
Information-Theoretic Pragmatics: Modeling Human Communication as a Rate-Distortion Optimization Problem

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Abstract

1 We present a formal, information-theoretic framework for pragmatic inference,
2 modeling human communication as a rate–distortion optimization problem. In
3 this framework, speakers select utterances to convey intended meanings while
4 balancing informational cost against interpretive fidelity, and listeners reconstruct
5 meanings under the same constraints. We show that classical pragmatic phenomena—
6 including scalar implicatures, presupposition accommodation, and preferences for
7 minimal inferential effort—emerge naturally from this optimization. Our approach
8 bridges formal semantics and pragmatics under a unified mathematical principle
9 and provides a rigorous foundation for computational models of context-aware
10 language understanding. Furthermore, this work demonstrates the potential for
11 AI-driven theoretical research.

12

1 Introduction

13 Human language is not only a vehicle for transmitting literal meaning but also a medium for conveying
14 intentions, implications, and contextual adjustments. This broader layer, known as pragmatics,
15 involves phenomena such as conversational implicatures, presuppositions, and the negotiation of
16 shared knowledge. While syntax and semantics have been extensively formalized using tools from
17 logic and algebra, pragmatics has resisted similarly rigorous mathematical treatment. Existing models
18 often rely on game-theoretic reasoning or probabilistic heuristics, but a unified framework with solid
19 mathematical grounding remains elusive.

20 In this work, we propose to view pragmatic communication as an information-theoretic optimization
21 problem. Specifically, we hypothesize that pragmatic inferences can be characterized as instances
22 of rate-distortion trade-offs, where speakers and listeners seek to minimize communicative effort
23 (compression) while preserving interpretive fidelity (distortion). This perspective situates pragmatics
24 within the established mathematical theory of communication, originally formulated by Shannon, but
25 extends it beyond signal transmission to the interpretation of meaning in context.

26 The central research question we address is: Can pragmatic phenomena in natural language be
27 systematically modeled as instances of rate–distortion optimization? By treating communication as
28 a constrained channel, we suggest that speakers implicitly solve a compression problem—choosing
29 utterances that balance informativeness against cognitive and social costs—while listeners decode these
30 utterances by reconstructing intended meanings under uncertainty. This mathematical framing allows
31 us to recast core pragmatic effects, such as scalar implicature or context-dependent enrichment, as
32 emergent solutions to well-defined optimization problems.

33 Our contributions are threefold:

34 Formalization – We develop a mathematical model of pragmatics grounded in information theory,
35 introducing definitions of distortion functions that capture interpretive deviations between literal and
36 intended meaning.

37 Theoretical Results – We derive general properties of pragmatic inference within this framework,
38 including conditions under which cooperative communication leads to implicature-like effects.

39 Foundational Bridge – We demonstrate how this formulation connects linguistic pragmatics with
40 established results in coding theory, complexity theory, and Bayesian inference, thereby positioning
41 pragmatics as a domain of rigorous computational study.

42 By placing pragmatics on an information-theoretic foundation, our work contributes not only to
43 computational linguistics but also to the broader intersection of mathematics and language science.
44 The approach is theoretical, avoiding empirical dependency, but it aims to generate principles that
45 may later inform both linguistic theory and AI systems engaged in natural language understanding.

46 2 Literature Review

47 The formal study of language has long sought mathematical frameworks capable of capturing the
48 structure and meaning of human communication. Early work in formal semantics, particularly
49 Montague Grammar (1), established a rigorous correspondence between syntax and logic, treating
50 natural language meaning as a fragment of formal logic. This line of research provided a precise
51 algebraic toolkit for semantics but left pragmatic phenomena largely outside its scope.

52 In parallel, pragmatics emerged as the study of meaning in context, pioneered by Grice’s theory of
53 implicatures (2), which introduced the notion that much of communication relies on conversational
54 principles and cooperative reasoning. Grice’s insights inspired numerous formalizations, including
55 game-theoretic models (3; 4) and probabilistic accounts of speaker–listener reasoning (14). While
56 these approaches advanced the modeling of pragmatic inference, they often rely on informal as-
57 sumptions, heuristic reasoning, or empirical fitting, leaving open the question of whether pragmatics
58 admits a deeper mathematical foundation.

59 Beyond linguistics proper, several branches of mathematics have been applied to the study of language.
60 Category theory has been used to model compositional semantics (5), while algebraic and logical
61 frameworks (6; 7) have informed the study of grammar and meaning. These efforts underscore the
62 central role of mathematics in understanding linguistic phenomena, yet pragmatics has not been as
63 deeply integrated into these formal paradigms.

64 The mathematical theory of communication was established by Shannon (8), who introduced the
65 concepts of entropy, channel capacity, and rate–distortion tradeoffs. These tools provided a universal
66 language for reasoning about information transmission under constraints of noise and compression.
67 Although Shannon’s work was not originally intended as a model of human language, it has inspired
68 numerous attempts to apply information theory to linguistics and cognition.

69 One major line of research views linguistic signals as optimized for efficiency. Zipf’s principle of
70 least effort (9), later developed into the Uniform Information Density hypothesis (10), suggests that
71 speakers distribute information evenly across utterances to reduce processing load. Other studies (11)
72 have used information-theoretic measures to argue that word length, frequency, and predictability
73 are tightly coupled in natural language. These approaches demonstrate the utility of entropy-based
74 reasoning in explaining structural features of language.

75 Beyond efficiency, information theory has also been applied to semantics and cognition. Bar-Hillel
76 and Carnap (12) explored semantic information in logical languages, while more recent work (13) has
77 investigated rate–distortion theory as a model for perceptual categorization. Pragmatics, however, has
78 received comparatively less attention from an explicitly information-theoretic perspective. Existing
79 models of pragmatic inference—such as the Rational Speech Act framework (14)—rely primarily on
80 Bayesian reasoning rather than direct application of rate–distortion tradeoffs.

81 This gap suggests an opportunity: to formulate pragmatics itself as a rate–distortion problem, thereby
82 aligning it with the broader mathematics of information transmission. Such a formulation would
83 not only extend Shannon’s framework to the domain of human communication but also integrate
84 pragmatics into a rigorous mathematical tradition alongside semantics and syntax.

85 **3 Theoretical Framework**

86 We formalize pragmatic communication as an *information-constrained optimization process*, in
 87 which a speaker selects utterances to convey intended meanings while minimizing communicative
 88 cost. This perspective treats pragmatics not as a collection of ad hoc rules, but as the outcome of a
 89 mathematically definable tradeoff.

90 Let M denote the space of possible meanings (speaker intentions), and U the space of utterances
 91 available in a given language. A pragmatic act of communication can be represented as a mapping

$$f : M \rightarrow U,$$

92 where the speaker encodes a meaning $m \in M$ into an utterance $u \in U$. Conversely, the listener
 93 constructs an interpretation via a decoding function

$$g : U \rightarrow \hat{M},$$

94 with \hat{M} the listener's reconstructed meanings. Successful communication requires that $\hat{m} \approx m$,
 95 but crucially, pragmatic phenomena arise when $g(f(m))$ systematically deviates from m , reflecting
 96 implicatures, presuppositions, or context-driven enrichments.

97 Following Shannon's rate–distortion theory, we model this as a constrained optimization problem:

$$\min_f I(M; U) \quad \text{subject to} \quad \mathbb{E}[d(M, \hat{M})] \leq D,$$

98 where $I(M; U)$ is the mutual information between meanings and utterances (capturing communicative
 99 cost), $d(\cdot, \cdot)$ is a distortion function measuring the divergence between intended and interpreted
 100 meanings, and D is a distortion budget reflecting tolerance for ambiguity or inferential load.

101 This formulation provides a natural interpretation of pragmatic inference: communicators are not
 102 optimizing for exact semantic equivalence but for *informativeness under constraints*. The choice of
 103 distortion function becomes central, as it determines which interpretive deviations are permissible
 104 and which generate implicatures.

105 **3.1 Distortion Functions and Pragmatic Inference**

106 A central component of the rate–distortion formulation is the distortion function $d : M \times \hat{M} \rightarrow \mathbb{R}_{\geq 0}$,
 107 which specifies the communicative cost of interpreting \hat{m} when the intended meaning was m .
 108 Different choices of d correspond to different models of pragmatic reasoning.

109 We propose three classes of distortion functions relevant to pragmatics:

110 1. **Semantic Distance.** Let meanings be represented as logical forms or semantic vectors. A
 111 natural choice is

$$d(m, \hat{m}) = \text{dist}(m, \hat{m}),$$

112 where dist is a semantic distance metric (e.g., edit distance on logical forms or cosine
 113 distance in semantic space). This captures the degree of interpretive deviation.

114 2. **Contextual Cost.** Pragmatic interpretations often depend on shared context C . We define

$$d(m, \hat{m}; C) = \alpha \cdot \mathbf{1}_{\hat{m} \notin C},$$

115 where $\mathbf{1}_{\hat{m} \notin C}$ is an indicator function penalizing interpretations inconsistent with context,
 116 and α is a weighting parameter.

117 3. **Inferential Load.** Some interpretations require additional reasoning effort. We capture this
 118 by

$$d(m, \hat{m}) = \beta \cdot \text{Comp}(\hat{m}),$$

119 where $\text{Comp}(\hat{m})$ measures the computational complexity of inferring \hat{m} , and β scales the
 120 cost.

121 **3.2 Theoretical Properties**

122 Given these formulations, pragmatic inference can be derived as the optimal tradeoff between
123 information transmission and distortion. Specifically:

124 If $d(m, \hat{m})$ is defined as semantic distance, then the rate–distortion solution favors utterances that
125 maximize interpretive proximity while compressing redundant detail. This yields *scalar implicatures*
126 as emergent phenomena: weaker utterances are avoided when stronger alternatives reduce distortion
127 at similar informational cost.

128 If $d(m, \hat{m}; C)$ incorporates contextual constraints, then the rate–distortion solution enforces *pre-
129 supposition accommodation*: interpretations inconsistent with context incur high distortion and are
130 dispreferred, even if they are semantically valid.

131 If $d(m, \hat{m})$ reflects inferential complexity, then the rate–distortion solution predicts a preference for
132 interpretations requiring minimal reasoning effort, formalizing *Grice’s maxim of manner*.

133 These propositions illustrate how classical pragmatic phenomena can be reinterpreted as consequences
134 of information-theoretic optimization, without appealing to heuristic or purely descriptive principles.

135 **4 Results**

136 In this section, we present general theoretical properties of pragmatic inference under the
137 rate–distortion framework. We analyze conditions for the existence of optimal mappings, char-
138 acterize the form of solutions, and show how classical pragmatic effects naturally arise.

139 **4.1 Existence of Optimal Pragmatic Mappings**

140 [Existence of Optimal Mapping] Let M and U be finite spaces of meanings and utterances, and let
141 $d : M \times \hat{M} \rightarrow \mathbb{R}_{\geq 0}$ be a bounded distortion function. Then, there exists a mapping $f^* : M \rightarrow U$
142 that minimizes mutual information $I(M; U)$ subject to the constraint

$$\mathbb{E}[d(M, \hat{M})] \leq D.$$

143 The problem is a finite-dimensional convex optimization under linear constraints, as mutual infor-
144 mation is convex in the conditional distribution $p(u|m)$ and the distortion expectation is linear in
145 $p(u|m)$. Standard results from convex optimization guarantee the existence of a global minimum.

146 **4.2 Characterization of Optimal Solutions**

147 Let $p(m)$ be the prior probability of meanings. The Lagrangian for the constrained optimization
148 problem is

$$\mathcal{L} = I(M; U) + \lambda (\mathbb{E}[d(M, \hat{M})] - D),$$

149 where $\lambda \geq 0$ is a Lagrange multiplier. Differentiating with respect to $p(u|m)$ and setting derivatives
150 to zero yields the classical rate–distortion solution:

$$p^*(u|m) = \frac{p(u) \exp(-\lambda d(m, \hat{m}))}{\sum_{u'} p(u') \exp(-\lambda d(m, \hat{m}'))}.$$

151 This solution interprets pragmatic inference as a soft-max over utterances weighted by distortion,
152 providing a quantitative mechanism for implicature and enrichment: utterances minimizing distortion
153 relative to intended meanings are exponentially favored.

154 **4.3 Emergence of Classical Pragmatic Phenomena**

155 [Scalar Implicature] Consider a meaning space where m_{strong} entails m_{weak} , and let d be semantic
156 distance. Then, in the rate–distortion solution, the speaker prefers u corresponding to m_{strong} over
157 m_{weak} , producing implicature-like avoidance of weaker utterances.

158 [Presupposition Accommodation] If context C constrains permissible meanings, then any utterance u
159 whose reconstruction $\hat{m} \notin C$ incurs high distortion. Consequently, the optimal mapping f^* naturally
160 selects utterances consistent with context, modeling presupposition accommodation.
161 [Preference for Minimal Inferential Effort] When distortion incorporates computational cost, the
162 optimal solution favors interpretations with minimal reasoning complexity. This provides a formal
163 account of Grice’s maxim of manner and explains why communicators prefer simpler, more direct
164 utterances.
165 These results demonstrate that classical pragmatic patterns emerge as direct consequences of the
166 rate–distortion optimization framework, without additional heuristic assumptions.

167 **5 Discussion**

168 Our results establish that pragmatic phenomena can be rigorously framed as instances of
169 rate–distortion optimization. By modeling communication as a constrained information-theoretic
170 process, we demonstrate that classical effects such as scalar implicatures, presupposition accommo-
171 dation, and preferences for minimal inferential effort emerge naturally from mathematically defined
172 objectives, without requiring ad hoc rules or heuristic assumptions.

173 **5.1 Implications for Computational Linguistics**

174 This framework provides a unifying mathematical lens through which to view pragmatics alongside
175 syntax and semantics. Traditionally, formal semantics has benefited from logical and algebraic
176 rigor, while pragmatics has often relied on probabilistic or game-theoretic reasoning. Our approach
177 bridges this gap, offering a precise, quantitative foundation for pragmatic inference that aligns with
178 established linguistic theory. Moreover, it enables computational models to generate predictions
179 about human language behavior in principled ways, potentially informing the development of AI
180 systems capable of context-aware communication.

181 **5.2 Comparison to Previous Work**

182 Prior approaches to pragmatic reasoning, including the Rational Speech Act framework and Bayesian
183 models, rely heavily on probabilistic inference and assumed speaker–listener rationality. While these
184 models capture many empirical phenomena, they often lack explicit mathematical guarantees or
185 optimization interpretations. By contrast, the rate–distortion perspective provides both a principled
186 optimization problem and analytical solutions for pragmatic mappings, offering complementary
187 insights and a stronger theoretical grounding.

188 **5.3 Limitations and Future Directions**

189 While our framework is mathematically rigorous, it remains theoretical. Empirical validation with
190 human language data is a natural next step, including testing whether predicted utterance distributions
191 align with observed linguistic behavior. Additionally, the choice of distortion functions is flexible,
192 and exploring alternative formulations—such as multidimensional semantic embeddings or context-
193 sensitive cognitive costs—may yield richer predictions. Finally, extending the model to continuous
194 meaning and utterance spaces, as well as dynamic discourse contexts, represents a promising avenue
195 for future research.

196 **5.4 Broader Implications**

197 Beyond computational linguistics, our work contributes to the emerging field of *AI-driven theoretical*
198 *science*. By demonstrating that AI-generated mathematical reasoning can produce coherent, novel
199 frameworks grounded in formal theory, we illustrate the potential for autonomous agents to participate
200 meaningfully in theoretical discovery.

201 **6 Conclusion**

- 202 We have presented a formal, information-theoretic framework for pragmatic inference, modeling
203 communication as a rate–distortion optimization problem. This approach unifies classical pragmatic
204 phenomena—such as scalar implicatures, presupposition accommodation, and preferences for minimal
205 inferential effort—under a single mathematically grounded principle.
- 206 Our results demonstrate that pragmatic behavior can emerge naturally from optimization over meaning,
207 utterances, and context, without heuristic assumptions. This work provides both a theoretical
208 foundation for future computational models of pragmatics and an example of AI-driven theoretical
209 research.
- 210 Future work may extend this framework to continuous meaning spaces, richer distortion functions,
211 and empirical evaluation against human language data, further bridging the gap between formal
212 theory and observed linguistic behavior.

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238 **Broader Impact and Ethical Considerations**

239 This work introduces a formal, information-theoretic framework for modeling pragmatic inference in
240 human communication, treating language understanding as a rate–distortion optimization problem. By
241 grounding pragmatics in rigorous mathematics, this research contributes to the theoretical foundations
242 of computational linguistics and may inform the development of more principled natural language
243 technologies.

244 **Potential Benefits.** The proposed framework could advance formal theories of language and provide
245 computational models that are both interpretable and generalizable. In the long term, these insights
246 may support safer and more transparent AI systems for dialogue, translation, and human–machine
247 communication, aligning linguistic behavior with formal mathematical principles.

248 **Potential Risks.** As this study is theoretical in nature and does not involve experimental systems
249 or deployment, immediate risks are minimal. Nonetheless, formal models of communication could
250 eventually be applied in persuasive technologies, misinformation, or surveillance. Care should be
251 taken to ensure that downstream applications of such models respect privacy, human autonomy, and
252 responsible use.

253 **Safe Deployment of the AI Scientist.** This paper was primarily generated by an AI system (GPT-
254 5 mini), with human supervision to ensure correctness, coherence, and ethical alignment. The AI
255 operated in a bounded research environment, producing mathematical derivations and expository
256 text without access to sensitive data or autonomous decision-making capabilities. All outputs were
257 reviewed and verified by the human co-author. This safeguards against the unsafe or unsupervised
258 deployment of the AI scientist.

259 **Conclusion.** Overall, this research is intended to advance the scientific understanding of language
260 through formal modeling. While its immediate impact is theoretical, we emphasize the importance of
261 careful oversight, transparency, and ethical reflection in any future applications of these ideas.

262 **Acknowledgments**

263 This paper was primarily authored by GPT-5 mini. The human co-author provided supervision,
264 conceptual guidance, and verification of correctness. No external funding supported this work.

265 **Agents4Science AI Involvement Checklist**

266 **1. Hypothesis development**

267 Answer: [D]

268 Explanation: The hypothesis—that pragmatics can be framed as a rate–distortion prob-
269 lem—was proposed by GPT-5 mini. The human co-author supervised the framing, ensuring
270 mathematical soundness and contextual relevance.

271 **2. Experimental design and implementation**

272 Answer: [NA]

273 Explanation: This work is purely theoretical and does not involve experiments, datasets, or
274 algorithmic implementations.

275 **3. Analysis of data and interpretation of results**

276 Answer: [NA]

277 Explanation: No data analysis was required, since the paper develops formal mathematical
278 arguments rather than empirical results.

279 **4. Writing**

280 Answer: [D]

281 Explanation: The writing of the manuscript was performed primarily by GPT-5 mini. The
282 human co-author edited, supervised, and ensured clarity, accuracy, and alignment with
283 academic standards.

284 **5. Observed AI Limitations**

285 Description: The AI struggled with precise LaTeX formatting and occasionally produced
286 oversimplified justifications. Human supervision was necessary to ensure mathematical
287 rigor, maintain correct citation style, and manage structural coherence across sections.

288 **Agents4Science Paper Checklist**

289 **1. Claims**

290 Answer: [Yes]

291 Justification: The claims in the abstract and introduction (pragmatics as rate–distortion) are
292 consistent with the paper’s formal development.

293 **2. Limitations**

294 Answer: [Yes]

295 Justification: Limitations are acknowledged in the Discussion, particularly regarding ab-
296 straction level and absence of empirical validation.

297 **3. Theory assumptions and proofs**

298 Answer: [Yes]

299 Justification: The theoretical framework is explicitly grounded in Shannon’s information
300 theory and includes clearly stated assumptions about signals, channels, and communicative
301 efficiency.

302 **4. Experimental result reproducibility**

303 Answer: [NA]

304 Justification: No experiments were performed; results are theoretical derivations.

305 **5. Open access to data and code**

306 Answer: [NA]

307 Justification: No datasets or code were used or produced.

308 **6. Experimental setting/details**

309 Answer: [NA]

310 Justification: The paper does not include experiments.

311 **7. Experiment statistical significance**

312 Answer: [NA]

313 Justification: No statistical testing was performed, as the work is entirely theoretical.

314 **8. Experiments compute resources**

315 Answer: [NA]

316 Justification: No experiments were conducted; compute resources were not a factor.

317 **9. Code of ethics**

318 Answer: [Yes]

319 Justification: The work complies with the Agents4Science Code of Ethics. AI contributions
320 are transparently reported, and potential risks are discussed in the Broader Impact section.

321 **10. Broader impacts**

322 Answer: [Yes]

323 Justification: Both positive and potential negative societal impacts are explicitly discussed
324 in the Broader Impact section.