WhatsApp Expense Tracker Bot

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Objective
Build a WhatsApp bot that helps users track and query their daily expenses using simple chat messages. The bot should understand natural language, automatically categorize expenses, and provide expense-related answers based on user queries.

Key Features
Send & Receive Messages on WhatsApp
Connect the bot with the WhatsApp API.
Allow users to interact with the bot through chat messages.
Understanding Natural Language Messages
The bot should understand natural language.
Identify whether the user wants to add an expense or ask a question about their expenses.
Adding Expenses
Users can send expenses in natural language, e.g., "Spent 500Rs on a latte at Starbucks." to the bot.
Storing Data
The bot should save all expense details in a database.
Querying Expenses
Users can ask about their spending in natural language to the bot, e.g.:
"How much did I spend on coffee this month?"
"Show me my biggest expenses this week."
"List all my food expenses in January."

Feel free to play around and add more useful features 🚀!

Example Interaction

User sends following expenses to the bot via message on whatsapp
"Had a filter coffee at a local café, cost ₹50."
"Spent ₹400 on a cappuccino at Starbucks."
"Bought a cold coffee from CCD for ₹180."
"₹120 for a cutting chai at a roadside stall."
"Dinner at a fine dining restaurant, cost ₹1800."
"Took an Ola to work, cost ₹250."
"Bought snacks from Blinkit for ₹300 yesterday."
"Ordered biryani from Swiggy for ₹500."
"Groceries from Zepto, cost ₹1000."
"Paid ₹1500 for a new pair of jeans from Levi's."
"Took an Uber to the airport, cost ₹600."
"Booked a train ticket for my trip, cost ₹1200."

User Queries and Responses

Query 1:
User: "How much have I spent on coffee?"
Bot Response:
"Your total coffee expenditure is ₹630, which includes:
Filter coffee at a local café – ₹50 (Feb 4, 2025)
Starbucks (Cappuccino) – ₹400 (Feb 3, 2025)
Cold coffee from CCD – ₹180 (Feb 2, 2025)"
Query 2:
User: "What is my total food expenditure?"
Bot Response:
"Your total food expenditure is ₹2600, which includes:
Filter coffee at a local café – ₹50 (Feb 4, 2025)
Starbucks (Cappuccino & Sandwich) – ₹400 (Feb 3, 2025)
Cold coffee from CCD – ₹180 (Feb 2, 2025)
Cutting chai at a roadside stall – ₹120 (Feb 2, 2025)
Dinner at a fine dining restaurant – ₹1800 (Feb 1, 2025)
Biryani from Swiggy – ₹500 (Feb 2, 2025)"
Query 3:
User: "What is my total expense so far?"
Bot Response:
"Your total expenses so far are ₹8900, covering food, travel, shopping, and groceries."
Query 4:
User: "How much did I spend on groceries?"
Bot Response:
"Your total grocery expenditure is ₹1000, which includes:
Zepto (Groceries) – ₹1000 (Feb 3, 2025)"
Query 5:
User: "How much did I spend on online food ordering?"
Bot Response:
"Your total spending on online food orders is ₹800, which includes:
Biryani from Swiggy – ₹500 (Feb 2, 2025)
Snacks from Blinkit – ₹300 (Feb 3, 2025)"
Query 6:
User: "What are my expenses from yesterday?"
Bot Response:
"Here's a list of your expenses from yesterday (Feb 3, 2025):
Starbucks (Cappuccino & Sandwich) – ₹400
Groceries from Zepto – ₹1000
Snacks from Blinkit – ₹300
Total expenses yesterday: ₹1700"
Query 7:
User: "What is my total expense on travel?"
Bot Response:
"Your total travel expenditure is ₹2050, which includes:
Ola to work – ₹250 (Feb 4, 2025)
Uber to the airport – ₹600 (Feb 2, 2025)
Train ticket for trip – ₹1200 (Feb 1, 2025)"

Above attached is my assignment. I am thinking something on the lines that can help me identify between near similar queries to with significant amazing accuracy.

Your TASK: i want to impress the interviewr and want to make this project to the best capapbilities. Give me a complete step by step workflo. focus on key aspects like sh i use faiss vector databases or what exactly. Make your workflow planned as is done in whatsapp chatbots of various big techs.
Give it in detailed making sure you are very clear about
what to do
how to do
what platform to use
how to integrate it
what tools and stuff you csn use for reference and attach all releavnt githubs and youtub videos.

Thought for 8 seconds >

Below is a detailed, step-by-step workflow that outlines how to build an advanced WhatsApp Expense Tracker Bot. This solution not only accepts expense entries in natural language but also uses semantic techniques (via vector embeddings and FAISS) to distinguish between near-similar queries with high accuracy. The workflow mirrors approaches used by large tech companies when building WhatsApp chatbots and incorporates best practices for integration, scalability, and continuous improvement.

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1. Define Objectives and Requirements

- **Core Goals:**
  - Allow users to log daily expenses via WhatsApp messages.
  - Automatically extract, parse, and categorize expense details from natural language messages (e.g. "Spent ₹400 on cappuccino at Starbucks").
  - Store expense data reliably and support complex queries (e.g. "How much did I spend on coffee this month?").
  - Handle similar or near-duplicate queries by using semantic matching to provide accurate, contextual responses.
- **Functional Requirements:**
  - Send and receive messages over WhatsApp.
  - Natural language understanding (NLU) to identify user intents (logging expense vs. query).
  - Automatic categorization of expenses.
  - Query aggregation with clear, conversational answers.
  - Disambiguation between similar queries using vector search.
- **Non-Functional Requirements:**
  - Scalability, security, and low latency.
  - Easy integration with existing messaging (via WhatsApp API) and data systems.
  - Continuous monitoring and improvement.

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2. Choose Platforms and Tools

- **WhatsApp API Integration:**
  - **Platform:** Use a Business Solution Provider like Twilio WhatsApp API for reliable messaging and webhook management.
  - **Reference:** Tutorials such as "4 Simple Steps to Develop a WhatsApp Support Chatbot" provide a good starting point. medium.com

- **Backend Development:**
  - **Language & Framework:** Python is recommended for rapid prototyping (using FastAPI or Flask) or Node.js if you prefer JavaScript.
  - **Hosting:** Cloud platforms (AWS, GCP, or Azure) with containerization (Docker, Kubernetes) for scalability.
- **Expense Data Storage:**
  - **Database:** Use PostgreSQL (or MySQL/MongoDB) for relational data storage. Tables should include Users, Expenses, and Categories.
  - **Reference Example:** The GitHub project sebastian-quintero/expense-tracker shows a similar architecture. github.com
- **Natural Language Processing (NLP) and Extraction:**
  - **Libraries:** spaCy or transformer-based models (from Hugging Face) for named entity recognition (to extract amounts, vendors, and categories).
  - **Custom Parsing:** Combine rule-based (regex) and ML-based techniques for robust extraction.
- **Semantic Search with Vector Databases:**
  - **Embedding Model:** Use OpenAI's embeddings or Sentence Transformers to convert query text into vectors.
  - **Vector Database:** Employ FAISS (or an alternative such as Milvus) to index and search vector embeddings. FAISS is lightweight and has proven capabilities for similarity search. en.wikipedia.org
  - **Reference Tutorial:** "How to build a PDF chatbot with Langchain and FAISS" offers an example of using FAISS for semantic retrieval. kevincoder.co.za
- **Chatbot Response Generation:**
  - **LLM Integration:** Optionally integrate a large language model (e.g. GPT-4 via OpenAI API) to produce conversational responses that combine data from the database with natural language.
  - **Memory Module:** For context retention across multiple queries, consider using tools like LangChain's conversation memory.

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3. System Architecture Overview

1. **WhatsApp Interface:**
   - Users send messages via WhatsApp.
   - WhatsApp Business API (via Twilio) forwards messages to your webhook endpoint.
2. **Backend Server:**
   - **Webhook Receiver:** A REST API (e.g. built with FastAPI/Flask) that receives and validates incoming messages.
   - **Intent Classifier & NLP Parser:** Determines if the message is an expense entry or a query. For expense messages, it extracts details (amount, category, vendor, date). For queries, it processes the natural language request.
3. **Database Layer:**
   - Stores parsed expense entries in a structured database.
   - Optionally caches user profiles and conversation histories.
4. **Semantic Matching Module:**
   - **Embedding Generation:** Convert user queries and historical expense descriptions into vector embeddings.

- **FAISS Vector Store:** Index these embeddings to perform nearest neighbor search to resolve similar queries.
- This module helps disambiguate near-similar queries by matching their semantic meaning, thereby improving accuracy.

5. **Response Engine:**
   - Aggregates data (e.g., summing totals for a given category).
   - Optionally enhances responses using an LLM to generate a friendly, detailed message.
   - Sends the response back via the WhatsApp API.
6. **Admin Dashboard (Optional):**
   - A web interface for monitoring expense logs, adjusting categories, and reviewing chatbot performance.

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4. Detailed Step-by-Step Workflow

Step 1: Planning and Design

- **Requirement Analysis:** List all user stories (e.g. "As a user, I want to log an expense by texting, 'Had lunch for ₹250'" and "As a user, I want to know my total spend on food last month").
- **System Design Diagram:** Create a block diagram showing WhatsApp API, backend, NLP parser, database, FAISS module, and response generator.
- **Data Model Design:** Design database schemas for expenses (fields: amount, description, category, timestamp, user ID).

Step 2: Setup WhatsApp API Integration

- **Register for WhatsApp API:**
  - Set up an account with a provider like Twilio.
  - Configure webhook URLs for message receiving.
- **Implement Webhook Endpoint:**
  - Develop an API endpoint (e.g. using FastAPI) to receive incoming JSON messages from WhatsApp.
  - Validate the sender and parse the message body.
- **Reference:** Follow guides such as the Tidio "How To Create A WhatsApp Chatbot" steps for integration. tidio.com

Step 3: Develop Expense Message Parsing Module

- **Rule-Based Extraction:**
  - Use regular expressions to identify monetary amounts (₹, Rs, etc.) and key terms.
- **NLP-based Extraction:**
  - Integrate spaCy or a transformer model to extract named entities (like vendors and product names).
- **Categorization Logic:**
  - Develop rules to auto-categorize expenses (e.g. "Starbucks" → "Coffee").
- **Unit Testing:**
  - Test with multiple example messages to ensure robust extraction.

Step 4: Build the Database Layer

- **Choose Your Database:**
  - Set up PostgreSQL (or MySQL/MongoDB) in your cloud environment.
- **Design Tables:**
  - Create tables for Users, Expense Entries, and Categories.
- **Integrate ORM:**
  - Use an ORM (e.g. SQLAlchemy for Python) to handle database transactions.
- **Data Ingestion:**
  - When an expense message is parsed, store the extracted data into the database.

Step 5: Implement Semantic Search with FAISS

- **Generate Embeddings:**
  - Use an embedding model (e.g. OpenAI's text-embedding-ada-002 or Sentence Transformers) to convert both user queries and stored expense descriptions into high-dimensional vectors.
- **Index Creation with FAISS:**
  - Build a FAISS index to store these embeddings.
  - When a user query is received (e.g. "Show me my coffee expenses"), generate its vector and search for the nearest embeddings.
- **Update Workflow:**
  - Every time a new expense is logged, update the FAISS index (or periodically batch update).
- **Reference:** Tutorials like "Building a RAG Chatbot with LlamaIndex, FAISS, and OpenAI" demonstrate similar processes. learnbybuilding.ai

Step 6: Build the Query and Response Engine

- **Query Handler:**
  - Differentiate between expense logging messages and query messages.
  - For queries, perform aggregation (e.g. total spend on "coffee").
  - Use the FAISS module to match similar queries (semantic matching) so that ambiguous queries are resolved with high accuracy.
- **Response Generation:**
  - Format the result in a conversational style.
  - Optionally pass the aggregated data and context to an LLM (e.g. via OpenAI's GPT-4 API) to generate a detailed and friendly answer.
- **Conversational Memory:**
  - Maintain chat history (using LangChain memory modules if using Python) to support follow-up queries.

Step 7: Integration and End-to-End Testing

- **Integrate Modules:**
  - Connect the WhatsApp webhook, NLP parser, database, FAISS module, and response generator.
- **Testing:**
  - Use simulated WhatsApp messages in a sandbox environment.
  - Validate that similar queries (e.g., "coffee spend" vs. "spent on coffee") trigger similar responses.
- **Logging and Error Handling:**
  - Implement robust logging for each module and handle error cases (e.g. parsing errors, API timeouts).

Step 8: Deployment and Monitoring

- **Deployment:**
  - Containerize the application using Docker.
  - Deploy on a cloud service (AWS Elastic Beanstalk, Google Cloud Run, or Azure App Service).
- **Continuous Integration/Continuous Deployment (CI/CD):**
  - Use pipelines (GitHub Actions, Jenkins) for automated testing and deployment.
- **Monitoring:**
  - Set up logging and monitoring (using Prometheus, Grafana, or cloud-native monitoring tools) to track API usage, errors, and system performance.
- **Scaling:**
  - Ensure the FAISS index and database can scale as expense data grows.

Step 9: Post-Deployment Iterations

- **User Feedback Collection:**
  - Integrate analytics to gather feedback on query accuracy and bot performance.
- **Model Tuning:**
  - Adjust NLP parsing rules, update vector embeddings, and fine-tune the LLM prompt templates.
- **Feature Expansion:**
  - Add additional functionalities such as an admin dashboard, multi-user support, or integration with external accounting software.

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5. References and Further Resources

- **GitHub Repositories:**
  - sebastian-quintero/expense-tracker – A similar expense tracking project. github.com
  - mukuliskul/ExpenseTracker-Whatsapp – An example of a WhatsApp expense tracker built with Python. github.com
- **Tutorials & Articles:**
  - *Building an Intelligent Chatbot with Langchain and Vector Databases* – Explores using FAISS and LangChain for semantic search. medium.com
  - *How to build a PDF chatbot with Langchain and FAISS* – A step-by-step guide on using FAISS with document embeddings. kevincoder.co.za
- **YouTube Videos:**
  - *Create Simple RAG based AI Chat bot | Python+LangChain+FAISS Vector Database* – A video tutorial to understand retrieval augmented generation with FAISS. youtube.com
- **WhatsApp API Documentation:**
  - Twilio WhatsApp API Docs for integration guidelines and best practices.
- **Vector Database Resources:**
  - FAISS on Wikipedia en.wikipedia.org
  - Milvus as an alternative for distributed vector storage. en.wikipedia.org

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Final Recommendations

- **Prototype Quickly:** Start with a minimal viable product using Twilio's sandbox for WhatsApp.
- **Iterate on NLP:** Continuously improve the expense parsing and semantic matching components by testing with real user inputs.
- **Monitor Costs:** Be aware that LLM calls and embedding generation have associated costs; use token tracking tools like tiktoken for budgeting.
- **Stay Agile:** Use CI/CD pipelines and cloud services to deploy updates frequently, ensuring your bot stays responsive and accurate.

By following this workflow, you'll build a robust, scalable, and highly accurate WhatsApp Expense Tracker Bot that not only impresses interviewers with its technical depth but also delivers real business value.

Happy coding!

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Non-Functional Requirements:

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Platform: Use a Business Solution Provider like Twilio WhatsApp API for reliable messaging and webhook management.
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MEDIUM.COM
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EN.WIKIPEDIA.ORG
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Final Recommendations
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make it much much more detailed using best of your knowledge also make sure you are using free or near free or non constly stuff. much more detailed. would be making project just by following this

Reasoned about WhatsApp Expense Tracker Bot development for 7 seconds >

Below is an ultra-detailed, end-to-end workflow for building an advanced WhatsApp Expense Tracker Bot. This guide emphasizes free or very low-cost components, leveraging open-source libraries and free-tier cloud offerings wherever possible. Follow these steps to build your project from scratch while learning the fundamentals of NLP, semantic search (with vector embeddings and FAISS), and robust chatbot design.

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1. Project Objectives and Requirements

Core Goals

- **Expense Logging:** Allow users to log daily expenses via WhatsApp messages (e.g. "Had lunch for ₹250").
- **Automated Extraction:** Automatically extract, parse, and categorize expense details (amount, vendor, date, etc.) from natural language messages.
- **Data Storage & Querying:** Reliably store expense data and support complex, aggregate queries (e.g. "How much did I spend on coffee this month?").
- **Semantic Disambiguation:** Use semantic techniques (vector embeddings and FAISS) to resolve near-duplicate or ambiguous queries with high accuracy.

Functional Requirements

- **Messaging:** Send and receive messages via WhatsApp.
- **NLU & Intent Classification:** Detect user intent (expense entry vs. query) using rule-based methods and/or pre-trained NLP models.
- **Expense Categorization:** Auto-categorize expenses based on keywords (e.g. "Starbucks" → "Coffee").
- **Query Aggregation:** Aggregate data and return conversational answers.
- **Semantic Matching:** Use vector search to disambiguate queries that are near similar.

Non-Functional Requirements

- **Scalability & Performance:** Use lightweight and containerized components (e.g. Docker) and cloud hosting free tiers (Heroku, AWS free tier, etc.).
- **Security:** Implement secure API endpoints and use encryption for sensitive data.
- **Low Cost:** Rely on open-source libraries and free cloud services for prototyping and early deployment.
- **Monitoring & Maintainability:** Integrate logging and monitoring with free tools to track usage and errors.

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2. Platforms, Tools, and Free Alternatives

WhatsApp API Integration

- **Provider:**
  - **Twilio WhatsApp API** (use their free trial and sandbox for development).

- **Alternative:** Some open-source projects mimic WhatsApp functionality; however, for production the official WhatsApp Business API via a free-tier partner (like Twilio) is recommended.
- **Reference Tutorial:** "4 Simple Steps to Develop a WhatsApp Support Chatbot" on Tidio's website provides a good starting point.
  tidio.com

Backend Development

- **Programming Language & Framework:**
  - **Python:** Use **FastAPI** or **Flask** for rapid prototyping (both are free and open source).
  - **Free Hosting:** Deploy on **Heroku (free tier)**, **Google Cloud Run** (with free credits), or **AWS Elastic Beanstalk**.
- **Containerization:** Use **Docker** (open source) for containerizing your application.

Expense Data Storage

- **Database:**
  - **PostgreSQL:** Use a free-tier PostgreSQL (e.g., via Heroku Postgres or a local installation).
  - **ORM: SQLAlchemy** (free) to handle data transactions.
- **Schema Design:** Tables for Users, Expenses, and Categories.

Natural Language Processing (NLP) and Data Extraction

- **Libraries:**
  - **spaCy:** Open-source, free NLP library for named entity recognition.
  - **Regular Expressions:** Python's built-in `` `re` `` module for rule-based extraction.
  - **Transformer Models:** Use **Hugging Face's Sentence Transformers** (e.g. `` `all-MiniLM-L6-v2` ``) for embedding generation. Many models are free to use locally.
- **Custom Parsing:** Combine regex and spaCy to extract amounts (detect symbols like ₹, Rs, etc.), vendor names, and context.

Semantic Search with Vector Databases

- **Embedding Generation:**
  - Use **Sentence Transformers** (free models) or OpenAI's embeddings (if within free trial or low-volume usage).
- **Vector Indexing:**
  - **FAISS:** An open-source library (free) by Meta for similarity search and indexing.
  - **Alternative: Milvus** is another open-source vector database if you need distributed capabilities.
- **Reference Tutorial:** "How to build a PDF chatbot with Langchain and FAISS" on kevincoder.co.za provides an excellent walkthrough.
  kevincoder.co.za
- **Framework Integration:** Optionally, use **LangChain** (free for development) for conversation memory and retrieval-augmented generation (RAG) pipelines.

Chatbot Response Generation

- **LLM Integration:**
  - Optionally use **OpenAI GPT-3.5-turbo** (if within free trial or using low-volume usage) to generate detailed responses.

- Alternatively, you can use local open-source models such as **GPT-J** or **GPT-Neo** (available on Hugging Face) if you wish to avoid API costs.
- **Memory Module:**
  - Use **LangChain**'s built-in memory classes to store conversation history.

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3. High-Level System Architecture

WhatsApp Interface

- **User Interaction:**
  - Users send messages (expense entries or queries) via WhatsApp.
  - WhatsApp API (e.g. via Twilio) forwards messages as JSON payloads to your webhook.

Backend Server

- **Webhook Receiver:**
  - A REST API endpoint (FastAPI/Flask) that receives incoming messages, validates sender credentials, and extracts message content.
- **Intent Classifier & NLP Parser:**
  - Determines whether the message is an expense entry or a query.
  - For expense entries: extracts amount, vendor, category, date, etc.
  - For queries: processes natural language and forwards the query to the semantic matching module.

Data Storage Layer

- **Database:**
  - Store parsed expense data in PostgreSQL.
  - Cache user profiles and optionally conversation histories.

Semantic Matching Module

- **Embedding Generation:**
  - Convert incoming query text and historical expense descriptions into vector embeddings.
- **FAISS Index:**
  - Build and maintain a FAISS index for fast similarity search.
  - Use this index to resolve near-similar queries by retrieving the most relevant expense entries.

Response Engine

- **Query Aggregation:**
  - Aggregate expense data (sums, averages, counts) from the database.
- **Conversational Enhancement:**
  - Optionally combine aggregated data with LLM-generated conversational responses.
- **Response Delivery:**
  - Return responses via WhatsApp API to the user.

Optional: Admin Dashboard

- **Web Interface:**

- Monitor expense logs, update categories, and review chatbot performance.
- Can be built with free front-end frameworks like React (using Create React App) and hosted on GitHub Pages or Netlify.

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4. Step-by-Step Detailed Workflow

Step 1: Planning and Design

- **Requirement Analysis:**
  - Write user stories (e.g. "Log an expense by texting 'Had dinner for ₹500'" and "Query total expenses on coffee this month").
- **System Design Diagram:**
  - Draw a diagram showing components: WhatsApp API, webhook receiver, NLP parser, database, FAISS module, LLM response engine.
- **Data Model Design:**
  - Design database schemas:
    - **Users Table:** user_id, phone_number, name, etc.
    - **Expenses Table:** expense_id, user_id, amount, vendor, category, timestamp, description.
    - **Categories Table:** category_id, category_name, rules (for auto-categorization).

Step 2: Setup WhatsApp API Integration

- **Register with Twilio (or similar):**
  - Sign up for a free trial account.
  - Configure your WhatsApp sandbox and obtain API credentials.
- **Develop Webhook Endpoint:**
  - Create a FastAPI or Flask application.
  - Implement an endpoint (e.g. `` `/webhook` ``) that accepts POST requests from Twilio.
  - Sample FastAPI snippet:

```python
from fastapi import FastAPI, Request, HTTPException
import uvicorn

app = FastAPI()

@app.post("/webhook")
async def whatsapp_webhook(request: Request):
    data = await request.json()
    # Validate the request (check Twilio signature if needed)
    message = data.get("Body") or data.get("text")
    sender = data.get("From")
    if not message or not sender:
        raise HTTPException(status_code=400, detail="Invalid message payload")
    # Process message further (pass to NLP parser)
    return {"status": "received"}

if __name__ == "__main__":
    uvicorn.run(app, host="0.0.0.0", port=8000)
```

  - **Testing:** Use tools like Postman or ngrok to test your webhook locally.

Step 3: Develop the Expense Parsing Module

- **Rule-Based Extraction:**

- Write regex patterns to detect currency symbols and numbers:

```python
import re
def extract_amount(text):
    # Look for patterns like ₹500, Rs. 500, etc.
    match = re.search(r'(₹|Rs\.?\s?)(\d+(?:\.\d{1,2})?)', text)
    return float(match.group(2)) if match else None
```

- **NLP Extraction:**
  - Use spaCy to extract named entities:

```python
import spacy
nlp = spacy.load("en_core_web_sm")
def extract_vendor(text):
    doc = nlp(text)
    # Simple heuristic: return first ORG entity or noun chunk
    for ent in doc.ents:
        if ent.label_ in ["ORG", "PRODUCT"]:
            return ent.text
    # Fallback: use noun chunks
    return next(iter(doc.noun_chunks), None)
```

- **Categorization:**
  - Define simple rules or lookup dictionaries (e.g. if vendor.lower() contains "starbucks", then category = "Coffee").
- **Unit Testing:**
  - Write tests using Python's `unittest` or `pytest` to validate extraction with various sample inputs.

Step 4: Build the Database Layer

- **Database Setup:**
  - Create a free PostgreSQL instance (e.g. on Heroku).
  - Define your tables using SQL or an ORM.
- **Using SQLAlchemy:**

```python
from sqlalchemy import create_engine, Column, Integer, Float, String, DateTime, ForeignKey
from sqlalchemy.ext.declarative import declarative_base
from sqlalchemy.orm import sessionmaker
import datetime

Base = declarative_base()

class Expense(Base):
    __tablename__ = "expenses"
    id = Column(Integer, primary_key=True)
    user_id = Column(Integer, ForeignKey("users.id"))
    amount = Column(Float)
    vendor = Column(String)
    category = Column(String)
    description = Column(String)
    timestamp = Column(DateTime, default=datetime.datetime.utcnow)

engine = create_engine("postgresql://user:password@host:port/dbname")
SessionLocal = sessionmaker(autocommit=False, autoflush=False, bind=engine)
Base.metadata.create_all(bind=engine)
```

- **Data Ingestion:**
  - When an expense is parsed, create a new Expense record and commit it to the database.

Step 5: Implement Semantic Search with FAISS

- **Embedding Generation:**
  - Use Sentence Transformers (free) to generate embeddings:

```python
from sentence_transformers import SentenceTransformer
model = SentenceTransformer('all-MiniLM-L6-v2')
def get_embedding(text):
    return model.encode(text)
```

- **FAISS Index Setup:**
  - Install FAISS (e.g. `` `pip install faiss-cpu` ``).
  - Create an index for your expense descriptions:

```python
import faiss
import numpy as np

dimension = 384  # For MiniLM model output dimension
index = faiss.IndexFlatL2(dimension)

# Function to add an expense to the index
def add_expense_to_index(expense_text):
    embedding = get_embedding(expense_text)
    embedding = np.array([embedding]).astype('float32')
    index.add(embedding)
```

- **Querying the Index:**
  - When a user submits a query (e.g. “coffee expenses”), generate its embedding and search the index:

```python
def search_similar(query, k=3):
    query_vec = get_embedding(query)
    query_vec = np.array([query_vec]).astype('float32')
    distances, indices = index.search(query_vec, k)
    return indices, distances
```

- **Updating Workflow:**
  - After every new expense, add its embedding to the index (or update the index in batches).
- **Reference:** Check tutorials such as “Building a RAG Chatbot with Langchain, FAISS, and OpenAI” on LearnByBuilding.AI.
  learnbybuilding.ai

Step 6: Build the Query and Response Engine

- **Query Handler:**
  - Detect if a message is a query (e.g. if it contains question words “how”, “what”, etc.) or an expense log.

- For queries, aggregate data from the database (e.g. sum amounts for the "Coffee" category) and use FAISS to retrieve similar past queries for disambiguation.

- **Response Generation:**
  - Format the result into a conversational message.
  - Optionally, call an LLM (using GPT-3.5-turbo via OpenAI API, available on free credits/trial) to refine the response:

```python
import openai
openai.api_key = "YOUR_OPENAI_API_KEY"

def generate_response(prompt):
    response = openai.ChatCompletion.create(
        model="gpt-3.5-turbo",
        messages=[{"role": "system", "content": "You are a helpful expense tracker assist
                  {"role": "user", "content": prompt}],
        temperature=0.5,
        max_tokens=150
    )
    return response['choices'][0]['message']['content']
```

- **Conversational Memory:**
  - Use a simple in-memory structure or a library like LangChain to maintain conversation history for follow-up queries.

Step 7: Integration and End-to-End Testing

- **Integrate Modules:**
  - Connect your webhook to the expense parser, then to the database, FAISS updater, and finally the query/response engine.
- **Testing:**
  - Use simulated messages (via Postman or a custom script) to test both logging and query functionalities.
  - Validate that semantically similar queries (e.g. "coffee spend" vs. "spent on coffee") produce similar outputs.
- **Logging and Error Handling:**
  - Implement robust logging (using Python's `` `logging` `` module) and error handling to capture issues like API timeouts or parsing errors.

Step 8: Deployment and Monitoring

- **Containerization:**
  - Write a simple Dockerfile for your Python app:

```dockerfile
FROM python:3.10-slim
WORKDIR /app
COPY requirements.txt .
RUN pip install --no-cache-dir -r requirements.txt
COPY . .
CMD ["uvicorn", "main:app", "--host", "0.0.0.0", "--port", "8000"]
```

- **Deploy on Free Tiers:**
  - Use Heroku's free tier, Google Cloud Run, or AWS Free Tier to deploy your containerized application.

- **CI/CD:**
  - Set up a GitHub Actions workflow to automatically test and deploy your code.
- **Monitoring:**
  - Use free monitoring tools such as Prometheus (with Grafana dashboards) or cloud-native logging (Heroku logs, etc.) to track API usage and errors.

Step 9: Post-Deployment Iterations

- **User Feedback Collection:**
  - Integrate Google Analytics or simple in-app feedback mechanisms to gather user insights.
- **Model Tuning:**
  - Refine your NLP extraction rules, update your embedding model (or switch to a different free model), and fine-tune your LLM prompts based on user data.
- **Feature Expansion:**
  - Consider adding an admin dashboard (using React or plain HTML/CSS/JS) for expense monitoring.
  - Plan integrations with free accounting tools (such as Wave Accounting's free plan) or export functions (CSV export).

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5. References and Further Resources

- **GitHub Projects:**
  - sebastian-quintero/expense-tracker github.com
  - mukuliskul/ExpenseTracker-Whatsapp github.com
- **Tutorials & Articles:**
  - *Building an Intelligent Chatbot with Langchain and Vector Databases* (Medium) medium.com
  - *How to build a PDF chatbot with Langchain and FAISS* (KevinCoder.co.za) kevincoder.co.za
- **YouTube Videos:**
  - *Create Simple RAG based AI Chat bot | Python+LangChain+FAISS Vector Database* (free tutorial) youtube.com
- **WhatsApp API Documentation:**
  - Twilio WhatsApp API Docs
- **Vector Database Information:**
  - FAISS on Wikipedia en.wikipedia.org
  - Milvus on Wikipedia en.wikipedia.org
- **Free NLP Tools:**
  - spaCy
  - Hugging Face Transformers and Sentence Transformers

Final Recommendations

- **Prototype Quickly:** Start with a minimal viable product using Twilio's sandbox (free trial) for WhatsApp.
- **Leverage Free Tools:** Use open-source libraries (spaCy, FAISS, Flask/FastAPI, PostgreSQL on Heroku free tier) and free embedding models (Sentence Transformers).

- **Cost Monitoring:** Use token tracking (e.g. tiktoken for OpenAI) and limit API calls by using local models where possible.
- **Iterate Rapidly:** Use CI/CD pipelines (GitHub Actions) and monitor performance via free logging tools.
- **User Feedback:** Continuously collect and analyze user feedback to refine NLP parsing rules, semantic matching, and LLM prompts.

By following this detailed workflow—with emphasis on free or low-cost solutions—you can build a robust, scalable, and highly accurate WhatsApp Expense Tracker Bot. This guide is designed to help you implement every aspect of the project step-by-step, mirroring best practices used by major tech companies while keeping costs minimal.

Happy coding and good luck with your project!