Text-to-SQL from Scratch — Tutorial For Dummies (Using PocketFlow!)

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> *Ever wished you could just ask your database questions in plain English instead of wre with complex SQL queries? This guide breaks down Text-to-SQL in the simplest way possible using the [PocketFlow Text-to-SQL Example](https://github.com/The-Pocket/PocketFlow)!*

Turn Your Questions into Database Answers, I SQL Requir

Have you ever stared ocl inside, but unsure hc . `GROUP BY ...` magi ge

AI for data insights, only to be told it doesn't know your specific database structu These are common hurdles when working with structured data, but there's a powe solution: **Text-to-SQL**.

In this beginner-friendly tutorial, you'll learn:

- The core concepts behind Text-to-SQL systems in plain language
- How Large Language Models (LLMs) can translate your questions into databa code (SQL)
- How to build a working Text-to-SQL system with just a few hundreds of lines code

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We'll use the [PocketFlow Text-to-SQL example](https://github.com/The-Pocket/PocketFlow) - a clear, step-by-step workflow built on simple PocketFlow framework. Unlike complex setups, PocketFlow lets you see exactly ho natural language question becomes a database query and how potential errors are hand giving you the fundamentals to understand and build your own conversational databa interfaces.

How Text-to-SQL Works: From Question to Answer

So, how does a computer turn your plain English question like "Show me sales fig for last month" into ... rt analyst assistant. He ... e i

1. **Understand the** ... t t are available (cu ... lur each table holds (`name`, `email`, `order_date`, `price`?).

2. **Translate the Request:** Based on your question and their knowledge of the database layout, they write the precise technical code (SQL) needed to find tha specific information.
3. **Fetch the Data:** They run this SQL code against the database.
4. **Handle Slip-ups:** If the database says "Error! I don't understand that code" (m a typo or wrong table name), the analyst looks at the error message, figures ou what went wrong, *corrects* the SQL code, and tries running it again.
5. **Present the Findings:** Once the code runs successfully, they gather the results show them back to you.

Text-to-SQL systems automate this entire process. Let's break down the crucial st

Step 1: Understanding the Database Layout (Schema)

Before the system can even *think* about answering your question, it needs a map of database. This map is called the **schema**. It details:

- **Tables:** What are the main categories of data stored (e.g., `customers`, `produ` `orders`)?
- **Columns:** Within each table, what specific pieces of information are tracked (in `customers`, there might be `customer_id`, `first_name`, `email`, `city`)?
- **Data Types:** What kind of information is in each column (e.g., text, numbers, dates)?
- (**Optional**) **Relationships:** How do tables connect (e.g., an `order` belongs to a `customer`)?

Why is this essential? An AI, even a powerful one, doesn't magically know your specific database. If y v there's a table called t tl schema, it's just gues

Typically, the system atic (using commands like `PRAGMA table_info` in SQLite or similar commands in o database systems) before trying to generate any SQL.

Step 2: Translating English to SQL (LLM Generation)

This is where the AI magic happens. A Large Language Model (LLM) acts as the translator. It receives:

1. Your natural language question (e.g., "What are the names of customers in Ne York?").
2. The database schema (the blueprint learned in Step 1).

Using this information, the LLM's job is to generate the corresponding SQL quer For the question above, knowing the schema includes a `customers` table with `first_name`, `last_name`, and `city` columns, it might generate:

```
SELECT first_name, last_name
FROM customers
WHERE city = 'New York';
```

Providing the LLM with clear instructions and the accurate schema is vital for get correct SQL output. Sometimes, the system might ask the LLM to format the SQL specific way (like within a YAML block) to make it easier for the system to extract reliably.

Step 3: Running the Code (SQL Execution)

Generating the SQL is just the first part; now the system needs to actually *run* it against the database. It connects to the database and sends the generated query.

The outcome depend

- `SELECT` **Queries** :ab sends back the n

- **Other Queries** (`UPDATE`, `INSERT`, `DELETE`): If the query modifies data, the database typically responds with a confirmation of success (e.g., "Query OK, 3 rows affected").

This step is the moment of truth – does the generated SQL actually work and retri the intended information?

Step 4: Fixing Mistakes (Error Handling & Debugging)

What happens if the LLM makes a mistake? Maybe it misspelled a column name, incorrect syntax, or tried to query a table that doesn't exist. The database won't ju guess – it will return an **error message**.

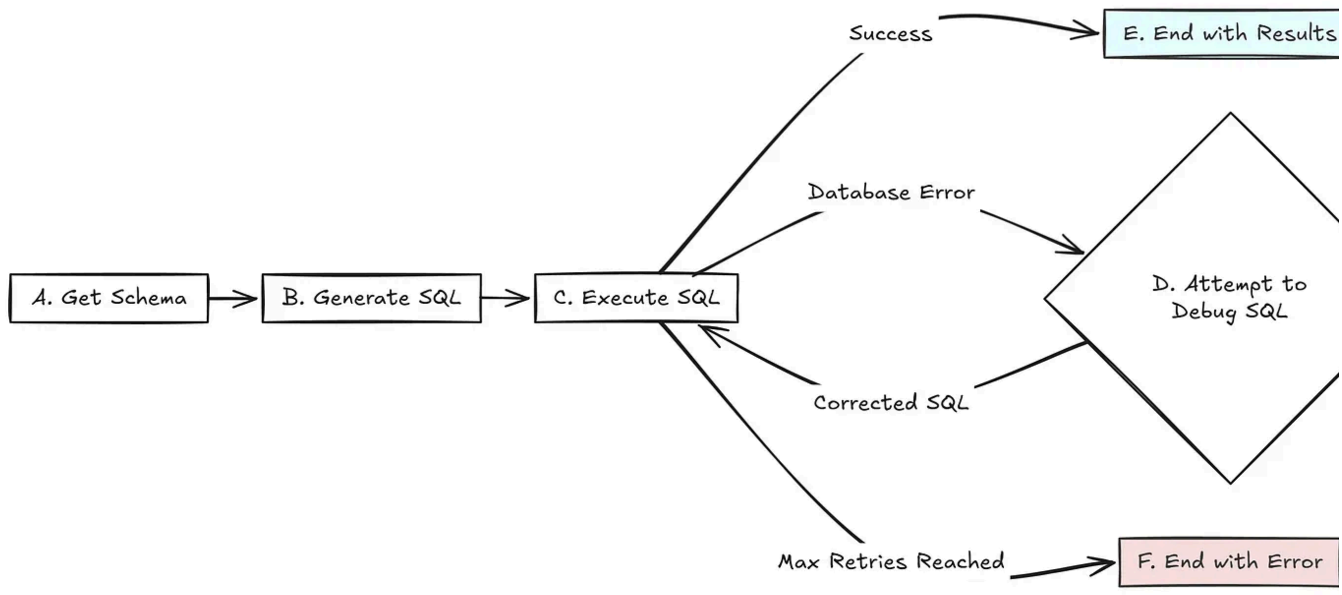
Instead of giving up, a smart Text-to-SQL system uses this error as valuable feedb This enables a **debugging loop**:

1. **Execution Fails:** The system tries to run the SQL (from Step 3) and gets an err message back from the database (e.g., "no such column: `customer_city`").
2. **Gather Clues:** The system takes the original question, the schema, the *failed* S query, and the *specific error message*.
3. **Ask for Correction:** It sends all this information back to the LLM, essentially asking, "This query failed with this error. Can you fix it based on the original request and schema?"
4. **Generate Corrected SQL:** The LLM attempts to provide a revised SQL query correcting `customer_city` to `city`).
5. **Retry Execution:** The system goes back to Step 3 to try running this *new* SQL query.

To prevent getting st ycl usually only repeats ils the maximum retries

Putting It All T

Unlike some AI processes that have separate offline preparation and online answe phases (like RAG), Text-to-SQL typically runs as a single, dynamic workflow every you ask a question. It combines the steps we've discussed into a sequence, includi the potential detour for debugging:



The Flow Explained:

1. The process starts by getting the database **Schema** (A).
2. It then uses the schema and your question to **Generate SQL** (B).
3. Next, it attempts to **Execute SQL** (C).
4. **If Execution Succeeds:** The workflow finishes, providing you the results (E).
5. **If Execution Fails:** It enters the debug loop. The error triggers an attempt to **Debug SQL** (D).
6. The debug step generates corrected SQL, which flows *back* to **Execute SQL** (C another try.
7. This loop (C -> D xin number of retry e (

The beauty of this workflow is its ability to translate your request, interact with the datal and even intelligently attempt to recover from errors, all orchestrated to get you the data asked for.

Building Workflows with PocketFlow: Keep It Simple!

Alright, we've seen the conceptual steps involved in tasks like Text-to-SQL. Now, do we actually *build* a system that automates these steps, especially handling conditional logic like error loops? This is where PocketFlow shines!

PocketFlow is designed to make building workflows refreshingly straightforward. Forget getting lost in layers of complex code – PocketFlow uses tiny, understandal building blocks (check out the core logic - it's surprisingly small!) so you can see exactly what's happening under the hood.

Let's imagine building *any* automated process, like summarizing a document, is lil setting up an assembly line:

- **Nodes are the Workstations:** Each station has one specific job (e.g., load the document, summarize it, save the summary).

```
# The basic blueprint for any workstation (Node)
class BaseNode:
    def __init__(self):
        # Where to go next? Depends on the outcome!
        self.params, self.successors = {}, {}

    # Define the                                         r',
etc.)
    def add_succe
        self.suc
        return nc
```

```
    # 1. Get ready: What inputs do I need from the central storage?
    def prep(self, shared): pass

    # 2. Do the work: Perform the station's main task.
    def exec(self, prep_res): pass

    # 3. Clean up & Decide: Store results back in central storage,
choose the next step.
    def post(self, shared, prep_res, exec_res): pass

    # The standard routine for running a station
    def run(self, shared):
        p = self.prep(shared) # Get ingredients/parts
        e = self.exec(p)      # Do the work
        return self.post(shared, p, e) # Store results & say what's ne
```

- **Flow is the Factory Manager:** This manager knows the overall assembly line process, directing the task from one station to the next based on the outcome the previous step. It ensures everything runs in the correct order.

```
# The Factory Manager (Flow) overseeing the process
import copy # Need copy to ensure nodes in loops run correctly

class Flow(BaseNode):
    def __init__(self, start): # Knows where the process begins
        super().__init__()
        self.start = start

    # Figures out which station is next based on the last outcome
    def get_next_node(self, curr, action):
        return curr.successors.get(action or "default")

    # Orchestrates the entire workflow from start to finish
    def orch(self
        curr = c
        p = (par
        while cu
            # Al                                                    l)
            # cu
            action = curr.run(shared) # Run the current station
            # Move to the next station based on the action return
```

```
            curr = copy.copy(self.get_next_node(curr, action))

    # Kicks off the whole process
    def run(self, shared):
        pr = self.prep(shared) # Any prep for the overall flow?
        self.orch(shared)      # Run the main orchestration
        return self.post(shared, pr, None) # Any cleanup for the flow?
```

- **Shared Store is the Central Parts Bin / Conveyor Belt:** This is where all static get their inputs (like a file path) and place their outputs (like the loaded text or final summary). Every station can access this shared space.

```
# Simple Example: Load text -> Summarize -> Save summary
# (Assuming LoadTextNode, SummarizeTextNode, SaveSummaryNode exist)

# Create the workstations
load_node = LoadTextNode()
summarize_node = SummarizeTextNode()
save_node = SaveSummaryNode()

# Connect the assembly line using the default path '>>'
load_node >> summarize_node >> save_node

# Create the Factory Manager, telling it where to start
summarization_flow = Flow(start=load_node)

# Prepare the initial inputs in the parts bin ('shared' dictionary)
shared_data = {
    "input_file": "my_document.txt",
    "output_file": "summary.txt"
}

# Tell the manager to start the assembly line!
summarization_flc

# After running,                                                pu
it there)
# and the summary
print(f"Summariza                                               )
# Example: print(shared_data.get('summary_text'))
```

Each **Node** (workstation) keeps things tidy by following three simple steps:

- **Prep:** Grab the necessary parts and information from the shared store.
- **Exec:** Perform its specific assembly task (like summarizing text).
- **Post:** Put the results back into the shared store (or save them) and signal to th manager what happened (e.g., "success, continue" or perhaps "error, stop").

The **Flow** (manager) then looks at that signal and directs the work to the appropri next station. This makes defining even complex processes with branches or loops our Text-to-SQL debugger will need) quite clear.

With these straightforward concepts – Nodes for tasks, Flow for orchestration, an Shared Store for data – PocketFlow makes building sophisticated workflows surprisingly manageable and easy to understand!

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*Okay, let's dive into building our Text-to-SQL assistant using PocketFlow. We'll create specialist stations (Nodes) for each step we discussed earlier and then connect them usin lab manager (Flow). We'll keep the code super simple here to focus on what each station Remember, the full working code with all the details is in the [PocketFlow Text-to-SQ Example](). *

Building the Text-to-SQL Workflow with PocketFlow Nodes

Think of each node as a Python class inheriting from `pocketflow.Node`. Each o will implement its `prep`, `exec`, and `post` methods.

Station 1: The as

This node's job is sin he schema).

```
class GetSchema(Node):
    def prep(self, shared):
        # Needs: The path to the database file
        return shared["db_path"]

    def exec(self, db_path):
        # Does: Connects to the DB and gets table/column info
        print(f"🔍 Getting schema for {db_path}...")
        conn = sqlite3.connect(db_path)
        cursor = conn.cursor()
        # Simplified way to get schema info (real code is more detaile
        cursor.execute("SELECT sql FROM sqlite_master WHERE
type='table';")
        schema_info = "\n".join([row[0] for row in cursor.fetchall()]
        conn.close()
        return schema_info # The schema as a string

    def post(self, shared, prep_res, schema_info):
        # Stores: The schema string on the shared whiteboard
        shared["schema"] = schema_info
        print("✅ Schema captured!")
```

- `prep`: Grabs the database file location from the shared whiteboard.
- `exec`: Connects to the database, runs a simplified query to get table structure and returns that schema information as a string.
- `post`: Puts the retrieved `schema` string onto the shared whiteboard for other nodes to use.

Station 2: The `GenerateSQL` Node - The AI Translator

This is where the magic happens! This node takes the user's question and the sche asks the LLM to tran


```
class GenerateSQl
    def prep(sel
        # Needs:
        return shared["natural_query"], shared["schema"]
```

```
    def exec(self, inputs):
        # Does: Asks the LLM to generate SQL
        natural_query, schema = inputs
        print(f"🤖 Asking LLM to translate: '{natural_query}'")
        prompt = f"Given schema:\n{schema}\n\nGenerate SQLite query fo
{natural_query}\nSQL:"
        sql_query = call_llm(prompt)
        return sql_query.strip()

    def post(self, shared, prep_res, sql_query):
        # Stores: The generated SQL query string
        shared["generated_sql"] = sql_query
        # Reset debug counter when generating fresh SQL
        shared["debug_attempts"] = 0
        print(f"✅ LLM generated SQL:\n{sql_query}")
```

- `prep`: Gets the human question (`natural_query`) and the `schema` from the whiteboard.
- `exec`: Creates a prompt combining the schema and question, sends it to the L (`call_llm`), and gets the generated SQL query back.
- `post`: Stores the `generated_sql` on the whiteboard and resets the `debug_attempts` counter (since this is a fresh attempt).

Station 3: The `ExecuteSQL` Node - Running the Code

Time to see if the LLM's SQL actually works! This node runs the query against the database. It's also the crucial point where we decide if we need to enter the debug loop.

```
class ExecuteSQL(Node):
    def prep(sel
        # Needs:
        return sh

    def exec(sel
        # Does: 
        db_path, sql_query = inputs
```

```
        print(f"🚀 Executing SQL:\n{sql_query}")
        try:
            conn = sqlite3.connect(db_path)
            cursor = conn.cursor()
            cursor.execute(sql_query)
            results = cursor.fetchall()
            conn.close()
            print("✅ SQL executed successfully!")
            return {"success": True, "data": results}
        except sqlite3.Error as e:
            # Houston, we have a problem!
            print(f"💥 SQL Error: {e}")
            if 'conn' in locals(): conn.close()
            return {"success": False, "error_message": str(e)}

    def post(self, shared, prep_res, exec_result):
        # Stores: Results OR error message. Decides next step!
        if exec_result["success"]:
            shared["final_result"] = exec_result["data"]
            print(f"📊 Got results: {len(exec_result['data'])} rows")
        else:
            # Store the error and increment attempt counter
            shared["execution_error"] = exec_result["error_message"]
            shared["debug_attempts"] = shared.get("debug_attempts", 0)
1

            max_attempts = shared.get("max_debug_attempts", 3)

            print(f"❗ Failed attempt {shared['debug_attempts']} of
{max_attempts}")

            if shared["debug_attempts"] >= max_attempts:
                print("🚫 Max debug attempts reached. Giving up.")
                shared["final_error"] = f"Failed after {max_attempts}
attempts. Last error: {exec_result['error_message']}"
            else:
                # Return 'error_retry': Signal to the Flow to go to th
DebugSQL node
```


- `prep`: Gets the d … rd.

- `exec`: Uses a `try...except` block. It attempts to connect and execute the S If it works, it returns success and data. If it catches an `sqlite3.Error`, it returns failure and the error message.
- `post`: This is the critical decision point!
    - If `exec` was successful, store the `final_result` and return `None` (signal the default "success" path).
    - If `exec` failed, store the `execution_error`, increment the `debug_attempts` counter. Check if we've hit the `max_debug_attempt` yes, store a `final_error` and return `None` (stop the loop). If no, return tl *specific action string* `"error_retry"` to tell the Flow manager to take the debugging path.

Station 4: The `DebugSQL` Node - The AI Code Fixer

This station jumps into action only if `ExecuteSQL` failed and signaled `"error_retry"`. Its job is to ask the LLM to fix the broken SQL.

```
class DebugSQL(Node):
    def prep(self, shared):
        # Needs: All context - question, schema, bad SQL, error messag
        return (
            shared["natural_query"],
            shared["schema"],
            shared["generated_sql"], # The one that failed
            shared["execution_error"]
        )

    def exec(self, inputs):
        # Does: Asks LLM to fix the SQL based on the error
        natural_
        print(f"
'{error_message}
        prompt =
Original Questio
Schema: {schema}
Failed SQL:
```

```
{failed_sql}
Error: {error_message}

Provide the corrected SQLite query:
SQL:"""
        corrected_sql = call_llm(prompt)
        return corrected_sql.strip()

    def post(self, shared, prep_res, corrected_sql):
        # Stores: Overwrites the bad SQL with the new attempt
        shared["generated_sql"] = corrected_sql
        shared.pop("execution_error", None)
        print(f"✅ LLM suggested fix:\n{corrected_sql}")
```

- `prep`: Gathers all the context needed for debugging from the whiteboard: the original question, schema, the SQL that *failed*, and the error message it produ
- `exec`: Constructs a prompt telling the LLM about the failure and asks for a correction. Calls the LLM.
- `post`: Crucially, it *overwrites* the `generated_sql` on the whiteboard with the LLM's *new attempt*. It also clears the `execution_error`. It returns `None`, signaling the default path, which (as we'll see next) leads back to the `Execute` node to try this revised query.

Connecting the Stations: Defining the Flow

Now we wire these stations together using PocketFlow's `Flow` and the connectior operators:

```
from pocketflow import Flow

# Create instance
get_schema_node =
generate_sql_node
execute_sql_node
debug_sql_node =

# --- Define the main path ---
```

```
# Use '>>' for the default success path
get_schema_node >> generate_sql_node >> execute_sql_node

# --- Define the debug loop path ---
# Use '- "action" >>' to specify a path for a specific action string
# If ExecuteSQL returns "error_retry", go to DebugSQL
execute_sql_node - "error_retry" >> debug_sql_node

# If DebugSQL finishes (returns None/default), go back to ExecuteSQL
debug_sql_node >> execute_sql_node

# Create the Flow Manager, telling it where to start
text_to_sql_flow = Flow(start=get_schema_node)

# --- Ready to Run! ---
# Prepare the initial inputs
# shared = { ... }
# text_to_sql_flow.run(shared)
```

Look how cleanly we defined the process:

1. Start with `GetSchema`, then `GenerateSQL`, then `ExecuteSQL`.
2. *If* `ExecuteSQL` specifically returns `"error_retry"`, then the flow jumps to `DebugSQL`.
3. After `DebugSQL` completes (its default path), the flow goes *back* to `ExecuteS`

And that's it! We've built the core logic of our Text-to-SQL assistant, complete with a automated debugging loop, using simple, focused PocketFlow nodes.

Conclusion: li

And there you have i
transforming simple v
understand the elegant dance between:

1. **Understanding the Map (Schema):** Giving the AI the blueprint of your databa
2. **AI Translation (LLM Generation):** Letting the LLM convert your request intc SQL code.
3. **Running the Code (Execution):** Actually talking to the database.
4. **Smart Error Fixing (Debugging Loop):** Giving the AI a chance to correct its o mistakes!

While the concept might seem complex initially, frameworks like PocketFlow reve the underlying simplicity. The entire process, even the clever debugging loop, boil down to a sequence of focused **Nodes**, orchestrated by a **Flow**, sharing informatio a **Shared Store**. It's a pattern that makes building powerful, resilient data interact tools surprisingly manageable.

The real magic of Text-to-SQL lies in breaking down the barrier between humans their data. No longer is database access solely the domain of SQL wizards. By grounding AI translation with specific database schemas and adding intelligent e handling, these systems make data insights accessible to everyone, faster and mor intuitively than ever before.

With the concepts and PocketFlow structure you've learned here, you're now equi to build your own conversational interfaces for databases in any domain!

Ready to build this yourself? Dive into the code and experiment:

- ***Get the Code:*** *Find the complete working example used in this tutorial at* [***GitHub: PocketFlow Text-to-SQL Cookbook***]*.*
- ***Explore PocketFlow:*** *Learn more about the simple framework powering this example the main* ***PocketF***
- ***Join the Commun*** *ect other developers o*

Go ahead, connect you

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Write a comment...

patcap Apr 26

Liked by Zachary Huang

What else can you do to improve the accuracy from there? I'm curious what would it take to some SOTA level system. Would it be something like this (https://arxiv.org/abs/2401.08500) generate 10s of samples and take majority vote + self reflection with errors + something els sure what that is).

LIKE (1) REPLY

4 replies by Zachary Huang and others

Mark Apr 27

Hi Zachary,

I came across yo ng created including

One thing hits m obc may I please kno or t

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