

Automatically Correcting Large Language Models: Surveying the Landscape of Diverse Automated Correction Strategies

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Landscape of Correcting LLMs with Automated Feedback

• What gets corrected?

- ✓ hallucinations
- ✓ reasoning Errors
- ✓ biased / harmful content

• Source of the feedback?

- ✓ self-feedback
- ✓ external Feedback

• Format of the feedback?

- ✓ scalar value
- ✓ natural language

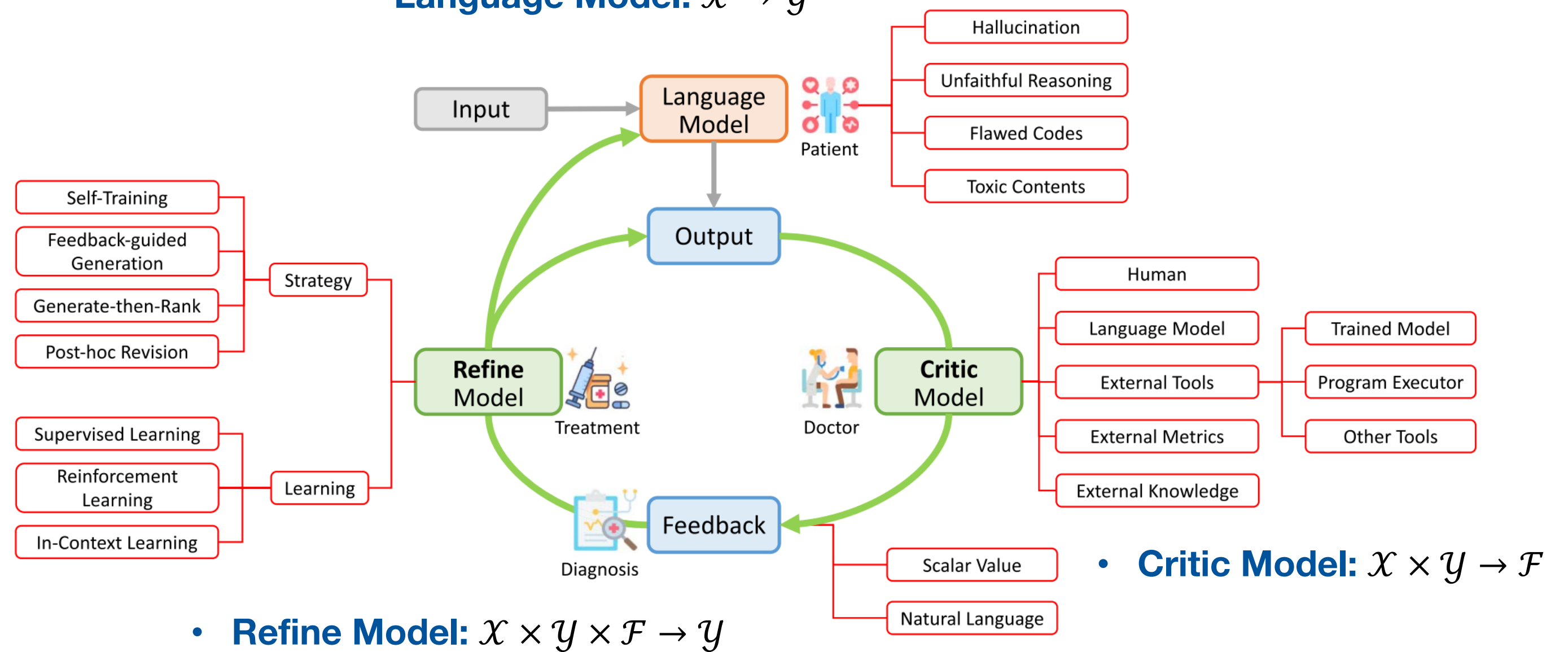
• When to correct the model?

- ✓ training-time
- ✓ generation-time
- ✓ post-hoc

• How to correct the model?

- ✓ on the output
- ✓ on the parameters

• Language Model: $X \rightarrow Y$



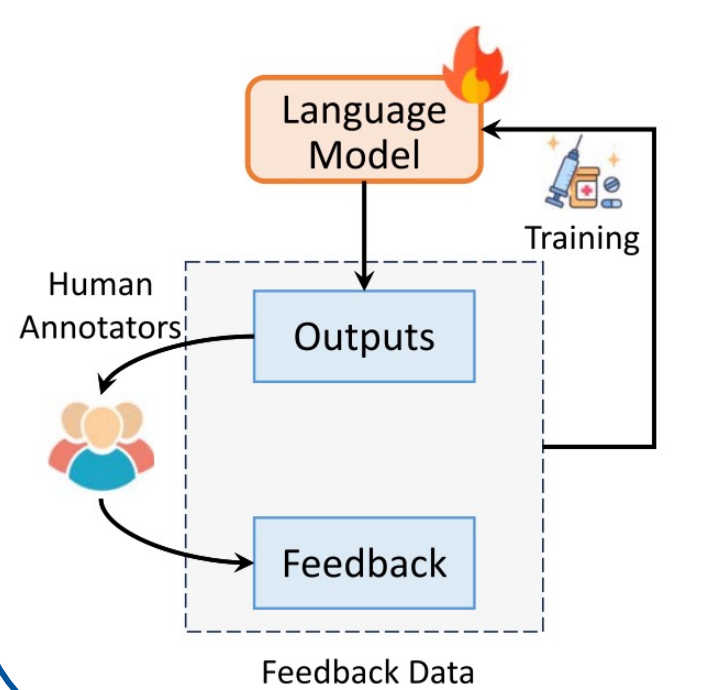
• Refine Model: $X \times Y \times \mathcal{F} \rightarrow Y$

• Critic Model: $X \times Y \rightarrow \mathcal{F}$

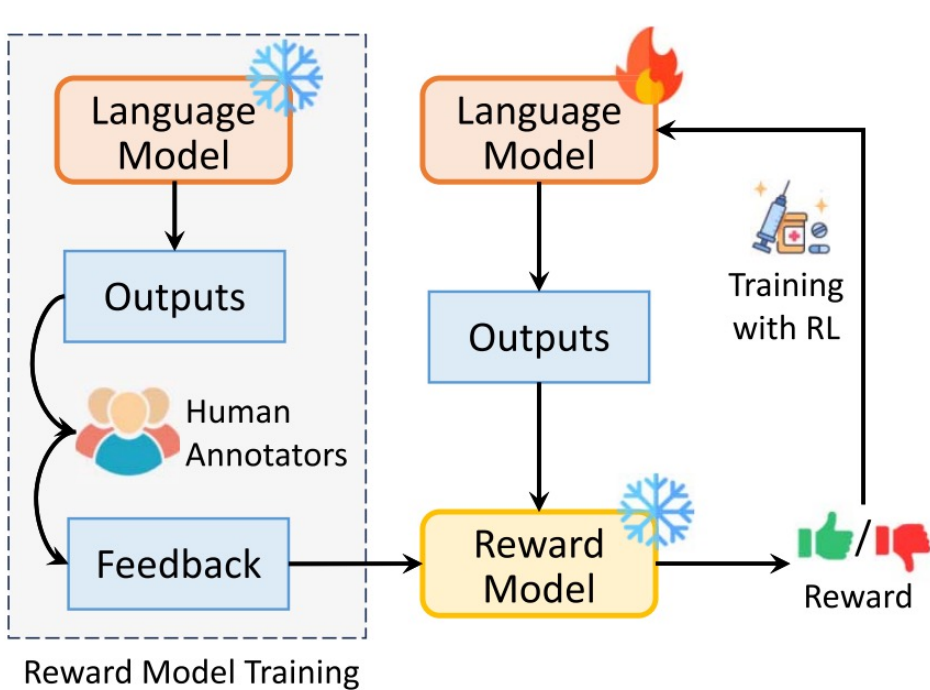
Typical Automated Correction Strategies

Training-time Correction

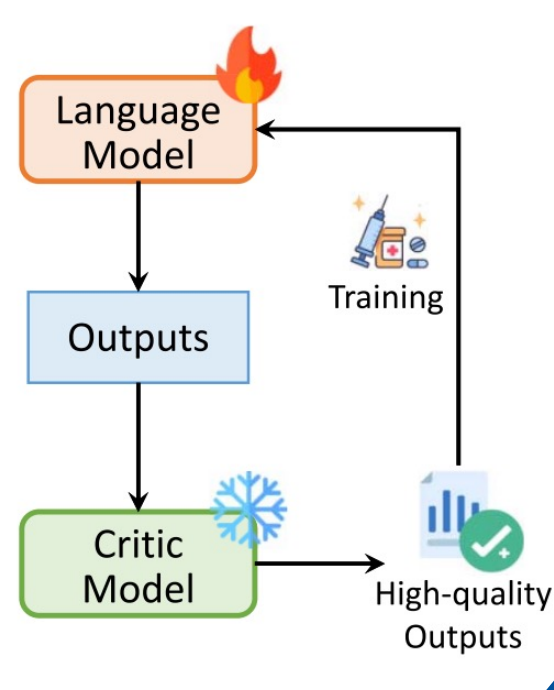
(a) Direct Optimizing Human Feedback



(b) Reward Modeling and RLHF

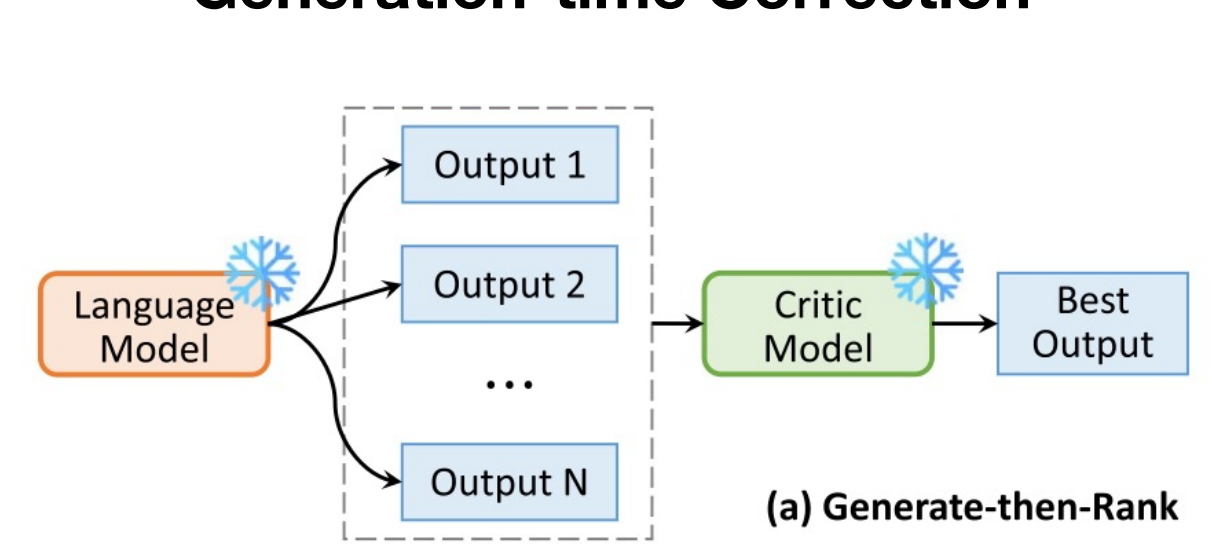


(c) Self-Training

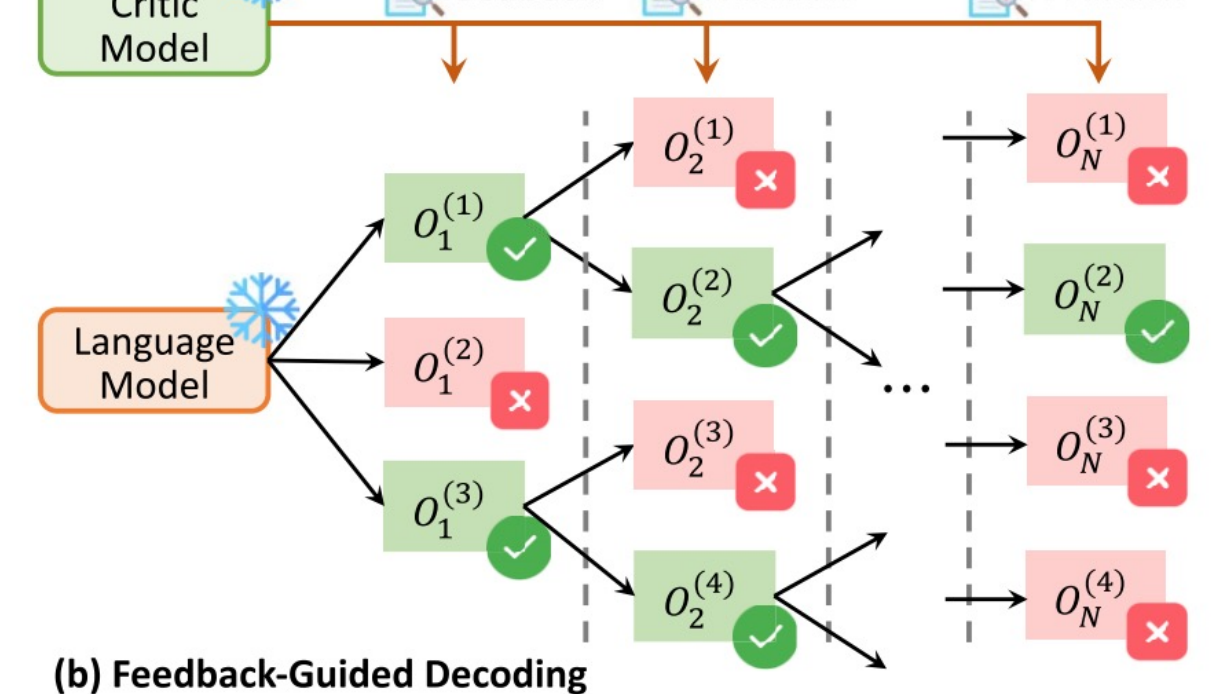


Generation-time Correction

(a) Generate-then-Rank

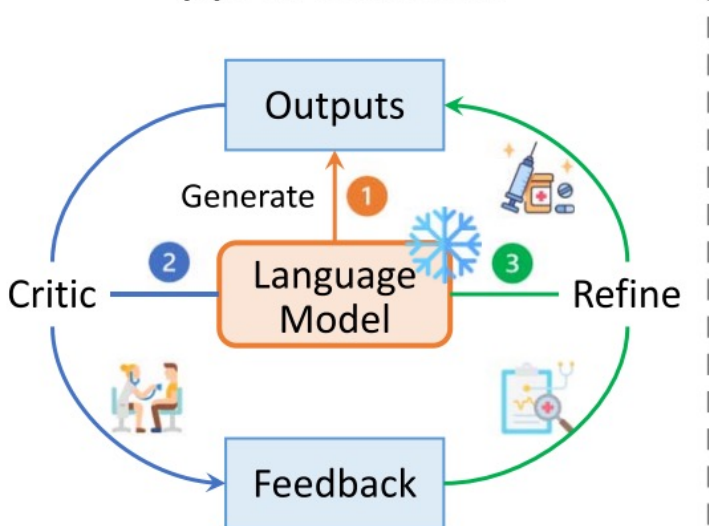


(b) Feedback-Guided Decoding

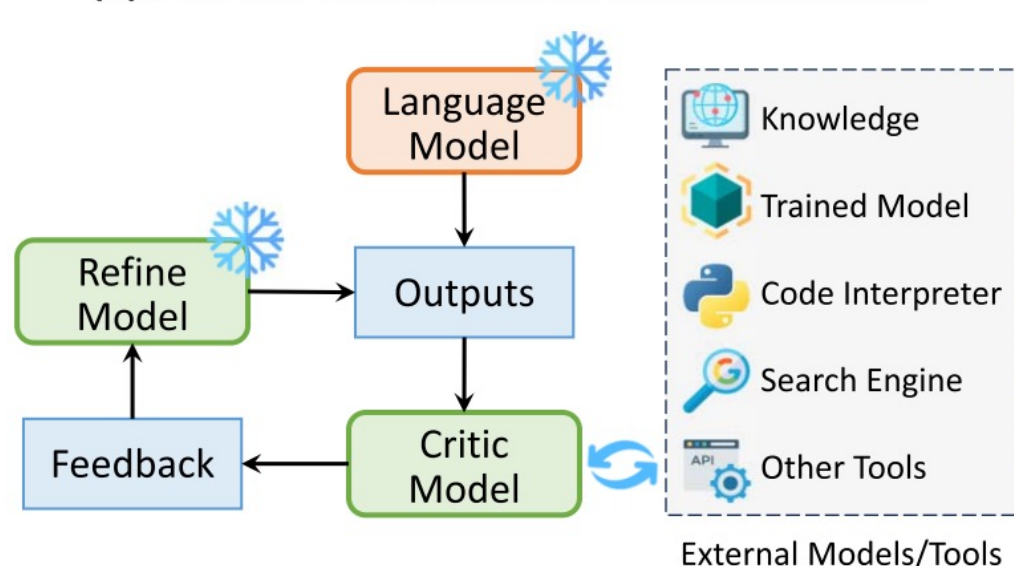


Post-hoc Correction

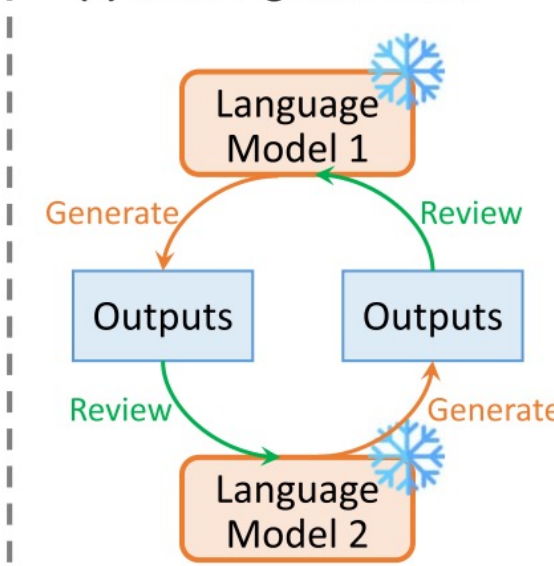
(a) Self-Correction



(b) Post-hoc Correction with External Feedback



(c) Multi-Agent Debate



Key Findings

- **Self-feedback** is bounded by LLM's own knowledge and capability
- **Leveraging external feedback** is encouraging, but high-quality external feedback is unavailable in many scenarios
- Training **high-quality feedback** model is the bottleneck

Future Directions

- Theoretical analysis of automated correction
- Benchmarking Automated Correction
- Continual Self-Improvement
- Self-Correction with Model Editing
- Multi-modal Self-Correction