

# **Artificial Knowledge of Language**

A Linguist's Perspective on Its Nature, Origins and Use

Edited by

**José-Luis Mendívil-Giró**

University of Zaragoza

**Series in Language and Linguistics**



**VERNON PRESS**

Copyright © 2026 by the authors.

All rights reserved. No part of this publication may be reproduced, stored in a retrieval system, or transmitted in any form or by any means, electronic, mechanical, photocopying, recording, or otherwise, without the prior permission of Vernon Art and Science Inc.

[www.vernonpress.com](http://www.vernonpress.com)

*In the Americas:*  
Vernon Press  
1000 N West Street, Suite 1200  
Wilmington, Delaware, 19801  
United States

*In the rest of the world:*  
Vernon Press  
C/Sancti Espiritu 17,  
Malaga, 29006  
Spain

Series in Language and Linguistics

Library of Congress Control Number: 2025945088

ISBN: 979-8-8819-0379-4

Product and company names mentioned in this work are the trademarks of their respective owners. While every care has been taken in preparing this work, neither the authors nor Vernon Art and Science Inc. may be held responsible for any loss or damage caused or alleged to be caused directly or indirectly by the information contained in it.

Cover design by Vernon Press with elements from Freepik.

Every effort has been made to trace all copyright holders, but if any have been inadvertently overlooked the publisher will be pleased to include any necessary credits in any subsequent reprint or edition.

*Although Markov, Turing, von Neumann, or Chomsky never got a Nobel Prize, technologists developing their foundational ideas into Large Language Models surprisingly did: in 2024. The present book delves into the (for now) state-of-the-art in this saga, presenting it as dispassionately as possible through eight prismatic chapters. If readers wonder how momentous an epilogue and beyond can be, they only need to imagine the offspring of a next generation of such devices - albeit built beyond classical presuppositions in hardware, logic, or even modeling. The latter no longer seems like a chimerical possibility; whether that is for better or for worse, surviving the future may tell.*

**Dr. Juan Uriagereka**

Professor, Linguistics & SLLC  
University of Maryland

*A comprehensive and wide-ranging overview of the issues (and non-issues) raised for linguistic theory, particularly Chomskyan linguistic theory, by the development of Large Language Models. The editor's introduction is particularly useful. Highly recommended for linguists, including computational linguists, of all persuasions, as well as computer scientists, philosophers and psychologists with an interest in language and AI.*

**Dr. Ian Roberts**

Professor of Linguistics  
University of Cambridge



# Table of Contents

	<b>List of figures</b>	vii
	<b>List of tables</b>	ix
	<b>Preface</b>	xi
Chapter 1	<b>How do large language models work, and what are they a model of?</b>	1
	José-Luis Mendívil-Giró <i>University of Zaragoza</i>	
Chapter 2	<b>The quo vadis of the relationship between language and large language models</b>	21
	Evelina Leivada <i>Autonomous University of Barcelona</i>	
	Vittoria Dentella <i>University of Pavia</i>	
	Elliot Murphy <i>University of Texas</i>	
Chapter 3	<b>Language models as function approximators of text data: disrupting comprehension through and adversarial attack</b>	45
	David J. Lobina <i>Rovira i Virgili University</i>	
Chapter 4	<b>On modern language models, impossible languages, and anti-science</b>	65
	Dan Milway <i>University of Toronto</i>	

Chapter 5	<b>What kind of linguistic knowledge is encoded in large language models?</b>	83
	Miguel López-Otal <i>University of Zaragoza</i>	
	Lucía Pitarch <i>University of Zaragoza</i>	
Chapter 6	<b>ChatGPT and linguistic theory, with a focus on morphology</b>	109
	Stela Manova <i>Manova AI</i>	
Chapter 7	<b>Evaluating the existence proof: LLMs as cognitive models of language acquisition</b>	147
	Héctor Javier Vázquez Martínez <i>University of Pennsylvania</i>	
	Annika Heuser <i>University of Pennsylvania</i>	
	Charles Yang <i>University of Pennsylvania</i>	
	Jordan Kodner <i>Stony Brook University</i>	
Chapter 8	<b>The creative aspect of human language use: How modern language models fare with an old idea</b>	187
	Vincent J. Carchidi <i>Independent Researcher</i>	
	<b>About the contributors</b>	217
	<b>Index</b>	221

# List of figures

<b>Figure 1.1:</b>	ChatGPT describes itself	2
<b>Figure 2.1:</b>	A stepwise risk assessment of LLMs	24
<b>Figure 2.2:</b>	ChatGPT fails to consistently detect attraction errors (October 2023). It also produces agreement errors of the same type in its output. Note that more recent models of ChatGPT get this correct (July 2025 testing), but see Murphy et al. (2025a) for more acute tests.	26
<b>Figure 2.3:</b>	An LLM failure to judge a semantically coherent and grammatical sentence of English as such.	27
<b>Figure 2.4:</b>	ChaptGPT (o3-mini-high) test of structural ambiguity (March 2025)	28
<b>Figure 2.5:</b>	Two LLM failures to generate factually correct content (October 2023)	29
<b>Figure 2.6:</b>	An LLM failure to distinguish between possible and impossible language.	31
<b>Figure 2.7:</b>	The circle of experimentation, taking language as the domain of study	35
<b>Figure 3.1:</b>	The Different Kinds of Artificial Intelligence	48
<b>Figure 3.2:</b>	Rough outline of a deep neural network	48
<b>Figure 3.3:</b>	Adversarial attack on a visual input	56
<b>Figure 3.4:</b>	How an LLM works	57
<b>Figure 3.5:</b>	What an LLM sees	57
<b>Figure 3.6:</b>	What an LLM sees under attack	58
<b>Figure 3.7:</b>	Affix attack on an LLM	58
<b>Figure 3.8:</b>	Two-step attack on an LLM	59
<b>Figure 6.1:</b>	-er (token as Text)	112
<b>Figure 6.2:</b>	-er (token ID)	113
<b>Figure 6.3:</b>	Tokens that are not linguistic units	113
<b>Figure 6.4:</b>	<i>er-</i> (token as text)	114
<b>Figure 6.5:</b>	<i>er-</i> (token ID)	115
<b>Figure 6.6:</b>	Token #1 in the List	115
<b>Figure 6.7:</b>	Token ID [0] in the Tokenizer	116
<b>Figure 6.8:</b>	'linguistic research' (Text)	118
<b>Figure 6.9:</b>	'linguistic research' (IDs)	118

<b>Figure 6.10:</b>	‘crosslinguistic’ (Text)	119
<b>Figure 6.11:</b>	‘crosslinguistic’ (IDs)	119
<b>Figure 6.12:</b>	‘cross-linguistic’ (Text)	120
<b>Figure 6.13:</b>	‘cross-linguistic’ (IDs)	120
<b>Figure 6.14:</b>	Native speakers’ accuracy of recognition of the 60 suffix combinations tested in the experiment (only statistically significant results).	132
<b>Figure 6.15:</b>	‘read’ is a single token	135
<b>Figure 6.16:</b>	‘reads’ is a single token	136
<b>Figure 6.17:</b>	‘organization’ is a single token	136
<b>Figure 6.18:</b>	‘organizations’ is a single token	137
<b>Figure 6.19:</b>	‘illegible’	138
<b>Figure 6.20:</b>	‘illogical’	139
<b>Figure 6.21:</b>	‘illiberal’	139
<b>Figure 6.22:</b>	‘illegal’	140
<b>Figure 7.1:</b>	LM performance on the LI-Adger dataset. Human performance is marked by the vertical line. Baby=BabyBERTa, CHI=AO-CHILDES, News=AO-NEWSELA, Wiki=Wikipedia-1.	173
<b>Figure 7.2:</b>	Correlation matrices of human judgments and LM output means (top) and standard deviations (bottom) on each sentence type on the LI-Adger dataset. Baby=BabyBERTa, CHI=AO-CHILDES, News=AO-NEWSELA, Wiki=Wikipedia-1.	174

## List of tables

<b>Table 6.1:</b>	Combinability of the English suffix <i>-ist</i>	129
<b>Table 6.2:</b>	Combinability of the Polish suffix <i>-arz</i>	131
<b>Table 7.1:</b>	Summary performance for 5-grams relative to BabyBERTa on Zorro and BLiMP. The number of paradigms in which a 5-gram model outperforms BabyBERTa and the overall average accuracy across paradigms are reported. Either = either 5-word or 5-tag outperformed BabyBERTa on the entire paradigm. Oracle = sentence pairs were marked correct if either 5-word or 5-tag made the correct prediction.	161
<b>Table 7.2:</b>	Word and tag-level 5-gram models trained on ao-childes plus 5-Gram Oracle and Simple Linear Rule Oracle for Zorro. 5-Gram and Simple Rule scores that are greater than BabyBERTa_ao-childes scores are bolded.	162
<b>Table 7.3:</b>	Word and tag-level 5-gram models trained on AO-CHILDES plus 5-Gram Oracle and Simple Linear Rule Oracle for BLiMP (ANAPHOR AGR through ELLIPSIS). 5-Gram and Simple Rule scores that are greater than BabyBERTa_AO-CHILDES scores are bolded.	163
<b>Table 7.4:</b>	Word and tag-level 5-gram models trained on AO-CHILDES plus 5-Gram Oracle and Simple Linear Rule Oracle for BLiMP (FILLER-GAP through SUBJECT-VERB AGR). 5-Gram and Simple Rule scores that are greater than BabyBERTa_AO-CHILDES scores are bolded.	164
<b>Table 7.5:</b>	Simple Linear Rule descriptions for Zorro. Rules that require sentences within a minimal pair to be compared are marked with an asterisk (in_question_with_aux).	167
<b>Table 7.6:</b>	Linear Rule descriptions for BLiMP (ANAPHOR AGR through ELLIPSIS). Rules that require sentences to be compared are marked with an asterisk.	168

<b>Table 7.7:</b> Linear Rule descriptions for BLiMP (Filler-gap through Subject-verb agr). Rules that require sentences to be compared are marked with an asterisk.	169
--	-----

# Preface

The objective of this volume is to gather linguistically informed opinions (from linguists or cognitive scientists with specialization in the study of language) on the nature, origins and use of the knowledge of language developed by the Artificial Intelligence systems called Large Language Models (LLMs).

The recent development and popularization of these systems has had a significant impact on the media, particularly the most well-known and widely used system, ChatGPT (developed by the company OpenAI). Similarly, this emergence has led to the proliferation of opinions regarding the relevance of LLMs beyond the practical (and typically commercial) purposes for which they have been designed, particularly in the fields of cognitive science and linguistic theory. Thus, it is not uncommon to find on social networks, blogs and popular magazines statements such as that LLMs have solved the problems that sciences such as linguistics aim to solve, that the success of LLMs in the generation of text can be considered a refutation of some notably influential theories of language (especially Noam Chomsky's approach and generative grammar, the tradition that arose from his ideas about language and the human mind), or the claim that LLMs are in fact scientific theories of language.

These statements appear to be founded upon the premise that the linguistic knowledge acquired by these systems is analogous to, or at least comparable to, that which is developed by human beings in a naturalistic manner. The objective of this book is to evaluate the extent to which this assumption is justified.

It is important to recall that Noam Chomsky, in his 1986 book *Knowledge of Language: Its Nature, Origins, and Use* (whose title serves as inspiration for that of the present volume), argued that the pivotal shift in the science of language that emerged with generative grammar and the so-called cognitive revolution in the 1950s was the realization that the object of linguistic inquiry, as part of the broader field of natural science, was not the observable linguistic behavior of speakers or the product of their language use, as was previously assumed, but rather the knowledge of language itself.

Consequently, the questions that the chapters gathered in this volume aim to answer, all of them related to the central issue of comparing natural and artificial knowledge of language, are the following:

- To what extent are LLMs models of human language?
- To what extent can it be asserted that, for example, ChatGPT has learned English (or any other language)?
- What, if any, are the differences between the knowledge of language possessed by LLMs and that of human beings?
- In what sense are LLMs relevant to our understanding of the processes by which humans acquire and use languages?
- Is there any component of the language faculty (semantics, syntax, pragmatics, morphology, phonology) in which LLMs' knowledge is more similar to that of humans than in others?
- What uses for language research can such systems have?
- What impact will the development of LLMs have on the field of linguistic theory as a scientific discipline?

The initial chapter presents an introduction to the fundamental operations of the so-called Large Language Models (especially ChatGPT) for readers lacking expertise in computational linguistics. Additionally, it offers an introduction to the structure and defining characteristics of the human faculty of language for readers lacking expertise in linguistics. Similarly, an initial examination of the concept of a model in the scientific context is provided, along with an overview of the remaining chapters in this volume, whose authors I sincerely thank for their willingness to get involved in the initiative to produce this book. I would also like to thank three anonymous reviewers who read the manuscript and provided valuable feedback that undoubtedly helped to improve it.

José-Luis Mendívil-Giró

## Chapter 1

# How do large language models work, and what are they a model of?

José-Luis Mendívil-Giró

*University of Zaragoza*

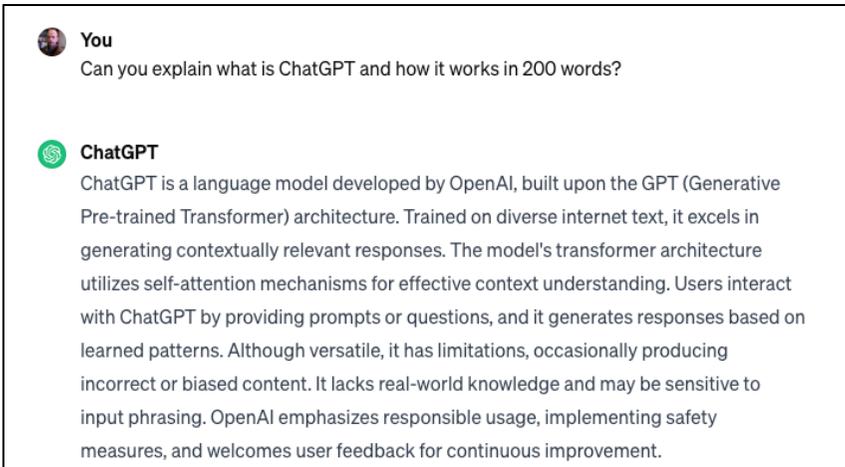
**Abstract:** The first chapter presents an introduction (adapted to readers who are not experts in computational linguistics) to the basic operation of the so-called Large Language Models (especially ChatGPT), and also an introduction (adapted to readers who are not experts in linguistics) to the structure of the human faculty of language and the properties that characterize it. The chapter introduces a crucial distinction between the internalist conception of language (which studies language as a system of knowledge) and the externalist conception (which studies language as a product or result of language use), and then shows that “language models” are models of the product of language use, not of the system of knowledge that underlies that use. Finally, an introduction to the content of the remaining chapters is provided.

**Keywords:** Knowledge of language, Linguistic Theory, Generative Grammar, Large Language Models, Artificial Intelligence

\*\*\*

If we ask ChatGPT (the most popular of the latest generation of large language models) what it is and how it works, it writes—in a couple of seconds—the text we have in Figure 1.1.

Although the reader will have understood the definition—which is essentially correct—the wonderful thing is that the algorithm that wrote it does not understand a word of what it says. It also didn’t know that humans would be reading its text, and it doesn’t even know what a human is.

**Figure 1.1:** ChatGPT describes itself

Nevertheless, it is clear that ChatGPT is an impressive and sophisticated engineering tool, as well as extraordinarily useful. Its potential, including its commercial use, is set to be enormous. Without a doubt, for better and worse, in natural language processing technology, there will be a before and after marked by this latest generation of large language models (LLMs). But surely there will be no such radical change, contrary to what numerous authors have suggested, with regard to our knowledge of human language and the human mind.

### 1. The human brain and the Chinese room

The Chinese Room is a renowned thought experiment proposed by John Searle to challenge the notion that machines are capable of understanding and processing information in a manner analogous to that of humans. In the *Gedankenexperiment*, Searle postulates a scenario in which an individual who is not proficient in the Chinese language (Searle himself) is confined within a room. The individual has a set of rules that enables him to manipulate Chinese symbols in response to specific inputs. To illustrate, if presented with a question in Chinese, the imaginary Searle will consult the rules and produce a response in Chinese, despite lacking a genuine comprehension of the language. Searle posits that, although the individual may produce responses that appear to be appropriate to native Chinese speakers, he does not actually comprehend the language. Similarly, Searle posits that a machine that emulates this form of

symbol processing cannot possess a genuine comprehension of language or the world in the same manner as humans.

Of course, some philosophers have argued that Searle's thought experiment does not serve to reject a real knowledge capacity of Artificial Intelligence (AI), since it may well be that our own brains (the standard we use to define *knowledge*) are also Chinese rooms. We should then conclude that even if there were a real Chinese speaker inside the famous room, her brain would function like the Chinese room she is in. In fact, there is no doubt that, at a certain level, our "knowledge," whether of Searle, of Chinese, or of ourselves, will be supported by groups of cells and tissues that behave like the individual in the Chinese room, or like the algorithm that powers ChatGPT: moving chunks of incomprehensible information from one site to another. Nevertheless, even if this is the case, it does not necessarily follow that we cannot assert that we possess knowledge and that we are aware of our possession of that knowledge.

In any case, beyond the deep paradoxes and mysteries of consciousness and the very nature of knowledge, the relevant question now is whether LLMs such as ChatGPT have a knowledge of language that is analogous or comparable to that which human beings have. The many scientists who believe so are those who defend that ChatGPT is a useful model to better explain how it is possible that we can learn and use the languages of the environment—and even some, like Steven Piantadosi (2023), affirm that these systems are authentic theories of language, while scientists who believe not—for example, Chomsky, Roberts and Watumull (2023)—are those who reject that LLMs are relevant to better understanding our language capacity, even though they are useful as engineering products.

In order to understand the manner in which these inconsistencies arise, it is essential to initially examine the fundamental mechanisms underlying the operation of these LLMs. It is only then that an evaluation can be made as to whether the knowledge currently held about the processes of language acquisition and use in the human brain is comparable or equivalent to that observed in these AI models.

## **2. Inside the stochastic parrot: how does ChatGPT work?**

Computational linguist Emily Bender (Bender et al. 2021) has popularized the name *stochastic parrots* for LLMs as it encapsulates two pivotal characteristics of their operation: the reliance on probability-based word prediction and the absence of comprehension.

And, in fact, what LLMs really do is calculate the probability that a graphic word appears, taking into account the graphic words that it already has chained together.<sup>1</sup>

I have purposely used the expression “graphic word” because, unlike what happens with human language, ChatGPT does not operate with authentic linguistic units (that is, morphemes and lexemes, entities with meaning), but with tokens, that is, sequences of very frequent combinations of letters or characters. Computational linguists had previously identified that the outcomes are enhanced when these tokens, which comprise approximately four characters in English, are utilized. Consequently, a single token is deemed to be analogous to approximately “three-quarters” of a graphic word in English (100 tokens = 75 graphic words). The tokens that ChatGPT manipulates are, in some ways, the written language equivalent of syllables in oral language: recurring sequences of basic units with no correlation to meaning. There is, apparently, no theoretical motivation behind this practice, but rather greater efficiency and flexibility in the task of predicting the next *word* (hereinafter understood as “frequent sequence of characters”), taking into account practically everything that has been written in English and was digitized.<sup>2</sup>

The key question is how to obtain the probabilities that the program uses to evaluate which word to write next to the one you just typed. Note that the aim is not to calculate the probability of the next word based on the last one used alone, but on all the words that have already been used. Otherwise, coherent and natural-looking text would not be generated, but rather a confusing and repetitive sequence. However, Wolfram’s calculations indicate that the quantity of written English text in existence is insufficient to enable the calculation of the probabilities associated with groups of words. Given a lexicon of approximately 50,000 words, the potential combinations of three-word sequences exceed 60 trillion. For 20-word sequences (a typical length of written sentences), the number of possibilities is greater than the number of particles in the universe. Consequently, there is not—nor could there ever be—enough written text in the world for those probabilities to be calculated.

So what ChatGPT does to instantiate its basic ability to guess how to continue the piece of text it is given is to use a *model* (a huge mathematical function) that

---

<sup>1</sup> In this brief description of how current LLMs work, I focus on ChatGPT and I rely on the (much more detailed and technical) characterization by Stephen Wolfram (2023).

<sup>2</sup> For a detailed explanation of the tokenization process in ChatGPT, see Manova’s chapter in this volume.

PAGES MISSING  
FROM THIS FREE SAMPLE

## About the contributors

Vincent J. **Carchidi** is a researcher in cognitive science and the philosophy of mind, with an interest in artificial intelligence. His work is interdisciplinary, most recently focusing on foundational issues in the generative linguistics tradition, including voluntary linguistic behavior. He likewise maintains an interest in moral cognition and human rights attitudes, focusing on leveraging the research strategies employed by generative linguistics for moral psychology. Carchidi's work appears in academic outlets including the *Human Rights Review*, *AI & Society*, *Biolinguistics*, and the *Cambridge University Press*. He also has an extensive publishing record on technology policy in outlets including *The Hill*, *National Interest*, *Military Strategy Magazine*, and *Defense One*, as well as with think tanks including the Middle East Institute, the Foreign Policy Research Institute, and the New Lines Institute.

Vittoria **Dentella** is a postdoctoral researcher in the Department of Brain and Behavioral Sciences at the University of Pavia. She holds a PhD in Cognitive Science and Language from Rovira i Virgili University in Tarragona, Spain, which was funded by a European MSCA grant. Her research focuses on the relationship between psycholinguistic theories of cognition and computation, with a focus on the role of computational models in advancing our understanding of human grammars.

Annika **Heuser** is a Ph.D. candidate in linguistics at the University of Pennsylvania, advised by Professor Charles Yang. She has a B.S. and M.Eng. from MIT in computer science and brain and cognitive sciences. She takes a computational approach, often using tools from natural language processing, in researching child language acquisition. More specifically, her research focuses on phonological development and how children learn discrete representations that differ from the continuous surface forms that they hear.

Jordan **Kodner** is a faculty member in the Department of Linguistics at Stony Brook University with additional appointments in Computer Science, the AI Innovation Institute, and the Institute for Advanced Computational Science. His work and teaching center on child language acquisition, language change,

and the evaluation of natural language processing models from the perspective of linguistics and cognitive science.

Evelina **Leivada** is a psycholinguist, currently an ICREA Research Professor at Universitat Autònoma de Barcelona. Her research brings together both the cognitive and the sociolinguistic aspects of the ability to acquire and use language through investigating the effects of developmental trajectory on language and cognition. More recently, she has focused on Large Language Models and how they deviate or match human baselines. Supporting an interdisciplinary approach to language, Evelina is Associate Editor for Psycholinguistics in the Diamond Open Access journal *Biolinguistics*.

David J. **Lobina** is the author of *Recursion* (2017, Oxford University Press) as well as of an increasing number of articles on what may be termed the theoretical repercussions of generative linguistics, not least as a Monday Columnist at *3 Quarks Daily*. A former *Marie Curie* fellow at the University of Oxford and a former *Juan de la Cierva* fellow at the University of Barcelona, he has also worked at the universities of Milano-Bicocca and Rovira i Virgili. As a result, he specialises in theoretical linguistics, psycholinguistics, cognitive psychology, and in the philosophies of cognitive science and psychology. He is currently spending much time thinking about the present status of the language-of-thought hypothesis and is quite tempted to rewrite *The Language of Thought* all over again.

Miguel **López-Otal** is a Ph.D. candidate in Computer Science at the University of Zaragoza. He holds a degree in Spanish Philology and an M.Eng. in Computational Linguistics from the University of the Basque Country. He specializes in Transformer-based models and the analysis of their linguistic capabilities. His current research focuses on ways large language models could better support minority languages with limited text corpora.

Stela **Manova** holds a PhD in General Linguistics from the University of Vienna, where she served as a senior researcher and lecturer. Her academic background spans mathematics, computer science, and languages, and she has published extensively across theoretical, computational, and experimental linguistics. Her key works include *Understanding Morphological Rules* (Springer, 2011),

*Affix Ordering Across Languages and Frameworks* (Oxford University Press, 2015), and *Diminutives Across Languages, Theoretical Frameworks and Linguistic Domains* (De Gruyter, 2024). She has edited and co-edited multiple special issues for the journals *Morphology* (Springer) and *Word Structure* (Edinburgh University Press), and contributed to leading handbooks and encyclopedias, including the forthcoming *Oxford Handbook of Iconicity in Language* (2026). Currently based in Vienna, Dr. Manova serves as CEO of MANOVA AI and Principal Investigator of *Gauss: AI Global*, where she applies her linguistic expertise to artificial intelligence research and development.

José-Luis **Mendívil-Giró** is a full professor of General Linguistics at the University of Zaragoza. His research has focused on the theory of grammar, the philosophy of linguistics, and the nature and extent of language change and diversity. He is the author of five books, including *On Biology, History and Culture in Human Language. A critical overview* (Equinox, 2014, with J.C. Moreno). His research articles have been published in journals such as *Folia Linguistica*, *Journal of Linguistics*, *Linguistics*, *Frontiers in Communication*, *Glossa*, *Biolinguistics*, and *Theoretical Linguistics*.

Dan **Milway** is a sessional lecturer of linguistics at the University of Toronto. His research focuses on syntactic theory and has published on the theory of grammatical agreement and on the nature of syntactic modification. He writes irregularly about linguistics, philosophy of science, and politics at his website milway.ca.

Elliot **Murphy** is a neuroscientist, linguist, philosopher and political economist at the Vivian L. Smith Department of Neurosurgery, McGovern Medical School, in Houston, Texas. His research concerns the neurobiological basis of syntax and semantics, using intracranial recordings from epilepsy and brain tumor patients. He is the author of numerous books, including *The Oscillatory Nature of Language*, and his research has appeared in *Nature Communications*, *PNAS*, *Journal of Neuroscience*, and *Progress in Neurobiology*.

Lucía **Pitarch** is a philologist (Spanish) and Ph.D. candidate in Computational Linguistics at the University of Zaragoza. She has collaborated in European projects such as *Nexus Linguarum*, focused on enhancing open and transparent

multilingual resources, and *4DPicture*, a project paving the way towards improving communication in the oncological environment. Her focus is on computational semantics, with contributions on lexico-semantic relation extraction and computational metaphor processing at top conferences like ACL, ESWC or LREC.

Héctor Javier **Vázquez Martínez** is a Ph.D. researcher in Computational Linguistics at the University of Pennsylvania, with a B.S. and M.Eng. in Electrical Engineering and Computer Science from MIT. His work sits at the intersection of deep learning, natural language processing, and linguistics, specializing in modeling human speech and exploring how it can be represented and acquired by both minds and machines.

Charles **Yang** teaches linguistics, computer science and psychology and directs the Cognitive Science Program at the University of Pennsylvania. He is the author of several books on language learning, variation, and change, including *Knowledge and Learning in Natural Language* (Oxford University Press, 2002), *The Infinite Gift* (Scribner, 2006) and *The Price of Linguistic Productivity* (MIT Press, 2016), which won the *Leonard Bloomfield Award* from the Linguistic Society of America.

# Index

## A

acceptability, 19, 75, 76, 152, 154,  
155, 172, 176  
Adger, 19, 154, 171, 172, 173, 174,  
176  
adversarial attacks, 54  
Aghazadeh, 100  
agreement, 26, 33, 70, 90, 94, 155,  
157, 158, 159, 162, 163, 164, 166,  
167, 171  
AI Winter, 47  
Al-Aqarbeh, 176  
Almeida, 25, 152, 172  
Amariucaí, 150  
Amini, 91, 101  
Amouyal, 86  
Anderson, 194, 197  
Aronoff, 128, 129  
Artificial Intelligence, 46, 48  
Asoulin, 189, 193, 195, 205, 208

## B

BabyBERTa, 88, 156, 160, 161, 162,  
163, 164, 166, 173, 174, 175  
BabyLM, 36, 148, 151, 156, 176  
Baggio, 33, 35  
Baldwin, 149  
Balling, 127  
Baroni, 52, 74, 148, 191  
Barwise, 38  
Batiukova, 32

Baumont, 37, 76, 77, 109  
Bayesian learning model, 151  
Belinkov, 90, 91, 94  
Belth, 177  
Benchmark, 155  
Bender, 3, 25, 26, 27, 29, 85, 102  
Bengio, 20  
Bergen, 88  
Berglund, 51  
BERT, 18, 86, 93, 94, 95, 97, 99,  
100, 101, 148, 174  
Berthet, 194  
Berwick, 177  
Bethard, 93  
Big O notation, 125  
Birhane, 27, 29  
BLiMP, 151, 152, 155, 156, 157, 158,  
159, 160, 161, 163, 164, 167, 168,  
169, 171, 172, 173  
Block, 72  
BLOOM, 88  
Blything, 190, 206  
Bobaljik, 111, 133  
Boeckx, 34, 194  
Boleda, 97  
Bonami, 111, 133  
Borer, 177  
Bornstein, 148, 153  
Bowerman, 177  
Bowers, 30  
Bowman, 149, 173  
Brill, 160  
Brill Tagger, 160  
Brosche, 130

Brown, 153, 176, 177  
 Burkacka, 130  
 byte pair encoding, 116

## C

CALU, 19, 188, 189, 191, 192, 193,  
 198, 199, 203, 204, 205, 206, 208,  
 209, 210, 211  
 Cappa, 66, 71  
 Carchidi, 19, 189, 193, 197, 198,  
 205, 210  
 Chalmers, 37  
 Chang, 88  
 Chao, 151  
 chatbot, 52, 54, 57, 58, 60, 86, 87,  
 110, 121, 122  
 ChatGPT, xi, xii, 1, 2, 3, 4, 5, 6, 7, 8,  
 9, 10, 12, 13, 14, 15, 17, 18, 20,  
 24, 26, 27, 29, 37, 52, 74, 83, 84,  
 86, 87, 88, 109, 110, 111, 114,  
 116, 117, 121, 122, 123, 124, 125,  
 126, 127, 129, 130, 133, 134, 135,  
 137, 138, 140, 141, 142  
 Chaves, 94  
 Chen, 176  
 Chersoni, 102  
 Chi, 92  
 child-directed speech, 151  
 CHILDES, 36, 156, 162, 163, 164,  
 173, 174  
 Chinchilla, 148  
 Chinese room, 2  
 Chin-Yee, 200  
 Chomsky, xi, 3, 7, 9, 10, 11, 14, 19,  
 20, 31, 33, 34, 35, 45, 55, 66, 67,  
 70, 71, 72, 75, 109, 121, 122, 141,  
 149, 150, 152, 177, 187, 188, 189,

190, 191, 192, 193, 195, 196, 197,  
 198, 204, 205, 208, 209, 210, 211  
 Choshen, 88  
 Chowdhury, 152  
 Church, 50  
 Collins, 194, 196, 206, 210  
 competence, 17, 23, 26, 30, 31, 32,  
 37, 68, 88, 91, 94, 124, 188, 189,  
 190, 192, 199, 200, 201, 202, 203,  
 204, 206, 208, 210  
 complexity, 125  
 compositionality, 25, 30, 38  
 conceptual-intentional system, 15  
 Conneau, 90  
 connectionism, 46  
 Contreras Kallens, 46, 54, 62, 203,  
 206  
 Cooper, 38  
 Cordemoy, 188, 193  
 Cotterell, 94, 177  
 Crain, 177

## D

Dagan, 101  
 data mining, 22  
 Davis, 25  
 DeepSeek-AI, 201  
 Demuth, 153  
 Dentella, 16, 21, 25, 54  
 derivation, 135  
 Descartes, 72, 188, 193  
 Devlin, 86, 95, 97  
 Di Marco, 86  
 distributed morphology, 111  
 Doctorow, 79  
 Dressler, 126  
 Dupre, 53, 55, 201

**E**

E-language, 8, 10  
Elazar, 92  
Elman, 150  
Embick, 111, 133  
empiricism, 71  
existence proofs, 148  
explainability, 85  
explanation, 73  
externalization, 14, 15, 16, 30, 54

**F**

Fabb, 128  
Facebook, 88  
factual knowledge, 95  
faculty of language, xii, 13, 16, 20  
Fedorenko, 31, 197, 198  
Felix, 34  
figurative language, 100  
Fine-tuning, 89  
Finkel, 111, 133  
Fitch, 14, 20  
Fodor, 51, 55, 56  
Fortescue, 141  
Fox, 207  
Frazier, 31  
Frigg, 22  
Fu, 56  
Fuhrhop, 128, 129  
Fukuda, 176  
function approximators, 61

**G**

Gagliardi, 16, 20  
Galileo Galilei, 65, 77  
Gates, 36  
Gauss-Jordan, 129

Gauthier, 79, 152  
Gebru, 101  
Gemini, 87  
Gillette, 149  
Gleitman, 149  
Goldin-Meadow, 149  
Goodfellow, 61, 62  
Goodman, 72  
GPT-2, 70  
GPT-4, 5, 27, 37  
Graff, 159  
grammaticality, 25, 38, 152, 154, 156  
Greco, 66, 71  
Grice, 99  
Grohmann, 34  
Gropen, 177  
Guarasci, 93  
Guasti, 55  
Guest, 22, 27  
Gulordava, 152  
Günther, 32  
Gupta, 151, 154

**H**

Hadley, 50, 51  
Haider, 109, 110, 124  
Hall Maudslay, 94  
Halle, 111, 133  
hallucination, 32  
Harbour, 38  
Harley, 111, 133  
Harnad, 37  
Hart, 153  
Hauser, 14, 20  
Hay, 138  
He, 18, 19, 33, 76  
Heinz, 69

Henry, 31  
 Heuser, 18, 147  
 Hewitt, 90, 91, 92, 94  
 hierarchical structure, 9, 11, 37, 67  
 Hill, 23, 25  
 Hornstein, 152, 176  
 Hu, 87, 152  
 Hudson, 150  
 Huebner, 36, 88, 148, 151, 156, 172  
 Huybregts, 197

## I

I-language, 7, 8, 10, 14, 15, 16  
 impossible languages, 17, 32, 60,  
 65, 66, 68, 69, 70, 71, 72, 73  
 inflection, 16, 111, 126, 127, 129,  
 133, 135  
 interpretability, 86, 92, 97, 101

## J

Jackendoff, 55  
 Jarmulowicz, 176  
 Jasbi, 148, 156

## K

Kallini, 66, 70, 71, 73  
 Kam, 150, 157  
 Kaplan, 69, 72, 77  
 Katz, 208  
 Katzir, 12, 13, 20, 38, 54, 109, 207  
 Kidd, 153  
 Kiparsky, 127  
 Kirov, 177  
 Klein, 172  
 Knell, 128, 129, 130  
 knowledge of language, xi  
 Kodner, 18, 69, 154

Koller, 25, 29, 102  
 Kovaleva, 89  
 Krakauer, 39  
 Krasnowska-Kieraś, 90  
 Kuczaj, 177

## L

Labov, 153  
 Lake, 52  
 Lakoff, 99  
 LaMDA, 23, 24  
 Lan, 37  
 Landau, 149  
 language acquisition, 3, 13, 15, 18,  
 37, 53, 133, 134, 147, 148, 149,  
 151, 152, 159, 166, 173, 175, 176  
 Large Language Models, xi, xii, 18,  
 22, 46, 83, 109  
 Lau, 172  
 Le Scao, 88  
 learnability, 149  
 Lederman, 203  
 Lee, 51  
 Leidinger, 87  
 Leivada, 16, 21, 25, 31, 199  
 Lemoine, 23, 24  
 Lenci, 101  
 Lewontin, 35  
 Li, 177  
 LI-Adger Dataset, 171  
 Liang, 91  
 Lidz, 16, 20  
 Lieber, 127  
 linear order, 67  
 Linzen, 148, 155, 158  
 Liu, 38, 101, 173  
 Llama, 88  
 Lobina, 7, 17, 45, 50, 53

Logan, 96  
 López-Otal, 18  
 Luo, 89

## M

machine learning, 11, 17, 46, 47,  
 49, 50, 53, 56, 60, 61, 121, 122,  
 150, 176  
 MacWhinney, 156  
 Madabushi, 89  
 Mahowald, 23, 25, 27, 30, 31, 32,  
 33, 190, 203, 210  
 Manning, 91, 92, 94  
 Manova, 4, 18, 109, 110, 126, 128,  
 129, 130, 133, 141  
 Mansfield, 133  
 Marantz, 111, 133  
 Marcolli, 79  
 Marcus, 25  
 Marvin, 153, 155  
 Mascarenhas, 52  
 McClelland, 177  
 McCoy, 36  
 McGilvray, 189, 192, 193, 195, 197,  
 198, 199, 202, 205, 207, 208, 211  
 McNeill, 150  
 Melançon, 160  
 Melis, 87  
 Mendivil-Giró, 1, 14, 20, 202, 204  
 Merge, 67  
 Mermin, 77  
 Meta, 88  
 metaphor, 100  
 metonymy, 100  
 Mikolov, 97  
 Milway, 17, 65, 68  
 Mintz, 160  
 Mitchell, 24, 30, 39

Moro, 60, 66, 68, 71, 72, 109, 191,  
 197, 200  
 morphology, xii, 13, 15, 16, 18, 26,  
 92, 109, 110, 111, 127, 130, 133,  
 137, 140, 141, 142, 176  
 morphosyntax, 93, 94, 102  
 Murphy, 16, 25, 26, 30, 31, 32, 78,  
 199

## N

neural network, 5, 6, 36, 46, 48, 61,  
 91, 110  
 neural networks, 36, 47, 48, 56, 61,  
 62  
 Newport, 150  
 N-Gram, 159  
 Nivre, 94  
 Niyogi, 149  
 Noyer, 111, 133

## O

OpenAI, xi, 70, 110, 111  
 OPT-125m, 75

## P

Pagnoni, 23, 29  
 Papadimitriou, 152  
 Paradigm Function Morphology,  
 111  
 Parmar, 20  
 Patterson, 177  
 Pauls, 172  
 Payne, 69  
 Pedinotti, 100  
 Peng, 97  
 performance, 36, 38, 69, 70, 89, 93,  
 94, 95, 148, 149, 154, 159, 160,

161, 171, 173, 174, 177, 188, 189,  
190, 192, 193, 195, 200, 201, 203,  
204, 205, 206, 208, 210

Peters, 200

Petroni, 95, 96

phonology, xii, 13, 15, 16, 26, 54,  
55, 137

Piantadosi, 3, 11, 13, 17, 19, 20, 23,  
25, 37, 66, 68, 69, 71, 72, 73, 74,  
76, 77, 78, 79, 109, 121, 141, 151,  
188, 189, 190, 191, 197, 203, 206,  
208, 209

Pietroski, 32

Pimentel, 91, 92

Pinker, 8, 20, 176

Pitarch, 18, 96, 97, 102

Plag, 127

Portelance, 148, 156

Potts, 25

Prasad, 151

prediction, 73

Probing, 90

Prompting, 86

Pruden, 149

Pustejovsky, 32

Pylyshyn, 47, 49, 53

Python, 37, 117, 122, 123, 124

## Q

Quilty-Dunn, 47, 50

## R

Ralph, 98

Rassin, 25

rationalism, 71

Rawski, 37, 76, 77, 109

reasoning, 98

Reeder, 160

Reiss, 190, 203

research questions, 34

Rey, 191, 192, 195, 196, 205, 210

Richter, 94, 177

Rinaldi, 32

Risley, 153

Roberts, 3, 20, 66, 70, 71

Rogers, 86, 90

Rooij, 22, 33, 35

Rumelhart, 177

Ryan, 133

## S

Sahlgren, 101

Samuels, 46

Sartran, 36

Sauerland, 19, 109

scientific model, 17, 22, 27, 73

Searle, 2, 3

self-attention mechanism, 84, 88,  
90, 91, 93

self-attention mechanisms, 84

Selkirk, 127

semantic bootstrapping, 55

semantics, xii, 13, 16, 18, 32, 37,  
38, 54, 55, 75, 84, 86, 92, 93, 95,  
96, 97, 98, 99, 100, 102, 109, 110,  
111, 121, 126, 127, 130, 134, 135,  
142, 155

Sennrich, 116

sensorimotor system, 14, 15

Shanahan, 52

Shapiro, 93

Shazeer, 20

Shi, 160

Shumailov, 75, 76

Siegel, 127

Sinclair, 152  
 Skinner, 195, 196, 197, 198  
 Slobin, 176  
 Smith, 68, 72  
 Solnit, 76  
 Spencer, 127  
 Sprouse, 25, 152, 154, 171, 172, 173, 176  
 Stańczak, 93  
 Stechly, 201  
 Štekauer, 127  
 stimulus-free, 19  
 stimulus-freedom, 189, 191, 195, 196, 197, 199, 203, 206, 207  
 stochastic parrot, 3, 6, 10  
 strong equivalence, 49  
 strong generative capacity, 53  
 structure-dependence, 30, 38  
 Stump, 111, 133  
 Summerfield, 193  
 syntactic bootstrapping, 55  
 syntax, xii, 9, 10, 12, 13, 14, 15, 16, 26, 30, 32, 33, 36, 38, 53, 54, 55, 76, 78, 90, 92, 93, 109, 134, 137, 151, 154  
 systematicity, 50  
 Szymanek, 128, 130

## T

Talamo, 129  
 Tam, 23  
 Tedeschi, 101  
 Tettamanti, 68, 72  
 text-processing, 22  
 Thornton, 177  
 thought, 2, 3, 14, 22, 31, 50, 75, 86, 187

token, 4, 5, 6, 22, 52, 56, 62, 71, 84, 111, 112, 113, 114, 115, 117, 134, 135, 136, 137, 140, 159  
 Tokenization, 115  
 Touvron, 88  
 Transformer, 6, 11, 36, 84, 86, 87, 88, 89, 90, 110  
 Trueswell, 150  
 Tsimpli, 68, 72  
 Tucker, 92  
 Turing, 193, 204

## U

Ullman, 177

## V

Valian, 160  
 Van Schijndel, 151  
 Varley, 31  
 Vaswani, 20, 84  
 Vázquez Martínez, 18, 147, 172  
 Velázquez, Diego de, 10  
 Veres, 37, 38  
 Volenec, 190, 203  
 Vong, 176

## W

Wang, 101, 151  
 Warstadt, 36, 148, 149, 150, 151, 154, 155, 159, 173  
 Watumull, 3, 20, 66, 70, 71, 189, 193  
 weak equivalence, 49  
 weak generative capacity, 53  
 Wei, 94  
 Weinberg, 209  
 Weissweiler, 94

Westergaard, 31

Wexler, 177

Wilcox, 38, 155

Willits, 156

Wolfram, 4, 5, 20

Woodard, 150

word counting, 124

Word2Vec, 97, 99, 101

word-formation, 111, 126, 127,  
128, 130, 133, 142

## X

Xu, 56

## Y

Yang, 18, 147, 149, 176

Yedetore, 36

Yun, 149

## Z

Zamparelli, 152

Zhang, 75, 87, 101

Zhao, 86, 90, 93, 101

Zhou, 99

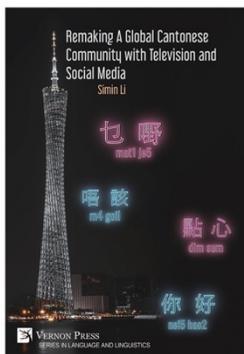
Zhu, 87

Zorro, 151, 156, 158, 160, 161, 162,  
166, 167, 171, 172, 173

Zou, 56, 58, 60

Zuboff, 77

## Other distinguished titles from “Series in Language and Linguistics”:



### Remaking a Global Cantonese Community with Television and Social Media

Simin Li

This book explores how Cantonese endures suppression and thrives globally through TV and social media, revealing deep links between language, identity, and grassroots resistance.

**\$50 | €47 | £40**

Subjects: History, Political Science and International Relations.

ISBN: 978-1-64889-049-9 | Hardback | 128 pp | 1/2024

Also available in Paperback and E-book.

[vernonpress.com/book/1113](http://vernonpress.com/book/1113)

### Italian as a foreign language

Teaching and acquisition in higher education

Alberto Regagliolo (Ed.)

This manual offers a rich, multidisciplinary approach to teaching Italian as a foreign language, covering topics from phonetics to subtitling, comics, academic writing, and more—ideal for students and teachers of Italian Studies.

**\$95 | €87 | £80**

Subjects: Education, Language and Linguistics.

ISBN: 978-1-64889-678-1 | Hardback | 363 pp | 9/2023

Also available in Paperback and E-book.

[vernonpress.com/book/1758](http://vernonpress.com/book/1758)



### Languaging Class

Reflecting on the Linguistic Articulations of Structural Inequalities

Claudia Ortu, Francesco Bachis (Eds.)

A practical guide for teaching Italian in academia, covering phonetics, translation, media, and pedagogy—ideal for students and teachers of Italian Studies.

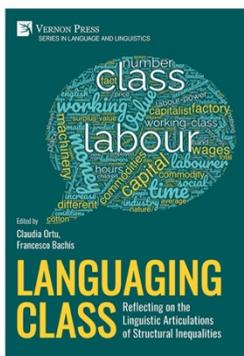
**\$85 | €80 | £70**

Subjects: Anthropology, Education, Language and Linguistics.

ISBN: 978-1-64889-586-9 | Hardback | 192 pp | 1/2023

Also available in Paperback and E-book.

[vernonpress.com/book/1664](http://vernonpress.com/book/1664)



Vernon Press is accepting proposals for monographs or multi-author volumes in this series.

For more information, visit <https://vernonpress.com/publish-with-us> or contact us directly at [submissions@vernonpress.com](mailto:submissions@vernonpress.com)