributions analyzed from 30 candidate papers, the learning model itself and the trichotomic error-tolerance results show no clear refutation across 10 examined candidates each. However, the claim about identifying all computable languages with perfect traces encountered one potentially refutable candidate among 10 examined. This suggests the core modeling contribution appears relatively novel within the limited search scope, while the result on universal computability may have closer connections to existing theoretical work. The modest search scale means these assessments reflect top-30 semantic matches rather than exhaustive coverage.

Given the limited literature search and the paper's position as the sole occupant of its taxonomy leaf, the work appears to explore a genuinely underexplored intersection between formal learning theory and computational trace augmentation. The analysis covers semantic neighbors and citation-expanded candidates but cannot rule out relevant work outside this scope, particularly in adjacent areas of computational learning theory or inductive inference that may not surface through language-identification-focused queries.

This paper presents **3 main contributions**, each analyzed against relevant prior work:

Contribution 1: Identification in the limit with trace learning model

Description: The authors propose a novel learning framework that extends Gold's language identification paradigm by equipping learners with computational traces (step-by-step execution sequences) alongside language examples. This model formalizes the role of chain-of-thought style reasoning in language learnability.

This contribution was assessed against **10 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

1. Do code semantics help? a comprehensive study on execution trace-based information for code large language models

URL: [View paper](#)

Brief Assessment

Execution Trace Semantics[42] focuses on integrating execution traces into code LLM training and inference for programming tasks, not on formal language identification theory or Gold's paradigm extensions.

2. A forced sampled execution approach to kernel rootkit identification

URL: [View paper](#)

Brief Assessment

Kernel Rootkit Identification[50] focuses on kernel rootkit detection using forced sampled execution and instruction sequence patterns, not on formal language identification or learning theory frameworks.

3. Guaranteed loop bound identification from program traces for WCET

URL: [View paper](#)

Brief Assessment

Loop Bound Traces[45] focuses on determining loop iteration bounds from program execution traces for worst-case execution time analysis, not on formal language identification or learnability theory. The candidate addresses a specific static analysis problem rather than extending Gold's language identification paradigm with computational traces.

4. Learning concise models from long execution traces

URL: [View paper](#)

Brief Assessment

Concise Trace Models[43] focuses on learning finite automata from execution traces of hardware/software systems using program synthesis techniques. The original paper introduces a theoretical framework for language identification with computational traces from Turing machines, which is fundamentally different from learning system models from execution traces.

5. Large Language Model Powered Symbolic Execution

URL: [View paper](#)

Brief Assessment

Symbolic Execution LLM[47] focuses on using LLMs for symbolic execution of programs with computational traces from execution sequences, not on formal language identification theory or Gold's learning paradigm.

6. Neural-Symbolic VQA: Disentangling Reasoning from Vision and Language Understanding

URL: [View paper](#)

Brief Assessment

Neural-Symbolic VQA[44] focuses on visual question answering by executing symbolic programs on scene representations, not on formal language identification theory or Gold's learning paradigm with computational traces.

7. Towards Using Inductive Learning to Adapt Security Controls in Smart Homes

URL: [View paper](#)

Brief Assessment

Inductive Smart Homes[49] focuses on using inductive logic programming (ILaSP) to learn security controls for smart home systems from execution traces, not on formal language identification theory or Gold's paradigm.

8. Inferring program extensions from traces

URL: [View paper](#)

Brief Assessment

Inferring Extensions[46] addresses program synthesis from execution traces (command sequences), focusing on inferring imperative program control flow. The ORIGINAL paper studies formal language identification with computational traces from automata/TMs, a fundamentally different problem domain despite both involving 'traces'.

9. Rigorous identification and encoding of trace-links in model-driven engineering

URL: [View paper](#)

Brief Assessment

Trace-Links Encoding[48] focuses on trace-links between models in model-driven engineering for software development, not on language identification or computational learning theory with execution traces.

10. A fast algorithm to locate concepts in execution traces

URL: [View paper](#)

Brief Assessment

Concepts Execution Traces[51] focuses on locating concepts in execution traces for debugging purposes, not on formal language identification theory or learnability frameworks.

Contribution 2: Identifiability of all computable languages with perfect traces

Description: The authors establish that when learners have access to perfect computational traces, they can identify any language recognizable by Turing machines in the limit. This result sharply contrasts with Gold's impossibility result for even simpler language classes like regular languages.

This contribution was assessed against **10 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

1. Language identification in the limit

URL: [View paper](#)

Brief Assessment

The candidate paper context is too fragmentary to assess whether it addresses identifiability of computable languages with computational traces. Only sentence fragments are visible, preventing meaningful comparison with the original paper's contribution.

2. A Characterization of List Language Identification in the Limit

URL: [View paper](#)

Brief Assessment

List Language Characterization[6] focuses on list identification in the limit (outputting k guesses) for language collections without computational traces, while the original work studies identification with computational traces from Turing machines. These are fundamentally different augmentation mechanisms for Gold's framework.

3. Normal numbers and limit computable Cantor series

URL: [View paper](#)

Brief Assessment

Normal Cantor Series[41] focuses on computability theory for real numbers and distribution-normality in Cantor series, not on language identification or computational traces for formal languages.

4. Limitative computational explanations

URL: [View paper](#)

Brief Assessment

The candidate paper (Limitative Explanations[40]) context is not available (marked as 'n/a'), making it impossible to assess whether it refutes the novelty of identifying computable languages in the limit using computational traces.

5. Do we live in a [quantum] simulation? Constraints, observations, and experiments on the simulation hypothesis

URL: [View paper](#)

Brief Assessment

Quantum Simulation Constraints[37] focuses on philosophical and physical constraints of simulating universes using quantum computers, not on formal language learning theory or computational trace-based identification of Turing-recognizable languages.

6. Learning Algorithms in the Limit

URL: [View paper](#)

Prior Art Analysis

Learning Limit Algorithms[35] demonstrates that the class of general recursive functions (equivalent to computable languages) can be learned in the limit when supplemented with computational observations. The candidate explicitly states that 'input-output observations do not suffice for learning the class of general recursive functions in the limit' but 'we overcome this learning barrier by imposing computational complexity constraints or supplementing with approximate time-bound observations.' This establishes prior work showing that computable functions/languages become learnable with computational trace information, directly challenging the novelty of the original paper's claim to be first in proving this result.

Evidence

Evidence 1 - **Rationale:** Both papers address the same fundamental problem: Gold's impossibility result prevents learning computable functions/languages from input-output alone, but both show this barrier can be overcome with computational observations. The candidate's 'general recursive functions' are equivalent to the original's 'computable languages (those recognizable by Turing machines)' - these are standard equivalent characterizations of the same computational class. - **Original:** we first prove that with perfect computational traces, the class of all computable languages (those recognizable by Turing machines) becomes identifiable in the limit. this stands in sharp contrast to Gold's famous impossibility result, which holds even for the simple class of languages that are rec... - **Candidate:** while input-output observations do not suffice for learning the class of general recursive functions in the limit, we overcome this learning barrier by imposing computational complexity constraints or supplementing with approximate time-bound observations.

Evidence 2 - **Rationale:** Both papers extend Gold's framework by adding computational information beyond input-output pairs. The original adds 'computational traces from the machine' while the candidate adds 'computational observations' including 'time-bound observations' and 'policy-trajectory observations'. Both represent the same conceptual approach of augmenting Gold's model with computational process information. - **Original:** we introduce a new learning model, identification in the limit with trace, which augments Gold's classic paradigm (Gold, 1967) by providing the learner not only with examples from a target language but also with computational traces from the machine that accepts them. - **Candidate:** this paper studies the problem of learning computable functions in the limit by extending Gold's inductive inference framework to incorporate $\{\text{computational observations}\}$ and $\{\text{restricted input sources}\}$. complimentary to the traditional input-output observations, we introduce time-bound...

7. Information Gain Limit of Biomolecular Computation.

URL: [View paper](#)

Brief Assessment

The candidate paper (Biomolecular Information Gain[36]) focuses on information gain limits in biomolecular computation systems, not on language identification or computational traces for learning formal languages.

8. Language barrier in theories of mind and limitations of the computational approach

URL: [View paper](#)

Brief Assessment

Language Barrier Mind[39] is a philosophical paper examining methodological limitations of computational approaches in philosophy of mind. It does not address language identification in the limit or computational trace-based learning theory, which are the core technical contributions of the original paper.

9. A Short Computer Program Which Computes in the Limit a Non-Computable Function from N to N

URL: [View paper](#)

Brief Assessment

Non-Computable Function[38] focuses on computing non-computable functions from N to N in the limit using equation systems, not on identifying computable languages using computational traces from Turing machines.

10. Computational limits on team identification of languages

URL: [View paper](#)

Brief Assessment

Team Computational Limits[16] focuses on team-based identification of languages with multiple learners, while the original paper studies single-learner identification augmented with computational traces. These are fundamentally different learning paradigms.

Contribution 3: Trichotomic results on error tolerance across Chomsky hierarchy

Description: The authors prove tight bounds on how much corruption in computational traces can be tolerated while still identifying languages. They show DFAs tolerate constant error rates, DPDAs require diminishing error rates, and Turing machines need bounded finite errors for successful identification.

This contribution was assessed against **10 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

1. Formal Logical Reasoning With Transformers and Their Place on the Chomsky Hierarchy.

URL: [View paper](#)

Brief Assessment

Transformers Chomsky[28] focuses on testing transformer and LSTM architectures on propositional logic derivation tasks, examining their place on the Chomsky hierarchy. It does not address error tolerance in language identification or establish bounds on corruption rates across different automata classes (DFAs, DPDAs, TMs).

2. Quantum artificial neural network architectures and components

URL: [View paper](#)

Brief Assessment

Quantum Neural Architectures[32] mentions the Chomsky hierarchy only in passing as a classification framework for neural architectures, not in the context of error tolerance in language identification or computational trace corruption.

3. Interactive foundations of computing

URL: [View paper](#)

Brief Assessment

Interactive Foundations[31] discusses interactive extensions of the Chomsky hierarchy and robustness of interactive models, but the provided context is too fragmentary to determine whether it addresses error tolerance in language identification with computational traces.

4. Formal languages and compilation

URL: [View paper](#)

Brief Assessment

Formal Compilation[27] is a textbook on formal languages and compilation that discusses Chomsky hierarchy and error handling in parsers, but does not present research results on error tolerance bounds for language identification across computational models.

5. Targeted syntactic evaluation on the Chomsky hierarchy

URL: [View paper](#)

Brief Assessment

Chomsky Hierarchy Evaluation[25] focuses on evaluating language models' ability to recognize syntactic phenomena at different Chomsky hierarchy levels using formal languages, not on proving bounds for error tolerance in computational trace corruption during language identification tasks.

6. CLeAR: Continual Learning on Algorithmic Reasoning for Human-like Intelligence

URL: [View paper](#)

Brief Assessment

CLeAR Algorithmic[26] focuses on continual learning of algorithmic reasoning tasks across Chomsky hierarchy levels, not on error tolerance in computational traces during language identification. The paper addresses catastrophic forgetting in sequential task learning rather than corruption tolerance in identification processes.

7. How chemistry computes: Language recognition by non-biochemical chemical automata. From finite automata to turing machines

URL: [View paper](#)

Brief Assessment

Chemical Automata[29] focuses on chemical computing implementations of automata, not error tolerance in language identification across the Chomsky hierarchy.

8. Organic Component Identification using Syntactic Pattern Recognition

URL: [View paper](#)

Brief Assessment

Syntactic Pattern Recognition[30] focuses on applying formal grammars to identify organic chemical structures and functional groups, not on error tolerance in computational language identification across the Chomsky hierarchy.

9. Bridging Neural and Symbolic Computation: A Learnability Study of RNNs on Counter and Dyck Languages

URL: [View paper](#)

Brief Assessment

Counter Dyck Learnability[33] focuses on RNN learnability for counter and Dyck languages under finite precision constraints, not on error tolerance in computational traces across the Chomsky hierarchy. The candidate examines practical learnability limitations of neural models rather than theoretical bounds on corruption tolerance in language identification.

10. Neural Networks and the Chomsky Hierarchy

URL: [View paper](#)

Brief Assessment

Neural Chomsky[34] studies neural network architectures' ability to learn formal languages across the Chomsky hierarchy, but does not address error tolerance in computational traces or language identification in the limit. The papers address fundamentally different problems: one focuses on learning with corrupted traces, the other on architecture capabilities for sequence prediction.

Appendix: Text Similarity Detection

Textual similarity detection checked 30 papers and found 1 similarity segment(s) across 1 paper(s).

The following **1 paper(s)** were detected to have high textual similarity with the original paper. These may represent different versions of the same work, duplicate submissions, or papers with substantial textual overlap. Readers are advised to verify these relationships independently.

1. Neural Networks and the Chomsky Hierarchy

Detected in: Contribution: contribution_3

△ **Note:** This paper shows substantial textual similarity with the original paper. It may be a different version, a duplicate submission, or contain significant overlapping content. Please review carefully to determine the nature of the relationship.

References

- [0] Language Identification in the Limit with Computational Trace [View paper](#)
- [1] Language Identification of Philippine Creole Spanish: Discriminating Chavacano From Related Languages [View paper](#)
- [2] Towards audio-based identification of Ethio-Semitic languages using recurrent neural network. [View paper](#)
- [3] Language Identification in Short Utterances Using Long Short-Term Memory (LSTM) Recurrent Neural Networks [View paper](#)
- [4] Language identification in the limit [View paper](#)
- [5] Identification of Indian Languages using Ghost-VLAD pooling [View paper](#)
- [6] A Characterization of List Language Identification in the Limit [View paper](#)
- [7] Exploring Residual Cepstral Features for Spoken Language Identification [View paper](#)
- [8] Script-Agnostic Language Identification [View paper](#)
- [9] LIMIT: Language Identification, Misidentification, and Translation using Hierarchical Models in 350+ Languages [View paper](#)
- [10] An automatic language identification system [View paper](#)
- [11] Enhancing human computer interaction with coot optimization and deep learning for multi language identification. [View paper](#)
- [12] Language Identification of Devanagari Poems [View paper](#)
- [13] Improved Language Identification Through Cross-Lingual Self-Supervised Learning [View paper](#)
- [14] Robust Open-Set Spoken Language Identification and the CU MultiLang Dataset [View paper](#)
- [15] Language identification in the limit [View paper](#)
- [16] Computational limits on team identification of languages [View paper](#)
- [17] Spoken Language Identification Using Deep Learning. [View paper](#)
- [18] Is Attention always needed? A Case Study on Language Identification from Speech [View paper](#)
- [19] Spoken Language Identification using ConvNets [View paper](#)
- [20] Open-Set Language Identification [View paper](#)
- [21] BERT-LID: Leveraging BERT to Improve Spoken Language Identification [View paper](#)
- [22] The WiLI benchmark dataset for written language identification [View paper](#)
- [23] Hierarchical Character-Word Models for Language Identification [View paper](#)
- [24] Profiling source language traces in contemporary literary translations [View paper](#)
- [25] Targeted syntactic evaluation on the Chomsky hierarchy [View paper](#)
- [26] CLeAR: Continual Learning on Algorithmic Reasoning for Human-like Intelligence [View paper](#)
- [27] Formal languages and compilation [View paper](#)
- [28] Formal Logical Reasoning With Transformers and Their Place on the Chomsky Hierarchy. [View paper](#)
- [29] How chemistry computes: Language recognition by non-biochemical chemical automata. From finite automata to turing machines [View paper](#)
- [30] Organic Component Identification using Syntactic Pattern Recognition [View paper](#)
- [31] Interactive foundations of computing [View paper](#)
- [32] Quantum artificial neural network architectures and components [View paper](#)
- [33] Bridging Neural and Symbolic Computation: A Learnability Study of RNNs on Counter and Dyck Languages [View paper](#)
- [34] Neural Networks and the Chomsky Hierarchy [View paper](#)
- [35] Learning Algorithms in the Limit [View paper](#)
- [36] Information Gain Limit of Biomolecular Computation. [View paper](#)
- [37] Do we live in a [quantum] simulation? Constraints, observations, and experiments on the simulation hypothesis [View paper](#)
- [38] A Short Computer Program Which Computes in the Limit a Non-Computable Function from N to N [View paper](#)
- [39] Language barrier in theories of mind and limitations of the computational approach [View paper](#)
- [40] Limitative computational explanations [View paper](#)
- [41] Normal numbers and limit computable Cantor series [View paper](#)
- [42] Do code semantics help? a comprehensive study on execution trace-based information for code large language models [View paper](#)
- [43] Learning concise models from long execution traces [View paper](#)

- [44] Neural-Symbolic VQA: Disentangling Reasoning from Vision and Language Understanding [View paper](#)
- [45] Guaranteed loop bound identification from program traces for WCET [View paper](#)
- [46] Inferring program extensions from traces [View paper](#)
- [47] Large Language Model Powered Symbolic Execution [View paper](#)
- [48] Rigorous identification and encoding of trace-links in model-driven engineering [View paper](#)
- [49] Towards Using Inductive Learning to Adapt Security Controls in Smart Homes [View paper](#)
- [50] A forced sampled execution approach to kernel rootkit identification [View paper](#)
- [51] A fast algorithm to locate concepts in execution traces [View paper](#)