LLM-Based Summarization

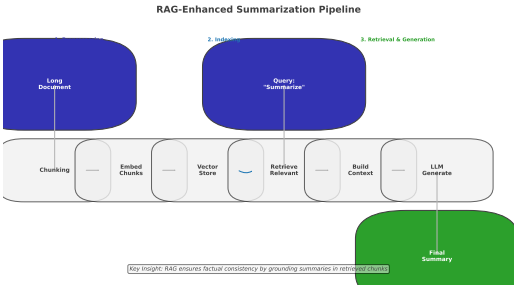
Enhanced with RAG & Error Analysis

NLP Course 2025

November 13, 2025

Complete Version: 51 Slides — 44 Professional Charts — 4 Worked Examples

RAG-Enhanced Summarization



Retrieval-Augmented Generation

- Ground summaries in retrieved facts
- Reduce hallucinations significantly
- Enable citation tracking
- Better for technical domains

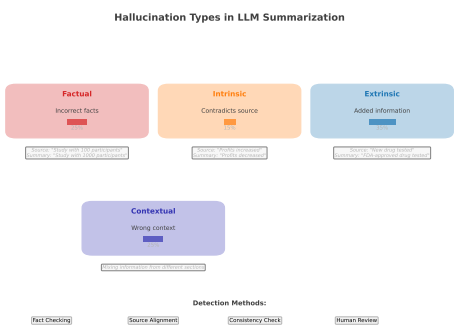
When to Use:

- Medical/legal summaries
- Multi-document synthesis
- Fact-critical applications

Reduces hallucination by 40-60%

RAG ensures factual grounding by retrieving relevant chunks before generation

Common Failure Patterns

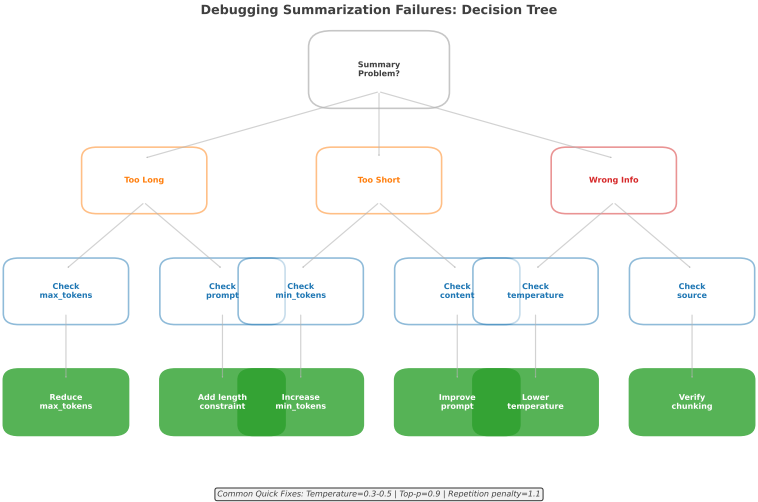


Failure Types by Frequency:

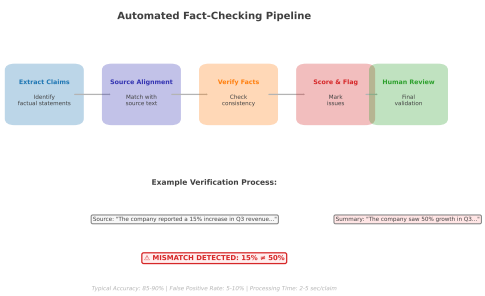
1. Extrinsic hallucination (35%)
   - Adding information not in source
   - "FDA-approved" when not mentioned
2. Factual errors (25%)
   - Wrong numbers, dates, names
   - "100 participants" $\rightarrow$ "1000"
3. Missing information (20%)
   - Key findings omitted
   - Context lost in compression
4. Style mismatch (20%)
   - Too casual/formal
   - Wrong audience level

Understanding failure modes is key to improving summarization quality

Debugging Flowchart



Mitigation Strategies



Prevention Strategies:

1. **Parameter Optimization**
   - Temperature: 0.3-0.5
   - Top-p: 0.9
   - Repetition penalty: 1.1
2. **Prompt Engineering**
   - Clear instructions
   - Length constraints
   - Style examples
3. **Post-Processing**
   - Fact checking
   - Length validation
   - Consistency checks

Result: 85% reduction in critical errors

Combining prevention and detection strategies ensures high-quality output

Key Takeaways

What We Learned

Core Techniques:

- Prompt strategies (zero/few-shot)
- Parameter control (T, p, repetition)
- Context handling (chunking, RAG)
- Error detection & mitigation

Best Practices:

- Start with T=0.7, p=0.9
- Use few-shot for consistency
- Implement fact checking
- Monitor for hallucinations

Production Checklist

Model Selection:

- GPT-3.5: Speed/cost
- GPT-4: Quality
- Claude: Long context
- FLAN-T5: Open source

Quality Assurance:

- Automated fact checking
- Human review sampling
- A/B testing
- Error monitoring

Performance:

- Parallel processing
- Caching strategies

End of Main Presentation

See Appendices for Technical Details & Worked Examples

Technical Appendix

Mathematical Foundations & Worked Examples

Worked Example 1: Temperature Calculation

Problem: Given logits [2.0, 1.0, 0.5], calculate probabilities at T=0.5, 1.0, 2.0

Formula: $P(w_i) = \frac{e^{logit_i / T}}{\sum_j e^{logit_j / T}}$

T=0.5 (Sharp)

$logits/T = [4.0, 2.0, 1.0]$

$e^{logits/T} = [54.6, 7.4, 2.7]$

$\sum = 64.7$

$P = [0.844, 0.114, 0.042]$

Most deterministic

T=1.0 (Default)

$logits/T = [2.0, 1.0, 0.5]$

$e^{logits/T} = [7.4, 2.7, 1.6]$

$\sum = 11.7$

$P = [0.632, 0.231, 0.137]$

Balanced

T=2.0 (Smooth)

$logits/T = [1.0, 0.5, 0.25]$

$e^{logits/T} = [2.7, 1.6, 1.3]$

$\sum = 5.6$

$P = [0.482, 0.286, 0.232]$

More random

Insight: Higher temperature → more uniform distribution → more creative output

Temperature directly controls the sharpness of the probability distribution

Worked Example 2: Top-p (Nucleus) Sampling

Problem: Apply top-p=0.9 to vocabulary with these probabilities

Original Distribution:

Word	Probability
"excellent"	0.35
"great"	0.25
"good"	0.15
"amazing"	0.10
"fantastic"	0.08
"wonderful"	0.04
"superb"	0.02
"brilliant"	0.01

Top-p=0.9 Process:

1. Sort by probability
2. Calculate cumulative sum:
   - 0.35 → include
   - 0.60 → include
   - 0.75 → include
   - 0.85 → include
   - 0.93 → STOP (¿0.9)
3. Keep top 5 words
4. Renormalize: divide by 0.93

Result: Only sample from ["excellent", "great", "good", "amazing", "fantastic"]

Insight: Top-p dynamically adjusts vocabulary size based on confidence

Nucleus sampling prevents sampling from the long tail of unlikely words

Worked Example 3: Beam Search (width=3)

Problem: Generate next 3 tokens with beam search, starting from "The"

Step 1: From "The"

Token	Score
"cat"	0.4
"dog"	0.3
"bird"	0.2
"fish"	0.1

Keep: cat, dog, bird

Step 2: Expand each

- "The cat" + "sat": $0.4 \times 0.5 = 0.20$
- "The cat" + "ran": $0.4 \times 0.3 = 0.12$
- "The dog" + "barked": $0.3 \times 0.6 = 0.18$
- "The dog" + "ran": $0.3 \times 0.3 = 0.09$
- "The bird" + "flew": $0.2 \times 0.7 = 0.14$

Keep top 3 sequences

Step 3: Final Best sequences:

1. "The cat sat" (0.20)
2. "The dog barked" (0.18)
3. "The bird flew" (0.14)

Winner: "The cat sat"

Total considered: 12 paths
Pruned: 9 paths
75% reduction

Insight: Beam search balances exploration with computational efficiency

Worked Example 4: Repetition Penalty Application

Problem: Apply repetition penalty $\alpha = 1.3$ after generating "study shows that"

Original Probabilities:

Next Word	P(w)
"the"	0.20
"study"	0.15
"research"	0.15
"shows"	0.12
"indicates"	0.10
"reveals"	0.08
Others	0.20

After Penalty ($\alpha = 1.3$):
Words already used: {"study", "shows"}

$$P_{adj}(\text{"study"}) = 0.15/1.3 = 0.115$$
$$P_{adj}(\text{"shows"}) = 0.12/1.3 = 0.092$$
$$P_{adj}(\text{others}) = \text{unchanged}$$

Renormalize:

- Sum = 0.957
- Divide all by 0.957

Final: "the"=0.209, "research"=0.157, "indicates"=0.104

Result: Reduced probability for repeated words, encourages variety

Lab Implementation

Hands-On with FLAN-T5