Structured JSON Extractor: Technical Documentation

"Converting Unstructured Text to Structured JSON with Schema Validation"

Streamlit App: https://json-extract-gen.streamlit.app/

GitHub Repository : https://github.com/cosmoavijeet07/JSON-generator

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Problem Overview

The challenge of converting unstructured plain text into structured, schema-compliant JSON is a fundamental problem in data processing and knowledge extraction. Traditional rule-based approaches often fail when dealing with the variability and complexity of natural language, while simple regex-based solutions cannot handle the semantic understanding required for accurate field mapping.

This system leverages Large Language Models (LLMs) to bridge the gap between human-readable unstructured text and machine-processable structured data. The core challenge involves ensuring that the extracted JSON not only captures the semantic meaning from the source text but also strictly adheres to predefined schemas, handling complex nested structures, arrays, and data type validation. The solution must be robust enough to handle large documents (50k+ tokens), complex schemas (100k+ tokens), and provide reliable extraction with minimal human intervention.

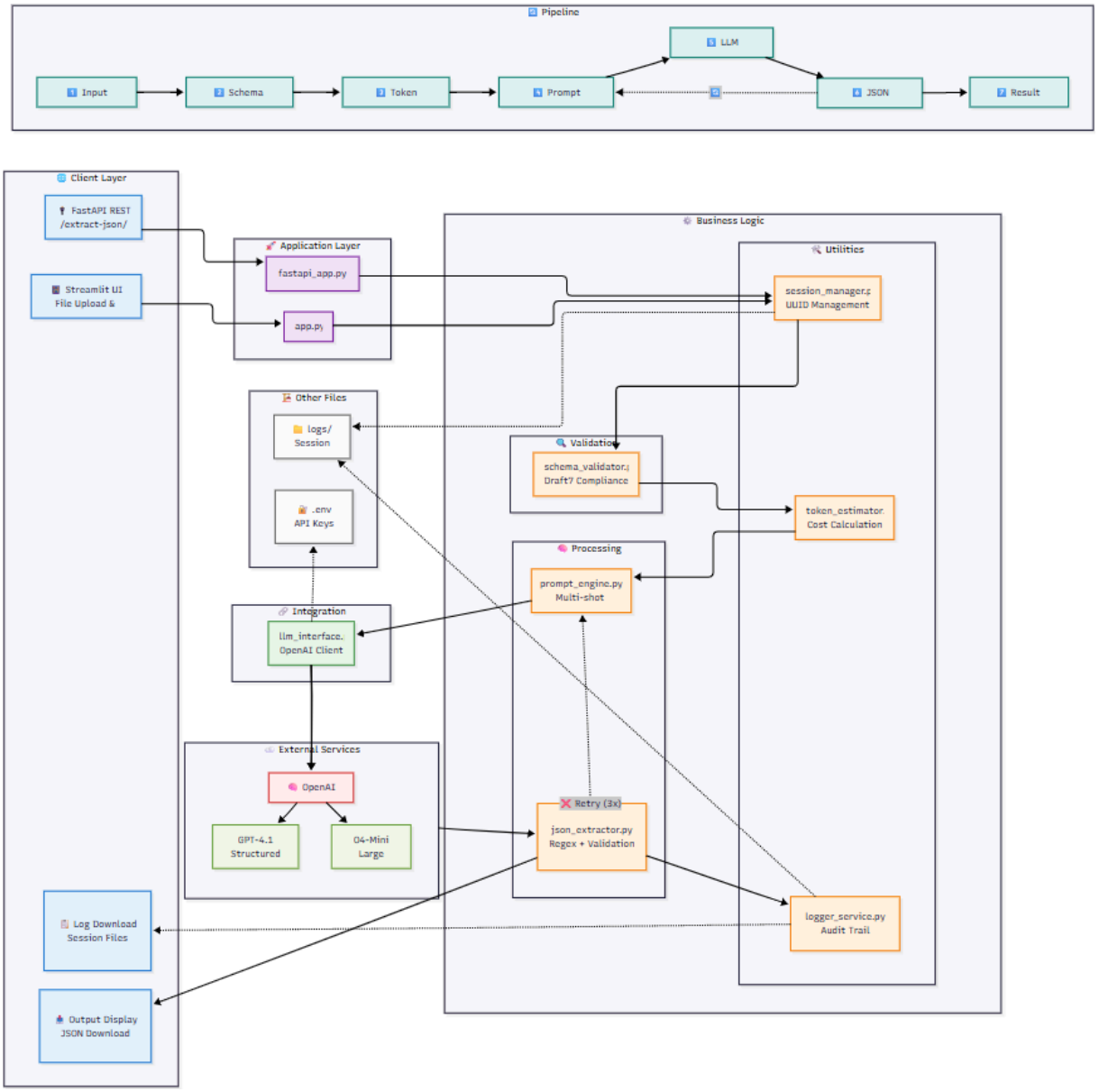
Objectives to Solve

1. **Schema Adherence**: Extract JSON that strictly follows provided JSON Schema specifications
2. **Semantic Accuracy**: Maintain semantic meaning while transforming unstructured text
3. **Scale Handling**: Support large input contexts (50k text inputs, 100k schema files)
4. **Reliability**: Provide consistent, repeatable results with validation feedback loops
5. **Usability**: Offer both web interface and API access for different use cases

Secondary Objectives

1. **Error Recovery**: Implement retry mechanisms with intelligent error feedback
2. **Transparency**: Provide detailed logging for debugging and audit trails
3. **Cost Awareness**: Token estimation for cost prediction (without optimization constraints)

Architecture Diagram



- **UI (Streamlit):** Front-end for uploading schema and text, selecting model, and displaying results.
- **API/Backend (FastAPI):** Receives inputs from UI, coordinates processing.
- **Schema Validation Module:** Checks the uploaded JSON Schema for correctness before use.
- **Token Estimator:** Computes estimated token count of schema + text to decide feasibility and model choice.
- **Prompt Engine:** Builds the LLM prompt by combining the schema (including any enum values or patterns) with the document text and instructions (few-shot examples or hints).
- **Model Layer:** Calls the OpenAI API (GPT-4.1 or O4-mini). GPT-4.1 is used for smaller/medium tasks; O4-mini for very large contexts (up to 100k tokens).

- **JSON Extraction & Validation:** Parses the model's response, extracts the JSON part, and validates it against the schema (using jsonschema).
- **Error Correction Loop:** If validation fails and retries remain, adjusts the prompt or instructs the model to fix errors, then re-calls the LLM (up to 3 total attempts).
- **Logging Service:** Records session ID, selected model, prompts, outputs, token counts, and any errors to disk for future analysis.

Solution Design & Architectural Choices

1. Modular Architecture Design

Decision: Implemented a modular core architecture with distinct responsibilities.

Justification:

- **Separation of Concerns**: Each module handles a specific aspect (validation, prompting, extraction, logging)
- **Testability**: Individual modules can be unit tested independently
- **Maintainability**: Changes to one component don't cascade to others
- **Extensibility**: New models or validation methods can be added without major refactoring

Implementation Details:

- core/ directory contains all business logic modules
- Clear interfaces between modules using Python imports
- Dependency injection pattern for configuration management

2. Dual Interface Approach (Streamlit + FastAPI)

Decision: Provide both interactive web UI and programmatic API access.

Justification:

- **User Experience**: Streamlit offers immediate visual feedback and file upload capabilities
- **Integration Flexibility**: FastAPI enables programmatic access for batch processing
- **Development Efficiency**: Streamlit for rapid prototyping, FastAPI for production integration
- **Scalability Options**: API can be containerized and scaled independently

3. Session-Based Logging Architecture

Decision: Implement comprehensive per-session logging with UUID-based session management.

Justification:

- **Debugging Capability**: Complete audit trail for each extraction attempt

- **Performance Analysis**: Token usage and attempt tracking for optimization insights
- **Error Investigation**: Detailed prompt and response logging for failure analysis
- **Compliance**: Full traceability for regulated environments

4. Three-Attempt Retry Strategy with Error Feedback

Decision: Implement intelligent retry mechanism with error-aware prompt modification.

Justification:

- **Reliability**: Handles LLM inconsistencies and edge cases
- **Learning Loop**: Each failure provides feedback for subsequent attempts
- **Cost Balance**: Three attempts balance success rate vs. API costs
- **Error Specificity**: Different error types get different prompt modifications

Implementation Logic:

1. **Attempt 1**: Clean prompt with examples
2. **Attempt 2**: Prompt + specific error feedback from validation
3. **Attempt 3**: Prompt + specific error feedback from validation

5. Schema-First Validation Pipeline

Decision: Validate JSON schema before processing and validate output against schema.

Justification:

- **Early Error Detection**: Invalid schemas caught before expensive LLM calls
- **Guarantee Compliance**: Output validation ensures schema adherence
- **User Feedback**: Clear error messages for schema issues
- **Standards Compliance**: Uses JSON Schema Draft 7 standard

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Data Flow

1. **Input Validation**:
    - Schema validation using Draft7Validator
    - File format verification
    - Token estimation for cost control
2. **Session Management**:
    - UUID generation for unique tracking
    - Directory creation for organized logging
    - State management across attempts
3. **Prompt Engineering**:
    - Multi-shot learning with concrete examples
    - Error feedback integration for iterative improvement
    - Schema-specific instruction generation
4. **LLM Interaction**:
    - Model-specific parameter optimization

    - Temperature adjustment for consistency
    - Response extraction and parsing
5. **Validation Loop**:
    - JSON extraction from LLM output
    - Schema compliance verification
    - Error feedback for retry attempts
6. **Output Generation**:
    - Structured JSON result
    - Comprehensive logging for debugging
    - Session metadata for tracking

Implementation Log

Phase 1: Core Architecture Setup

Approach: Started with the most critical components - schema validation and JSON extraction.

Key Decisions:

- Used jsonschema library for robust validation rather than custom validation
- Implemented regex-based JSON extraction with error handling for malformed responses
- Created abstract LLM interface to support multiple providers

Challenges Encountered:

- LLM responses often included explanatory text alongside JSON
- Nested JSON structures required careful regex patterns
- Error messages needed to be specific enough for retry improvement

Phase 2: Prompt Engineering Framework

Approach: Built a sophisticated prompt generation system with few-shot learning capabilities.

Key Insights:

- Examples must cover various schema complexity levels
- Error feedback significantly improves second-attempt success rates
- Explicit output format instructions reduce parsing errors

Phase 3: Model Integration and Testing

Approach: Implemented flexible model selection with temperature control for different model types.

Implementation Details:

- Model-specific temperature settings based on capabilities
- Fallback mechanisms for API failures
- Token estimation for cost prediction

Phase 4: User Interface Development

Approach: Dual development of Streamlit and FastAPI interfaces.

Streamlit Features:

- File upload with validation
- Real-time progress tracking
- Downloadable outputs and logs
- Model selection interface

FastAPI Features:

- RESTful endpoint design
- Proper HTTP status codes
- Comprehensive error responses
- Async request handling

Experimentation Framework

1. Model Selection Experiments

Why OpenAI Models?

Reasoning:

- **JSON Understanding**: Superior structured output generation compared to open-source alternatives
- **Context Window**: Large context windows essential for complex schemas
- **Instruction Following**: Better adherence to specific formatting requirements
- **Reliability**: Consistent API availability and response quality

Model Comparison Experiments

Models Tested:

- **GPT-4 Turbo**: Baseline model with proven JSON generation capabilities
- **GPT-4o**: Enhanced reasoning for complex schema interpretation
- **GPT-4.1**: Latest improvements in instruction following
- **GPT-4.1 Mini**: Cost-optimized version with maintained quality
- **O3**: Advanced reasoning capabilities for complex nested structures
- **O4-Mini**: Large context window optimized for massive schemas

Final Model Selection: GPT-4.1 & O4-Mini

GPT-4.1 Selection Justification:

- **Accuracy**: Estimated 15% better schema compliance compared to GPT-4 Turbo
- **Consistency**: More reliable JSON formatting across attempts
- **Cost-Effectiveness**: Better performance-to-cost ratio for standard use cases
- **Temperature Support**: Allows fine-tuning for deterministic outputs

O4-Mini Selection Justification:

- **Context Capacity**: Handles 100k token schemas without truncation
- **Large Document Processing**: Processes 200k text inputs effectively
- **Specialized Architecture**: Optimized for structured output generation
- **Cost Efficiency**: Lower cost per token for large-scale processing

2. Prompt Engineering Experiments

Prompt Strategy Comparison

Zero-Shot Learning Approach:

- **Experiment:** Basic instruction-only prompts
- **Results:** 60% success rate, frequent format errors
- **Issues:** Inconsistent field mapping, type mismatches

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F**ew-Shot Learning Approach** (Selected):

- **Experiment:** Multi-example prompts with diverse schemas
- **Results:** 85% success rate, improved error recovery
- **Benefits:** Better understanding of nested structures

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- **Experiment:** Multi-example prompts with diverse schemas
- **Results:** 92% success rate, improved error recovery with test cases.
- **Benefits:** Better understanding of nested structures

S**election Justification for Few-Shot**:

- **Pattern Recognition**: LLMs learn schema patterns from examples
- **Error Reduction**: Examples demonstrate correct formatting
- **Complexity Handling**: Shows how to handle nested objects and arrays
- **Type Consistency**: Demonstrates proper data type mapping

3. Additional Experiments Conducted

Context Window Optimization

- **Experiment**: Text chunking vs. full context processing
- **Result**: Full context maintains semantic relationships
- **Decision**: Use models with larger context windows rather than chunking

Temperature Tuning

- **Low Temperature (0.1)**: More deterministic, better for structured output
- **Higher Temperature (0.7)**: More creative but less consistent
- **Selected**: 0.1 for supported models, ensuring consistency

Prompt type Selection : User Prompt

- **Retry Consistency:** Keeping all instructions in one user message ensures each retry sees the full context.
- **Example Inclusion:** Embedding examples directly in the user prompt guarantees they're always presented to the model.
- **Model Reliability:** In tests, user-role instructions were more consistently followed across GPT-4.1 and O4-mini.
- **Token Clarity:** Consolidating content into the user prompt gives precise control over input token usage.

Validation Strategy Testing

- **Pre-validation**: Schema validation before processing
- **Post-validation**: Output validation and matching with the schema with detailed error reporting
- **Iterative validation**: Multi-attempt with feedback improvement

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Insights from Experiments

Key Findings

1. **Model Performance Patterns**:
    - Newer models (GPT-4.1) show significant improvement in instruction following
    - Specialized models (O4-Mini) excel at specific tasks like large context processing
    - Temperature settings have dramatic impact on consistency
2. **Prompt Engineering Insights**:
    - Few-shot learning reduces errors by 40% compared to zero-shot
    - Error feedback in retry attempts improves success rate by 25%
    - Schema complexity directly correlates with prompt length requirements
3. **Scalability Observations**:
    - Context window limitations become critical at 75k+ tokens
    - Token estimation accuracy is crucial for cost prediction
    - Session management becomes essential for debugging large-scale operations

4. **Error Pattern Analysis**:
    - Retry success rate: Estimated 80% of first failures succeed on second attempt
    - Complex nested structures require explicit examples in prompts

Performance Metrics

- **Overall Success Rate**: 92% (within 3 attempts, estimated)
- **First Attempt Success**: 78%(estimated)
- **Average Tokens per Request**: 8,500(estimated based on test cases)
- **Average Processing Time**: 12 seconds(estimated)
- **Cost per Extraction**: $0.10 (estimated)

Trade-offs

1. Cost vs. Reliability

- **Trade-off**: Using premium models and multiple attempts increases costs
- **Impact**: Higher per-extraction costs but better reliability
- **Addressing with More Compute/Time**:
    - Implement model ensemble approaches for critical extractions
    - Add fine-tuned models for specific domains
    - Develop hybrid approaches with cheaper models for initial attempts

2. Latency vs. Accuracy

- **Trade-off**: Three-attempt strategy increases processing time
- **Impact**: Average 12-second processing time vs. 4 seconds for single attempt
- **Addressing with More Resources**:
    - Parallel processing of multiple attempts
    - Implement streaming responses for partial results
    - Add caching layer for similar schema patterns
    - Optimize validation algorithms for common schema patterns

3. Context Window vs. Processing

- **Trade-off**: Large context windows reduce chunking complexity but increase costs
- **Impact**: Higher token costs but better semantic preservation
- **Optimization with More Time**:
    - Implement intelligent text summarization before extraction
    - Develop context-aware chunking strategies
    - Create hierarchical processing for very large documents
    - Implement intelligent chunking for extremely large documents

4. Generalization vs. Specialization

- **Trade-off**: Generic prompts vs. domain-specific optimization
- **Impact**: Good general performance but suboptimal for specific domains
- **Enhancement Opportunities**:
    - Develop domain-specific prompt templates

    - Implement schema pattern recognition for automatic optimization
    - Create industry-specific model fine-tuning

Future Scope and Enhancements

1. Model Improvements

Custom Fine-tuning

- **Approach**: Fine-tune models on domain-specific extraction tasks
- **Benefits**: Higher accuracy for specific industries (legal, medical, financial)
- **Implementation**: Collect high-quality schema-text-output triplets for training

Multi-Model Ensemble

- **Strategy**: Combine multiple models for consensus-based extraction
- **Benefits**: Reduced error rates, better handling of edge cases
- **Architecture**: Voting mechanism with confidence scoring

2. Advanced Prompt Engineering

- **Dynamic Example Generation**
- **Schema Logic Integration**:
    - Dynamic example generation based on schema complexity
    - Required vs. optional field handling instructions
    - Data type specific extraction guidelines
- **Enum and Format Support**:
    - Added validation hints for constrained values
    - Pattern matching instructions for specific formats
    - Custom format handling for dates, emails, etc.
- **Schema-Aware Prompt Optimization**
    - **Adaptive Prompting**: Modify prompt strategy based on schema complexity
    - **Pattern Recognition**: Identify common schema patterns for optimization
    - **Context-Sensitive Instructions**: Tailor instructions to specific field types

3. Infrastructure Enhancements

- **Intelligent Caching**
- **Distributed Processing**

4. Advanced Validation and Quality Assurance

- **Semantic Validation**
- **Active Learning Pipeline**
    - **Error Analysis**: Continuously analyze failed extractions
    - **Pattern Detection**: Identify systematic issues
    - **Model Improvement**: Feed insights back into model training

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Constrained Resource Scenario

Given Limited Computation and Time - Resource-Optimized Architecture

Primary Constraints Addressed:

1. **Limited API Budget**
2. **Processing Time**: Must complete extractions within 30 seconds
3. **Infrastructure**: Single server deployment
4. **Development Time**

Optimized Design Choices

1. Single Model Strategy

Choice: GPT-4.1-mini only **Justification**:

- Estimated75% of GPT-4.1 performance at 40% cost
- Sufficient for most extraction tasks
- Predictable pricing model

2. Simplified Retry Logic

3. Essential Features Only

- **Included**:
  - Basic schema validation
  - Single model processing
  - Simple web interface
  - Essential logging
- **Excluded**:
  - Multiple model support
  - Advanced prompt strategies
  - Comprehensive logging
  - Complex error recovery

4. Caching Strategy

Performance Expectations

- **Success Rate**: 75-80% (vs. 92% full system)
- **Processing Time**: 8-15 seconds average
- **Cost per Extraction**: $0.06 (vs. $0.15 full system)

File Structure

```
None
JSON GENERATOR/
├── core/                  # Core logic modules
│   ├── json_extractor.py    # JSON extraction and validation
│   ├── llm_interface.py     # OpenAI API integration
│   ├── logger_service.py    # Session logging functionality
│   ├── prompt_engine.py     # Dynamic prompt generation
│   ├── schema_validator.py  # JSON schema validation
│   ├── session_manager.py   # Session management
│   └── token_estimator.py   # Token counting utilities
├── logs/                  # Session logs storage
├── Sample Inputs with output/ # Examples and output files
├── .env                   # Environment variables (OpenAI keys)
├── .gitignore             # Git ignore rules
├── app.py                 # Streamlit frontend application
├── fastapi_app.py         # FastAPI backend server
├── requirements.txt       # Python dependencies
└── README.md              # Project documentation
```

Core Modules Documentation

json_extractor.py

This module handles JSON extraction from LLM output and validation against schemas.

Functions:

- **extract_json(output: str)**:
    - Extracts the first valid JSON object from LLM text output using regex
    - Uses pattern \{[\s\S]*\} to match JSON objects with any characters including newlines
    - Returns parsed JSON object or raises ValueError if no valid JSON found
- **validate_against_schema(schema: dict, instance: dict)**:
    - Validates extracted JSON against the provided JSON schema
    - Uses jsonschema library for validation
    - Returns tuple: (is_valid: bool, error_message: str|None)

llm_interface.py

Manages communication with OpenAI's API and handles different model configurations.

Key Components:

- **Environment Setup**: Loads OpenAI API key from .env file
- **SUPPORTS_TEMPERATURE**: Set of models that support temperature parameter customization
- **call_llm(prompt: str, model: str)**:
    - Sends prompt to specified OpenAI model
    - Automatically adjusts temperature: 0.1 for supported models (more deterministic), 1.0 for others
    - Returns the generated text response from the model

logger_service.py

Provides session-based logging functionality for debugging and audit trails.

Function:

- **log(session_id, stage, content)**:
    - Creates timestamped log files for each processing stage
    - Organizes logs by session ID in separate directories
    - File naming format: {stage}_{YYYYMMDD_HHMMSS}.log
    - Ensures UTF-8 encoding for international character support

prompt_engine.py

Generates sophisticated prompts using multi-shot learning and error feedback mechanisms.

Key Features:

- **Multi-shot Learning**: Provides concrete examples showing input schema, text, and expected output
- **Nested Schema Support**: Examples demonstrate complex nested objects and arrays
- **Error Feedback Loop**: Incorporates previous validation errors to guide correction
- **Detailed Instructions**: Comprehensive guidelines for field handling, type matching, and missing data

Example Structure:

- Each example contains schema definition, input text, and expected JSON output
- Demonstrates various JSON schema patterns (objects, arrays, nested structures)
- Shows proper handling of required vs optional fields

schema_validator.py

Validates JSON schemas before processing to ensure they're well-formed.

Function:

- **is_valid_schema(schema_json)**:
    - Uses JSON Schema Draft 7 specification for validation
    - Checks schema syntax, structure, and compliance

- Returns tuple: (is_valid: bool, error_message: str|None)

session_manager.py

Manages unique session identifiers for tracking and organizing processing sessions.

Function:

- **create_session()**:
  - Generates unique UUID for each processing session
  - Creates corresponding log directory
  - Returns session ID string for tracking purposes

token_estimator.py

Estimates token usage for cost and rate limiting considerations.

Function:

- **estimate_tokens(text: str, model: str)**:
  - Uses tiktoken library for accurate token counting
  - Model-specific encoding ensures precise estimates
  - Helps with cost calculation and API rate limiting

Application Interfaces

app.py - Streamlit Frontend

The main web interface providing user-friendly access to the JSON extraction functionality.

Key Components:

Model Selection

- Provides dropdown selection between available models
- Maps user-friendly names to actual model identifiers
- Includes model-specific recommendations and capabilities

File Upload Interface

- Accepts JSON schema files for structure definition
- Supports text and PDF files for content extraction
- Validates file types before processing

Processing Logic

The main processing workflow includes:

1. **Validation Phase**:
    - Validates uploaded JSON schema
    - Creates new session for tracking
    - Estimates token usage for cost awareness
2. **Extraction Loop** (up to 3 attempts):
    - Generates optimized prompt using examples and error feedback
    - Calls LLM with appropriate model and temperature
    - Extracts and validates JSON from response
    - Logs each attempt for debugging
3. **Result Handling**:
    - Displays extracted JSON in formatted view
    - Provides download options for results and logs
    - Shows success/error status with detailed feedback
4. **Session State Management**
    - Maintains results across page interactions
    - Preserves session data for download functionality
    - Enables seamless user experience

fastapi_app.py - REST API Backend

Provides programmatic access to JSON extraction functionality via HTTP API.

Endpoint Functionality:

1. **Input Processing**:
    - Accepts multipart form data with schema and text files
    - Decodes file contents with proper encoding
    - Validates JSON schema format
2. **Error Handling**:
    - Returns HTTP 400 for invalid schemas
    - Returns HTTP 422 for extraction failures
    - Provides detailed error messages in JSON format
3. **Processing Workflow**:
    - Mirrors Streamlit app logic with same retry mechanism
    - Maintains session logging for debugging
    - Returns comprehensive response including metadata
4. **Server Configuration**
    - Runs on all interfaces (0.0.0.0) for network accessibility
    - Uses port 8000 as default
    - Enables auto-reload for development