Airline Policy Assistant Service

Architecture Changes: From GPU-Dependent to CPU-Only Stack

> [!WARNING]
>
> Latest changes!
>
> Initially, this project relied on a GPU-dependent stack using libraries like `unstructured` for PDF processing and OCR. However, this approach introduced significant robustness issues:
>
> - **CUDA Dependency Problems**: `unstructured` required NVIDIA CUDA drivers and GPU hardware. It failed in environments without compatible GPUs (e.g., AMD/ATI GPUs, cloud instances without GPU allocation, or local machines with driver issues).
> - **Inconsistent Performance**: Builds and runs were unreliable across different architectures, leading to deployment failures.
> - **Complexity**: Managing GPU drivers and versions added unnecessary overhead for a technical challenge focused on core functionality.
> - **Docker and Architecture Issues**: Building Docker images with GPU dependencies was challenging and unreliable. Additionally, since the final execution environment's architecture (GPU type or presence) was unknown, we couldn't assume NVIDIA libraries or graphical capabilities.
>
> To address this, we switched to a **CPU-only stack** for maximum robustness and portability.
>
> We removed `unstructured` and replaced it with `pypdf` for PDF text extraction and `pytesseract` with `tesseract-ocr` for OCR:
>
> We also developed a custom PDF loader that processes documents page by page, integrating text extraction, OCR with image enhancement, and optional debugging for maximum control and accuracy.
>
> - **PDF Text Extraction**: Uses `pypdf` for direct text extraction from PDFs.
> - **OCR Processing**: Uses `pytesseract` with `tesseract-ocr` for image-based text recognition, running entirely on CPU.
> - **No GPU Requirements**: Works on any machine, regardless of GPU type (NVIDIA, AMD, or none).
> - **Docker Compatibility**: Docker images now work independently of the host architecture, as the stack is CPU-only and doesn't require GPU-specific drivers.
> - **OCR Debugging**: Optional debugging mode (via config) saves original images, enhanced images, and extracted texts for inspection.
> - **OCR Improvements**: We studied and improved OCR processing techniques, such as image enhancement for better text recognition.
>
> This change ensures the system runs reliably in any environment, prioritizing simplicity and compatibility over raw performance.
>
> For complex images, the existing LLM-based loader can always be used.
>
> ---

A Retrieval-Augmented Generation (RAG) chatbot application that allows users to query airline policies using natural language. The system uses Large Language Models (LLMs) for understanding questions and a vector database for efficient document retrieval.

Overview and Purpose

This application was developed as part of the Flight Center AI Center Of Excellence technical challenge. It demonstrates the integration of LLMs with vector databases to create an intelligent assistant that can answer questions about airline policies from multiple carriers.

The system processes airline policy documents (PDF and Markdown), creates embeddings, stores them in a ChromaDB vector database, and uses a conversational AI interface powered by OpenAI's GPT models to answer user questions.

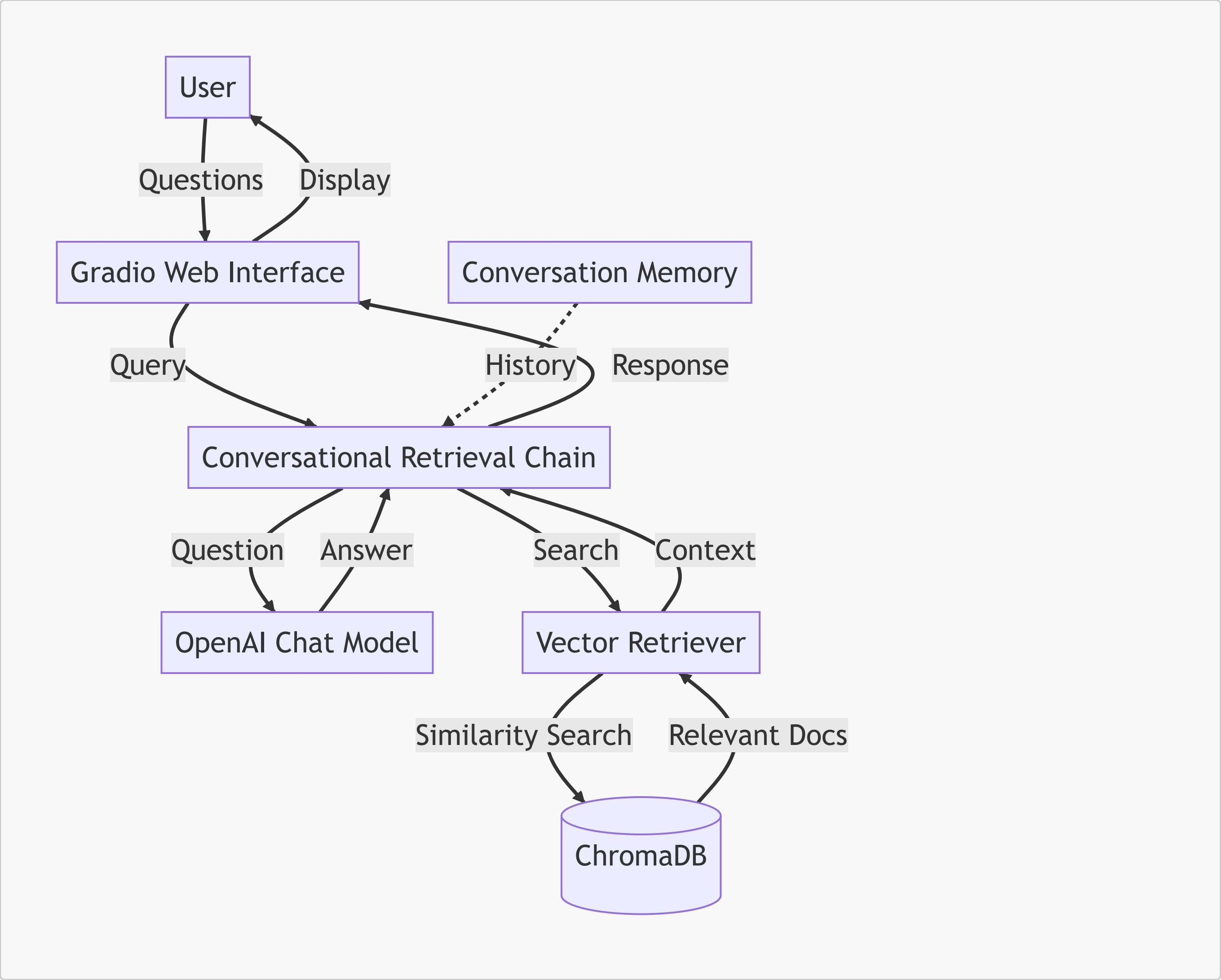
Key Features:

- Web-based chat interface using Gradio
- Support for multiple airlines (American Airlines, Delta, United)
- Advanced PDF processing with three levels: basic text extraction, OCR, and LLM-based chunking
- Conversational memory for context-aware responses
- Dockerized deployment with development and production modes

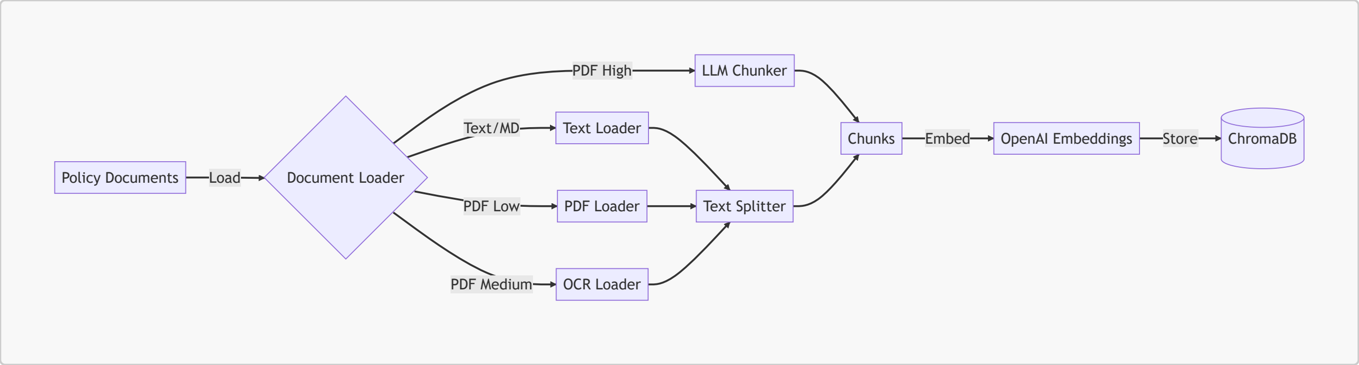
Architecture and Folder Structure

```
ai_technical_challenge/
├── app/                       # Main application package
│   ├── __init__.py            # Package initialization
│   ├── __main__.py            # Entry point for the Gradio service
│   ├── config.py              # Configuration management
│   └── embeddings/            # Document processing and embedding logic
│       ├── __init__.py        # Package initialization
│       ├── embeddings.py      # Core embedding functions
│       ├── llm_chunker.py     # LLM-based document chunking
│       └── pdf_loader.py      # PDF loading and OCR processing
├── policies/                  # Airline policy documents
│   ├── AmericanAirlines/      # American Airlines policies (Markdown)
│   ├── Delta/                 # Delta Airlines policies (Markdown)
│   └── United/                # United Airlines policies (PDF)
├── tools/                     # Utility scripts
│   ├── API_test.py            # Test LLM API endpoint
│   ├── cleanup_chroma.py      # Clean vector database
│   ├── embed_company.py       # Embed documents for a company
│   ├── initialize.sh          # Initialize database with all policies
│   └── querier.py             # REPL-based query tool
├── dockers/                   # Standalone Docker configurations
│   ├── chromadb/              # ChromaDB standalone setup
│   └── portainer/             # Portainer management UI
├── docker-compose.yaml        # Development deployment
├── docker-compose-prod.yaml   # Production deployment
├── Dockerfile                 # Multi-stage Docker build
├── Pipfile                    # Python dependencies (Pipenv)
├── template.env               # Environment variable template
├── setup.cfg                  # Code quality tool configurations
└── ruff.toml                  # Ruff linter configuration
```

System Architecture



Data Processing Pipeline



Getting Started

Prerequisites

- Docker and Docker Compose
- Python 3.13 (if running locally without Docker)
- OpenAI API access

Installation

1. **Clone the repository:**

   ```
   git clone https://github.com/Carbaz/ai_technical_challenge.git
   cd ai_technical_challenge
   ```

2. **Create environment configuration:**

   Copy the template and configure your environment variables:

   ```
   cp template.env .env
   ```

   Edit `.env` and set your API credentials:

   - `FCM_APA_LLM_API_URL`: Your LLM API base URL
   - `FCM_APA_LLM_API_KEY`: Your LLM API key

3. **Start the services:**

   For development mode with code mounting:

   ```
   docker-compose up
   ```

   For production mode:

   ```
   docker-compose -f docker-compose-prod.yaml up -d --build
   ```

4. **Initialize the database:**

   On first run, you need to populate the vector database with airline policies:

   ```
   docker-compose --profile reload up backend_init -d --build
   ```

   Or manually run the initialization script inside the container.

5. **Access the application:**

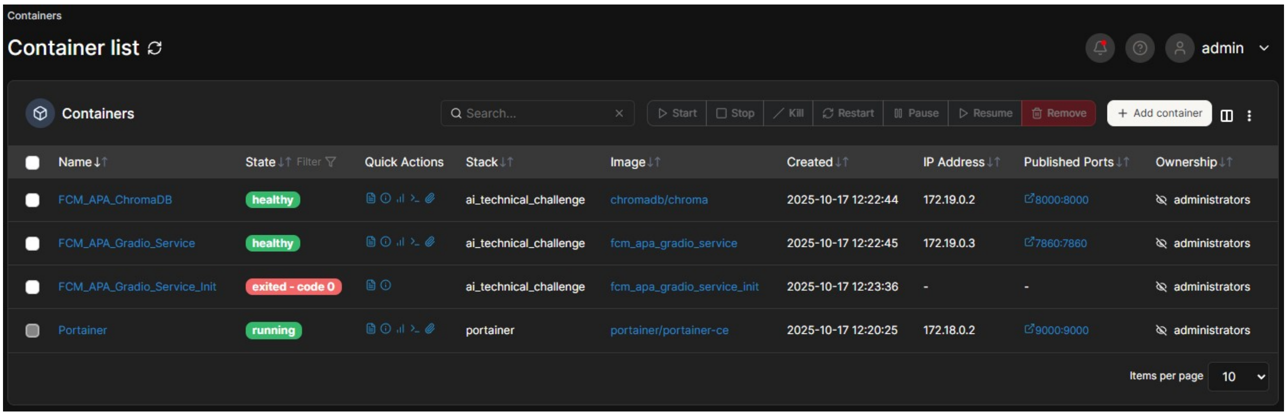
   Open your browser and navigate to:

   ```
   http://localhost:7860
   ```

6. **Monitor containers:**

   A Portainer service is included in the `dockers` folder to provide a Docker management interface.

   Any other container management tool can be used, but Portainer is provided for convenience.



Container list

Containers

Name	State	Quick Actions	Stack	Image	Created	IP Address	Published Ports	Ownership
FCM_APA_ChromaDB	healthy		ai_technical_challenge	chromadb/chroma	2025-10-17 12:22:44	172.19.0.2	8000:8000	administrators
FCM_APA_Gradio_Service	healthy		ai_technical_challenge	fcm_apa_gradio_service	2025-10-17 12:22:45	172.19.0.3	7860:7860	administrators
FCM_APA_Gradio_Service_Init	exited - code 0		ai_technical_challenge	fcm_apa_gradio_service_init	2025-10-17 12:23:36	-	-	administrators
Portainer	running		portainer	portainer/portainer-ce	2025-10-17 12:20:25	172.18.0.2	9000:9000	administrators

Items per page 10

Usage Guide

Running Locally with Standalone ChromaDB

If you prefer to run ChromaDB separately:

1. **Start ChromaDB:**

   ```
   cd dockers/chromadb
   docker-compose up -d
   ```

2. **Configure environment:**

   Set these variables in your `.env`:

   ```
   FCM_APA_CHROMADB_HOST=localhost
   FCM_APA_CHROMADB_PORT=8000
   ```

3. **Install Python dependencies:**

   ```
   pip install pipenv
   pipenv install
   ```

4. **Initialize the database:**

   ```
   pipenv run python -Bm tools.cleanup_chroma
   pipenv run python -Bm tools.embed_company -s policies/United -c United
   pipenv run python -Bm tools.embed_company -s policies/Delta -c Delta
   pipenv run python -Bm tools.embed_company -s policies/AmericanAirlines \
       -c AmericanAirlines
   ```

5. **Run the application:**

   ```
   pipenv run python -Bm app
   ```

Running in Development Mode (Docker Compose)

Development mode mounts the source code into the container, allowing for real-time code changes without rebuilding:

```
docker-compose up -d --build
```

Features:

- Source code mounted as volume (`./:/service`)
- Internal/external visibility of code changes
- Development dependencies installed
- Accessible at `http://localhost:7860`

Running in Production Mode (Docker Compose Prod)

Production mode copies the code into the image for isolated deployment:

```
docker-compose -f docker-compose-prod.yaml up -d --build
```

Features:

- Code copied into image (not mounted)
- Optimized for deployment
- Only production dependencies
- Smaller image size
- Accessible at `http://localhost:7860`

Database Initialization Profile

Both compose files include a `backend_init` service with the `reload` profile for database initialization:

```
docker-compose --profile reload up backend_init -d --build
```

This service runs the `initialize.sh` script which:

1. Cleans the ChromaDB database
2. Processes and embeds all airline policies
3. Exits after completion

Configuration

Configuration is managed through environment variables with the `FCM_APA_` prefix. All variables can be set in the `.env` file.

Available Configuration Options

Variable	Default	Description
`FCM_APA_LOG_LEVEL`	`INFO`	Logging level (DEBUG, INFO, WARNING, ERROR)
`FCM_APA_LLM_API_URL`	None	Base URL for the LLM API
`FCM_APA_LLM_API_KEY`	None	API key for authentication
`FCM_APA_CHAT_MODEL`	`gpt-4.1-mini`	Model for chat interactions
`FCM_APA_CHUNKING_MODEL`	`gpt-5-mini`	Model for LLM-based chunking
`FCM_APA_EMBEDDING_MODEL`	`text-embedding-3-small`	Model for embeddings
`FCM_APA_OCR_DEBUG`	`false`	Enable OCR debugging mode to save images and texts
`FCM_APA_PDF_PROCESSING_LEVEL`	`MEDIUM`	PDF processing: LOW, MEDIUM, HIGH
`FCM_APA_CHROMADB_HOST`	`localhost`	ChromaDB hostname
`FCM_APA_CHROMADB_PORT`	`8000`	ChromaDB port
`FCM_APA_GRADIO_SERVER_NAME`	`0.0.0.0`	Gradio server bind address
`FCM_APA_GRADIO_HTTP_PORT`	`7860`	Gradio HTTP port

PDF Processing Levels

The application supports three levels of PDF processing:

- **LOW:** Basic text extraction without OCR
- **MEDIUM:** Advanced extraction with OCR for images (default)
- **HIGH:** LLM-based intelligent chunking and processing

Example configuration:

```
FCM_APA_PDF_PROCESSING_LEVEL=MEDIUM
```

Main Dependencies

Core Framework

- **Python 3.13:** Modern Python runtime with enhanced performance
- **Gradio:** Web UI framework for machine learning applications
- **LangChain:** Framework for building LLM applications
- **ChromaDB:** Vector database for embeddings

LLM Integration

- **OpenAI:** Official OpenAI Python SDK for API access
- **langchain-openai:** LangChain integration for OpenAI models
- **langchain-chroma:** LangChain integration for ChromaDB

Document Processing

- **pypdf**: PDF text extraction library
- **pytesseract**: Python wrapper for Tesseract OCR
- **tesseract-ocr**: OCR engine (system-level installation required)
- **RecursiveCharacterTextSplitter:** Intelligent document chunking

Development Tools

- **Pipenv:** Dependency management and virtual environments
- **Ruff:** Fast Python linter
- **isort, mypy, pytest:** Code quality and testing tools

Tools

The `tools/` directory contains utility scripts for managing the system:

`embed_company.py`

Processes and embeds documents for a specific airline company.

Usage:

```
pipenv run python -Bm tools.embed_company \
    -s policies/Delta \
    -c Delta \
    -z 1000 \
    -o 100
```

Arguments:

- `-s, --sources`: Path to the policy documents directory
- `-c, --company`: Company name (metadata tag)
- `-z, --size`: Chunk size in characters (default: 1000)
- `-o, --overlap`: Chunk overlap in characters (default: 100)

`cleanup_chroma.py`

Removes all embeddings from the ChromaDB database.

Usage:

```
pipenv run python -Bm tools.cleanup_chroma
```

`querier.py`

REPL-based tool for testing similarity search directly against the vector database.

Usage:

```
pipenv run python -Bm tools.querier
```

Allows interactive querying by company and displays retrieved document chunks.

`initialize.sh`

Bash script that initializes the database with all airline policies.

Usage:

```
bash tools/initialize.sh
```

Executes in sequence:

1. Database cleanup
2. Embedding of United policies
3. Embedding of Delta policies
4. Embedding of American Airlines policies

`API_test.py`

Tests connectivity and lists available models from the LLM API endpoint.

Usage:

```
pipenv run python -Bm tools.API_test
```

Strategic Decisions

Multi-Stage Docker Build

The Dockerfile uses a multi-stage build strategy:

- **Base stage:** Common dependencies (Python, CUDA libraries, Pipenv)
- **Init stage:** Includes policies for database initialization
- **Development stage:** Adds dev dependencies for local development
- **Production stage:** Minimal runtime-only image

Rationale: Reduces production image size while maintaining flexibility for different deployment scenarios.

ChromaDB as Vector Database

ChromaDB was chosen for its:

- Lightweight deployment
- Built-in filtering capabilities
- Seamless LangChain integration
- Docker-friendly architecture

Three-Tier PDF Processing

Supports different processing strategies based on document complexity:

- **LOW:** Fast processing for text-based PDFs
- **MEDIUM:** OCR for scanned documents (balanced approach)
- **HIGH:** LLM-based semantic chunking for complex documents

Rationale: Allows optimization between processing time, cost, and quality based on document characteristics.

Conversational Memory

Uses `ConversationBufferMemory` to maintain chat history within the retrieval chain.

Rationale: Enables context-aware follow-up questions without requiring users to repeat context.

Metadata-Based Company Filtering

Each document chunk includes company metadata, enabling filtered similarity search.

Rationale: Ensures responses draw from the correct airline's policies, preventing cross-contamination of information.

Configuration via Environment Variables

All configuration through the `environs` library with the `FCM_APA_` prefix.

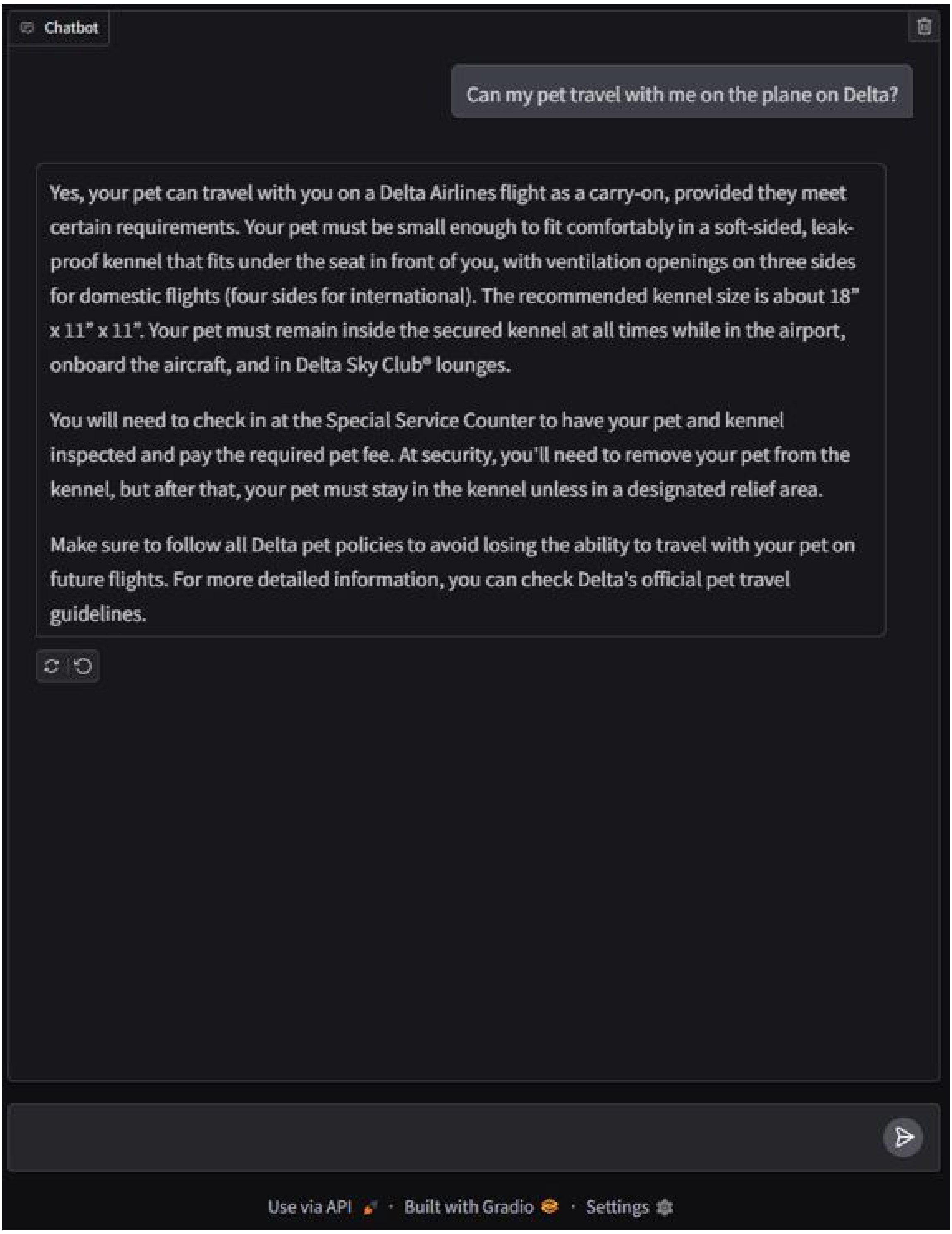
Rationale: Follows the 12-factor app methodology, enabling easy containerization and deployment across environments.

Usage Examples

Here are real-world queries the system can answer:

Query:

```
Can my pet travel with me on the plane on Delta?
```



Can my pet travel with me on the plane on Delta?

Yes, your pet can travel with you on a Delta Airlines flight as a carry-on, provided they meet certain requirements. Your pet must be small enough to fit comfortably in a soft-sided, leak-proof kennel that fits under the seat in front of you, with ventilation openings on three sides for domestic flights (four sides for international). The recommended kennel size is about 18" x 11" x 11". Your pet must remain inside the secured kennel at all times while in the airport, onboard the aircraft, and in Delta Sky Club® lounges.

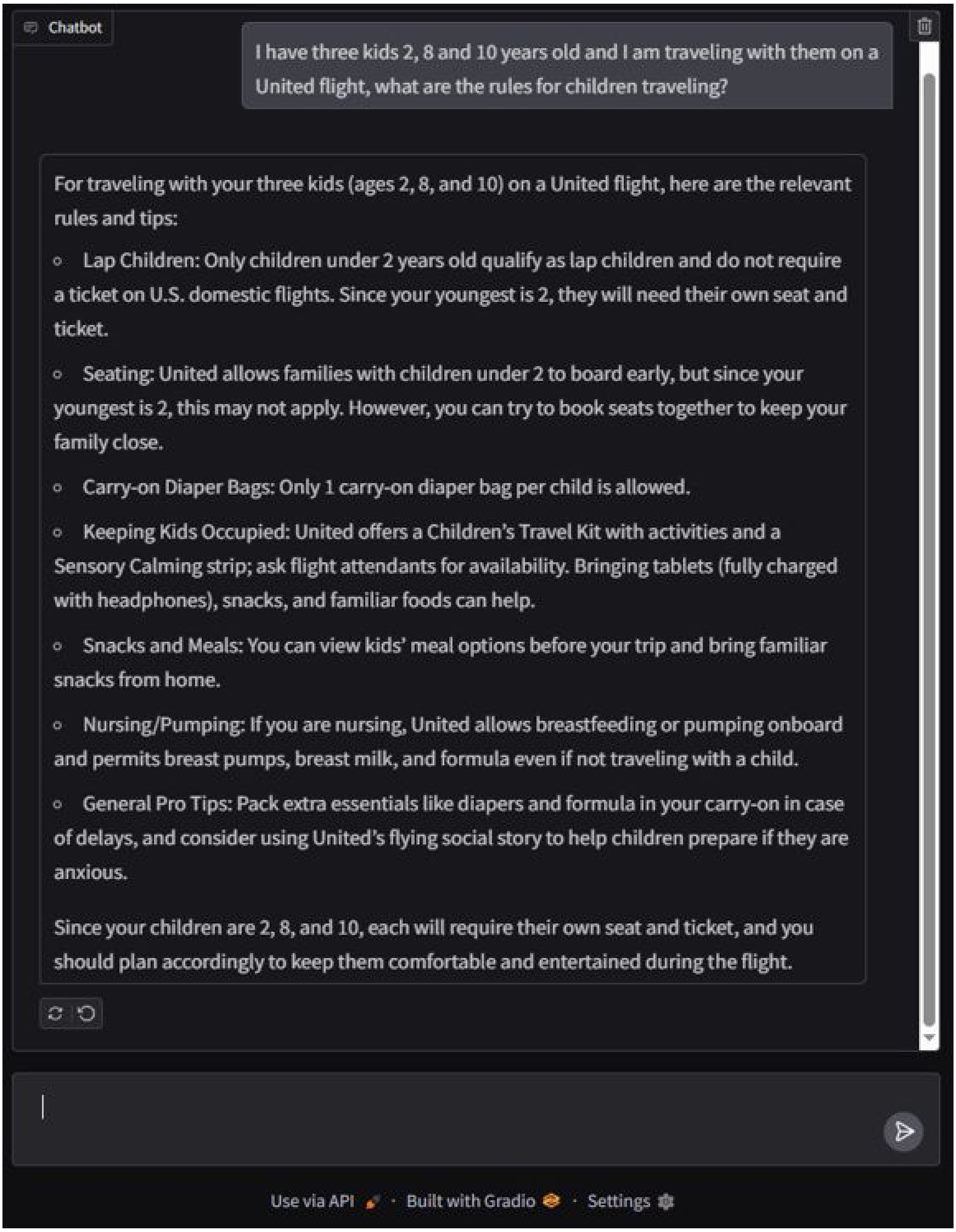
You will need to check in at the Special Service Counter to have your pet and kennel inspected and pay the required pet fee. At security, you'll need to remove your pet from the kennel, but after that, your pet must stay in the kennel unless in a designated relief area.

Make sure to follow all Delta pet policies to avoid losing the ability to travel with your pet on future flights. For more detailed information, you can check Delta's official pet travel guidelines.

Response Type: Information about Delta's pet policies, including cabin restrictions, carrier requirements, and fees.

Query:

```
I have three kids 2, 8 and 10 years old and I am traveling with them on a
United flight, what are the rules for children traveling?
```



I have three kids 2, 8 and 10 years old and I am traveling with them on a United flight, what are the rules for children traveling?

For traveling with your three kids (ages 2, 8, and 10) on a United flight, here are the relevant rules and tips:

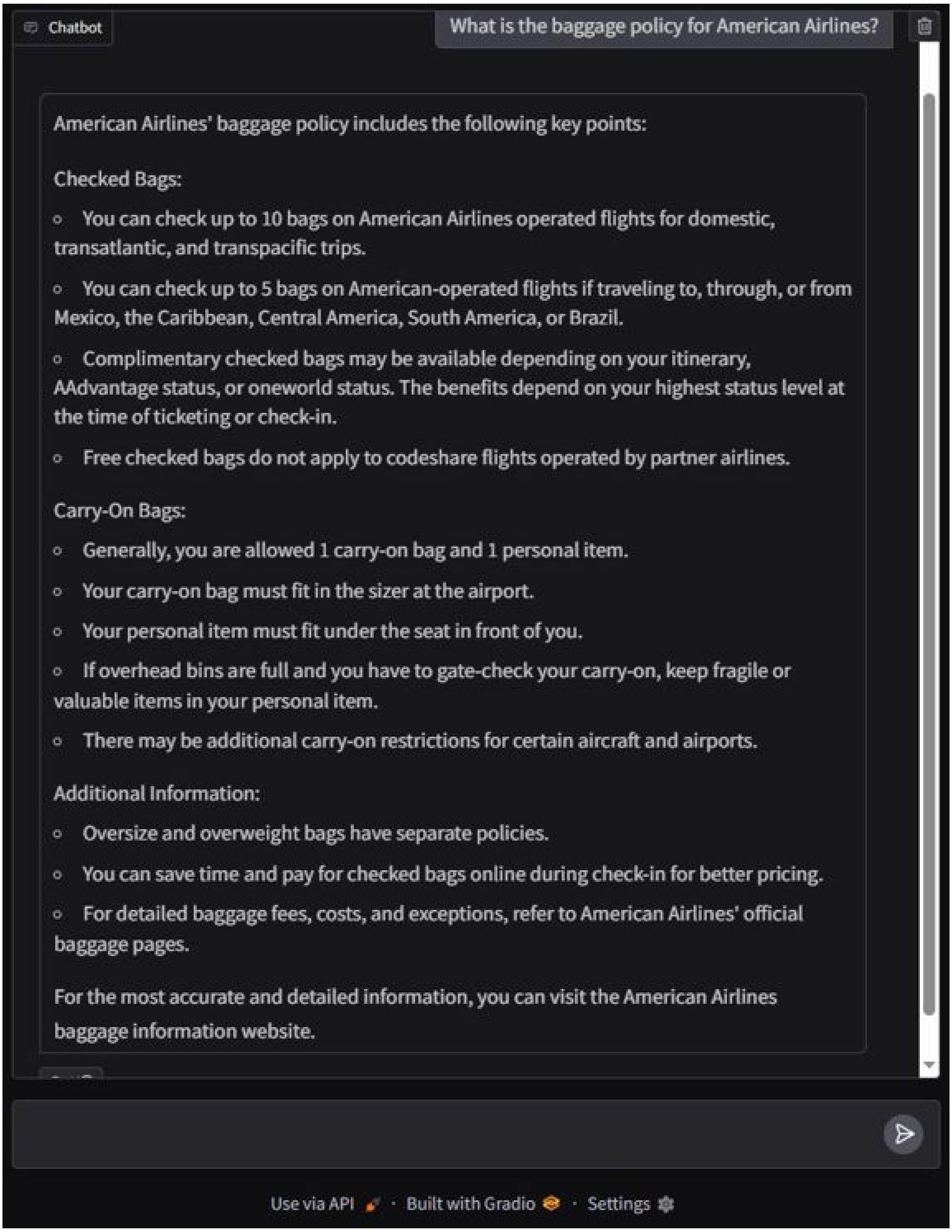
- Lap Children: Only children under 2 years old qualify as lap children and do not require a ticket on U.S. domestic flights. Since your youngest is 2, they will need their own seat and ticket.
- Seating: United allows families with children under 2 to board early, but since your youngest is 2, this may not apply. However, you can try to book seats together to keep your family close.
- Carry-on Diaper Bags: Only 1 carry-on diaper bag per child is allowed.
- Keeping Kids Occupied: United offers a Children's Travel Kit with activities and a Sensory Calming strip; ask flight attendants for availability. Bringing tablets (fully charged with headphones), snacks, and familiar foods can help.
- Snacks and Meals: You can view kids' meal options before your trip and bring familiar snacks from home.
- Nursing/Pumping: If you are nursing, United allows breastfeeding or pumping onboard and permits breast pumps, breast milk, and formula even if not traveling with a child.
- General Pro Tips: Pack extra essentials like diapers and formula in your carry-on in case of delays, and consider using United's flying social story to help children prepare if they are anxious.

Since your children are 2, 8, and 10, each will require their own seat and ticket, and you should plan accordingly to keep them comfortable and entertained during the flight.

Response Type: Details about United's policies for traveling with children, including infant requirements, unaccompanied minor rules, and family boarding.

Query:

```
What is the baggage policy for American Airlines?
```



What is the baggage policy for American Airlines?

American Airlines' baggage policy includes the following key points:

Checked Bags:

- You can check up to 10 bags on American Airlines operated flights for domestic, transatlantic, and transpacific trips.
- You can check up to 5 bags on American-operated flights if traveling to, through, or from Mexico, the Caribbean, Central America, South America, or Brazil.
- Complimentary checked bags may be available depending on your itinerary, AAdvantage status, or oneworld status. The benefits depend on your highest status level at the time of ticketing or check-in.
- Free checked bags do not apply to codeshare flights operated by partner airlines.

Carry-On Bags:

- Generally, you are allowed 1 carry-on bag and 1 personal item.
- Your carry-on bag must fit in the sizer at the airport.
- Your personal item must fit under the seat in front of you.
- If overhead bins are full and you have to gate-check your carry-on, keep fragile or valuable items in your personal item.
- There may be additional carry-on restrictions for certain aircraft and airports.

Additional Information:

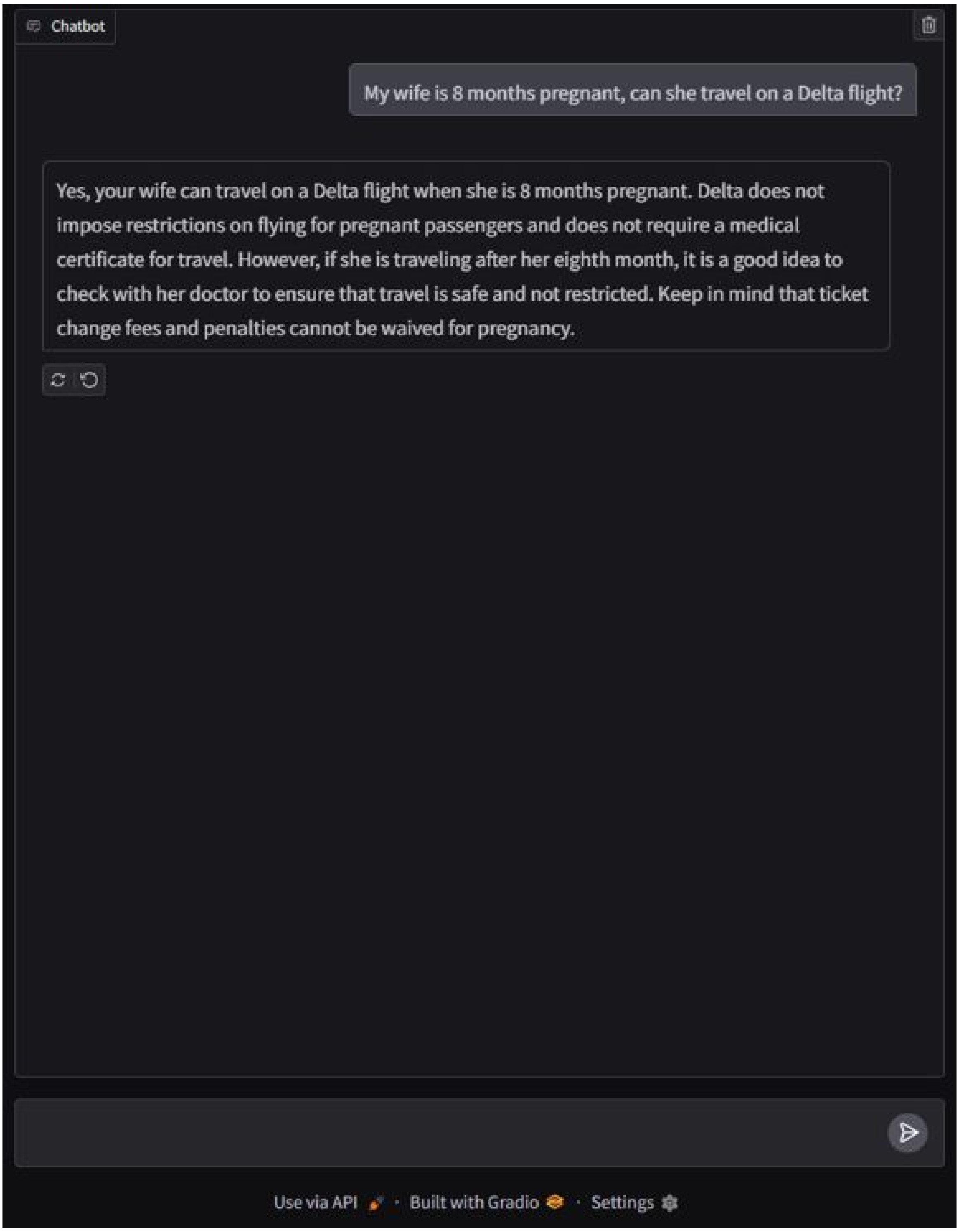
- Oversize and overweight bags have separate policies.
- You can save time and pay for checked bags online during check-in for better pricing.
- For detailed baggage fees, costs, and exceptions, refer to American Airlines' official baggage pages.

For the most accurate and detailed information, you can visit the American Airlines baggage information website.

Response Type: Comprehensive baggage information including size limits, weight restrictions, and fees.

Query:

```
My wife is 8 months pregnant, can she travel on a Delta flight?
```



My wife is 8 months pregnant, can she travel on a Delta flight?

Yes, your wife can travel on a Delta flight when she is 8 months pregnant. Delta does not impose restrictions on flying for pregnant passengers and does not require a medical certificate for travel. However, if she is traveling after her eighth month, it is a good idea to check with her doctor to ensure that travel is safe and not restricted. Keep in mind that ticket change fees and penalties cannot be waived for pregnancy.

Response Type: Delta's policies on pregnant passengers, including restrictions and medical documentation requirements.

Code Example: Embedding Workflow

From `embeddings.py`:

```python
def embed_directory(directory, metadata, model_name,
                    chunk_size, chunk_overlap, db_host, db_port):
    """Embed documents from directory."""
    # Process text and Markdown documents.
    text_chunks = chunk_directory_text(directory, chunk_size, chunk_overlap)
    # Process PDF documents.
    pdf_chunks = chunk_directory_pdf(directory, chunk_size, chunk_overlap)
    # Combine all chunks.
    chunks = text_chunks + pdf_chunks
    if not chunks:
        _logger.info(f'NO DOCUMENTS FOUND AT "{directory}"')
        return
    # Update metadata and embed all chunks.
    _logger.info(f'UPDATING METADATA')
    chunks = update_metadata(chunks, metadata)
    embedding_model = OpenAIEmbeddings(model=model_name,
                                       api_key=LLM_API_KEY,
                                       base_url=LLM_API_URL)
    _logger.info(f'EMBEDDING DOCUMENTS')
    embed_documents(chunks, embedding_model, db_host, db_port)
```

Code Example: Chat Interface

From `__main__.py`:

```
# Set up the conversation chain with the Chat LLM, the vectorstore and the
# memory.
conversation_chain = ConversationalRetrievalChain.from_llm(
    llm=llm,
    retriever=retriever,
    memory=memory)


# Chat function for Gradio interface.
# * "history" isn't used as the memory is included on the
#   ConversationalRetrievalChain.
def _chat(message, history):
    result = conversation_chain.invoke({"question": message})
    return result["answer"]


try:
    view = gr.ChatInterface(_chat, type="messages").launch(
        server_name=GRADIO_SERVER_NAME, server_port=GRADIO_HTTP_PORT)
except Exception as ex:
    _logger.critical(f'CRITICAL ERROR ON GRADIO SERVICE: {ex}')
    exit(1)
```

Limitations and Future Improvements

Known Limitations

- **Single-collection ChromaDB:** All companies share one collection with metadata filtering. Multiple collections could improve isolation.
- **In-memory conversation history:** Memory resets when the service restarts. Persistent storage would enable session recovery.
- **Deprecated conversational chain:** `ConversationalRetrievalChain` is deprecated and should be migrated to use `create_history_aware_retriever` together with `create_retrieval_chain` instead:
  - https://python.langchain.com/api_reference/langchain/chains/langchain.chains.conversational_retrieval.base.ConversationalRetrievalChain.html
- **No authentication:** The Gradio interface is publicly accessible without user authentication.
- **Limited error handling for API failures:** Network issues or API rate limits may cause ungraceful failures.
- **Fixed chunk parameters:** Chunk size and overlap are configured per embedding run, not optimized per document type.
- **OCR accuracy:** OCR accuracy may vary with complex images; use LLM loader for better results.

Future Improvements

- **Separate Loader and Chat services:** Separate services will allow a much more manageable Loader without overloading the service or project repository.
- **Multi-user support:** Add session management and user authentication
- **Persistent conversation history:** Store users chat history in a database
- **Citation support:** Display source document references with answers
- **Advanced RAG techniques:** Implement hybrid search (keyword + semantic), re-ranking, or query expansion
- **Monitoring and observability:** Add metrics, logging aggregation, and performance monitoring
- **API endpoint:** Expose a REST API alongside the Gradio interface
- **Document versioning:** Track policy document updates and version history
- **Optimize OCR preprocessing:** For specific document types.

Referenced Files

The following project files were used as reference to generate this documentation:

- `ai_technical_challenge/CHALLENGE.md`
- `ai_technical_challenge/Pipfile`
- `ai_technical_challenge/Dockerfile`
- `ai_technical_challenge/docker-compose.yaml`
- `ai_technical_challenge/docker-compose-prod.yaml`
- `ai_technical_challenge/template.env`
- `ai_technical_challenge/setup.cfg`
- `ai_technical_challenge/ruff.toml`
- `ai_technical_challenge/app/__main__.py`
- `ai_technical_challenge/app/config.py`
- `ai_technical_challenge/app/embeddings/embeddings.py`
- `ai_technical_challenge/app/embeddings/llm_chunker.py`
- `ai_technical_challenge/app/embeddings/pdf_loader.py`
- `ai_technical_challenge/tools/embed_company.py`
- `ai_technical_challenge/tools/cleanup_chroma.py`
- `ai_technical_challenge/tools/querier.py`
- `ai_technical_challenge/tools/initialize.sh`
- `ai_technical_challenge/tools/API_test.py`