Database agent:
Chat with your SQL database

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The opportunity

The problem

Our focal organisation is a mid-sized SaaS company (approximately 100 people) providing **all-in-one HR software** that lets customers manage payroll, benefits, performance management, attendance etc.

The organisation is divided into the product development team, data team, customer support team, sales and marketing team, and implementation and training team.

Data about subscriptions, customer profiles, customer employees and usage of various modules are stored in the company's SQL database. Teams rely on **dashboards built by the in-house data team** to gain access to the data they need.

However, the adoption rate of these dashboards is low. The data team's lack of understanding of the company's business and the lack of coordination between the various teams have resulted in dashboards that **do not meet the needs of most stakeholders**. As a result, they would often submit ad hoc data requests to the data team.

However, as the data team is extremely lean, it is inundated with requests and each request is added to a backlog. It can take **multiple days** for the data team to resolve a request, by which time the data requester is likely to have **"missed the opportunity"**.

Our solution

We propose to develop **a chatbot that allows any user to query the company's database using natural language instead of SQL**

- **Stronger employee engagement**

  Creating an environment of data transparency and empowering team members with the tools to access data independently can improve employee engagement, leading to a more motivated workforce

- **Greater capacity for innovation**

  Team members gain more access to data and can develop a deeper and more holistic understanding of the business. As a result, they are better positioned to come up with innovative ideas that can create value for the organisation.

- **Direct cost savings**

  Value of time saved from the data team due to reduced handling of adhoc data requests and maintenance of dashboards. Reduction in subscription fees to BI software providers (eg Tableau)

- **Higher productivity and improved decision-making**

  Instant access to accurate and relevant data allows team members to make informed decisions quickly, leading to better business outcomes

Exploring our SQL database

The contents of our database

For this project, we have created a synthetic SQLite database that is designed to resemble a real-world database for a typical HR SaaS company. There are 17 tables in total.

The database allows for a wide range of possible queries, from simple single-table queries to complex multi-table queries. It will provide a comprehensive and robust test of our chatbot's abilities.

Descriptions of each table:

```
TABLES_DESCRIPTIONS = {
    "AttendanceRecords": "Tracks daily attendance of our customers' employees",
    "Bonuses": "Contains information about bonuses awarded to our customers' employees",
    "Companies": "Contains information about our customers. The CompanyID column is the primary key for this table, and is a foreign key in several other tables",
    "Deductions": "Contains information about deductions from our customers' employees payroll",
    "Departments": "Contains information about our customers' departments",
    "Employees": "Contains information about our customers' employees. The EmployeeID column is the primary key for this table, and is a foreign key in several other tables",
    "FeatureUsage": "Contains information about our customers' usage of our platform features",
    "Feedback": "Contains information about our customers' feedback on our platform",
    "Goals": "Contains information about the goals set for our customers' employees",
    "Invoices": "Contains information about invoices issued to our customers",
    "LeaveRequests": "Contains information about leave requests submitted by our customers' employees",
    "LeaveTypes": "Contains information about leave types available for each customer",
    "PayrollRecords": "Contains information about our customers' employees' payroll records",
    "PerformanceReviews": "Contains information about performance reviews submitted by our customers' employees",
    "Positions": "Contains information about all the work positions at each company",
    "Subscriptions": "Contains information about subscriptions purchased by our customers",
    "UserSessions": "Tracks user sessions to analyse login frequency and session duration",
}
```

Examples

Companies table:

	CompanyID	CompanyName	Industry	LeadSource	CustomerSince	Geography
0	22	CV Summit	Consumer Staples	Website	6/12/14	Thailand
1	26	Pearl Holdings	Consumer Discretionary	Referral	8/7/14	Indonesia
2	23	PT Horizon	Energy	Referral	7/4/16	Philippines
3	52	Lotus Innovations	Materials	Referral	25/3/18	Thailand
4	95	Rudbeckia Ventures	Communication Services	Direct	11/12/18	Hong Kong
5	50	Cypress Ventures	Energy	Social Media	10/6/23	Indonesia
6	70	Marigold Ventures	Health Care	Website	26/11/14	Indonesia
7	32	Amethyst Innovations	Consumer Discretionary	Direct	13/1/16	Philippines
8	21	Industries Indo	Health Care	Social Media	20/7/17	Malaysia
9	69	Lavender Enterprises	Consumer Discretionary	Referral	30/7/17	Thailand

Positions table:

	PositionID	CompanyID	PositionTitle	DepartmentID	SalaryGrade
0	802	41	Accountant, chartered certified	401	A
1	896	45	Conservator, furniture	448	A
2	565	29	Administrator, local government	283	D
3	562	29	Publishing rights manager	281	D
4	1637	82	Manufacturing systems engineer	819	E
5	197	10	Technical author	99	E
6	1473	74	Museum/gallery exhibitions officer	737	D
7	1472	74	Radiographer, diagnostic	736	A
8	1207	61	Financial risk analyst	604	C
9	1190	60	Museum/gallery conservator	595	C

Payroll records table:

	PayrollID	EmployeeID	PayPeriodStart	PayPeriodEnd	GrossSalary	Deductions	NetSalary	PaymentDate
0	2640	2640	2024-03-18	2024-04-17	6469.88	305.21	6164.67	2024-04-22
1	2958	2958	2024-05-06	2024-06-05	6052.66	299.06	5753.6	2024-06-10
2	220	220	2023-05-26	2023-06-25	6294.39	279.67	6014.72	2023-06-30
3	1010	1010	2024-03-11	2024-04-10	5092.17	473.08	4619.09	2024-04-15
4	4567	4567	2024-02-20	2024-03-21	6214.99	369.85	5845.14	2024-03-26
5	1197	1197	2023-07-10	2023-08-09	6210.52	440.71	5769.81	2023-08-14
6	2825	2825	2023-09-10	2023-10-10	4088.67	323.7	3764.97	2023-10-15
7	1986	1986	2023-06-11	2023-07-11	3505.62	387.17	3118.45	2023-07-16
8	931	931	2023-09-13	2023-10-13	4395.51	253.21	4142.3	2023-10-18
9	4023	4023	2023-08-22	2023-09-21	6968.74	473.69	6495.05	2023-09-26

Invoices table:

	InvoiceID	CompanyID	InvoiceDate	DueDate	Amount	PaymentStatus	PaymentDate
0	477	96	2023-06-11	2023-07-11	2400	Unpaid	
1	238	48	2023-06-13	2023-07-13	2900	Unpaid	
2	254	51	2023-10-02	2023-11-01	1000	Overdue	
3	333	67	2023-06-17	2023-07-17	1000	Overdue	
4	161	33	2023-09-02	2023-10-02	2500	Paid	2023-09-25
5	276	56	2024-03-08	2024-04-07	1000	Overdue	
6	263	53	2024-01-09	2024-02-08	3000	Overdue	
7	113	23	2024-05-01	2024-05-31	2200	Overdue	
8	444	89	2023-07-01	2023-07-31	1800	Paid	2023-07-06
9	498	100	2023-06-28	2023-07-28	1900	Overdue	

Leave requests table:

	LeaveRequestID	EmployeeID	LeaveTypeID	StartDate	EndDate	RequestStatus	RequestDate	ApproverID	LeaveReason	LeaveDuration
0	4300	2116	214	2023-12-31	2024-01-08	Approved	2023-08-19	2118	Heritage event	8
1	315	170	20	2022-07-01	2022-07-06	Rejected	2023-02-11	154	Disaster preparedness training	5
2	5531	2780	280	2023-01-30	2023-02-02	Pending	2023-11-07	2772	Smart city workshop	3
3	9458	4708	474	2023-08-17	2023-08-24	Rejected	2022-12-13	4749	Policy workshop	7
4	3069	1526	154	2023-02-28	2023-03-07	Pending	2024-02-16	1549	Trademark filing	7
5	6120	3072	308	2022-06-17	2022-06-17	Pending	2023-08-27	3070	Client site visit	0
6	8997	4473	447	2024-04-28	2024-04-28	Rejected	2022-11-04	4471	Shareholder meeting	0
7	4379	2172	219	2023-11-21	2023-11-26	Pending	2022-11-17	2191	Lab work	5
8	1828	939	91	2024-03-02	2024-03-10	Pending	2023-01-12	908	Emotional intelligence workshop	8
9	2491	1235	123	2022-06-04	2022-06-11	Rejected	2022-07-22	1210	Conflict resolution training	7

Building our agent

Deciding on framework, model and architecture

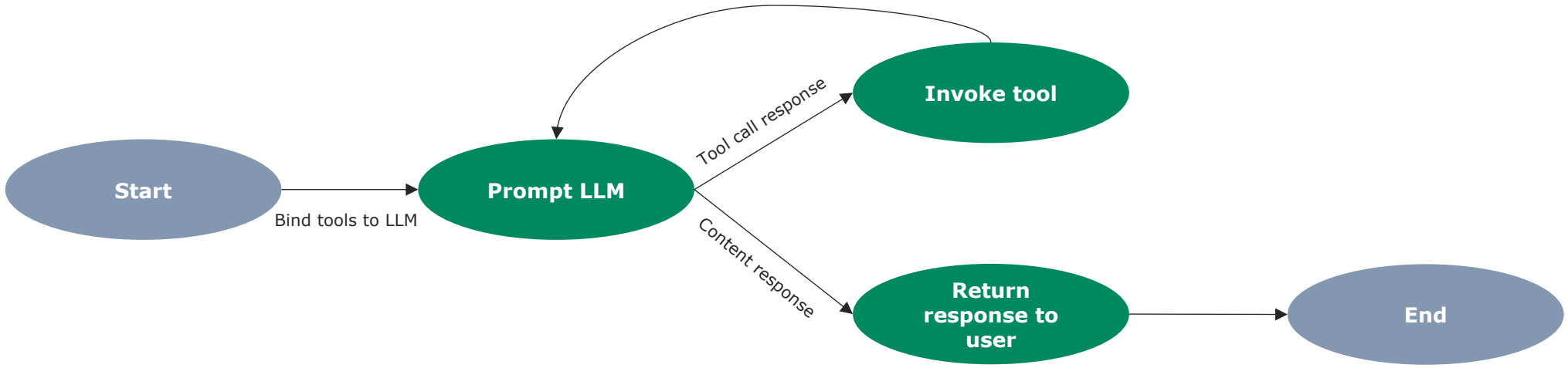
Decision	Considerations / questions	Choice
Choice of architecture - agentic or non-agentic?	• Can we perform the same sequence of steps to answer all possible queries? • Is there any scenario where we would need to perform iteration?	Agentic architecture. Depending on the complexity of the query, we would likely need to perform different sequences to generate the right SQL command. We would also need to iterate if the LLM generates an incorrect command which results in an error response from the database
Choice of agent type – autonomous or custom?	• Autonomous: LLM has full power to determine the control flow of the app • Custom: Developer plans the control flow, but LLM has ability to influence the control flow by routing between different steps • How should we trade off flexibility vs reliability?	Both options could be viable. We will try an autonomous architecture first as we think it is more efficient. If we were to plan the control flow, we would need to ensure that it can cater for the most complex queries. This results in redundant processes for most queries which may potentially lead to lower performance and higher cost/latency
Choice of LLM	• Model cost and size • Closed-source or open-source • Overall model performance across public benchmarks • Data security requirements • Choice of cloud provider / access to GPUs	Based on our specific needs (e.g. data security requirements, cloud infrastructure), we will identify a list of leading models of different sizes from different providers. Prior to deployment, we will conduct an evaluation of all shortlisted models using a custom Q&A dataset. We will then select the winning LLM based on accuracy, cost and latency For our prototype, we will prioritize accuracy first and go with a large, top-performing model - GPT 4o
Choice of software framework	Examples: • LangChain • LlamaIndex • AutoGen	LangChain. It has decent documentation / resources, a large developer community, and offers a variety of ready-made tools useful for SQL-related tasks. It is also interoperable with all leading LLMs. Its recent LangGraph extension enables us to build agents with persistence (long-term memory) easily. This is crucial in enabling conversational flow with users, human-in-the-loop interactions and ability to debug / modify agent behavior

ReAct agent

ReAct = Reasoning + Action

We will start by binding a set of tools to our LLM and pass a prompt that contains information about its role and some guidance on how best to use certain tools

The LLM will then reason and decide which tool it should use. We will trigger the tool, retrieve the output and append it to the prompt. We pass the updated prompt to the LLM for it to observe the output, and it proceeds to reason again. This continues in a loop until the LLM is ready to produce a response to the user's question



Designing tools for our agent

Tool	Purpose	Output
sql_db_query_checker	Get LLM to check if a SQL command is syntactically correct and fix any errors if needed	SQL command that is syntactically valid and ready for execution
sql_db_query	Connect to database and execute query	Database response to the query
sql_db_schema	Gives LLM information on the structure and contents of a table	Column names, data types and sample rows from the table
get_tables_descriptions	Gives LLM basic idea of the contents stored in each table	A short description of each table in the database, e.g. PerformanceReviews: Contains information about performance reviews submitted by our customers' employees
get_today_date	Enables LLM to know the date today so it can generate correct command for queries involving date filters	Today’s date
get_distinct_values_from_table	Enables LLM to know all distinct values in each text column in a table so that it can better answer queries involving text-related comparisons	A list of unique values for each text column in a table

System prompt

```
You are a world class data analyst at a HR SaaS startup called Omni. Omni's customers are companies based in Asia
who subscribe to its platform to help them better manage their HR needs.

Your role is to help your colleagues from Omni interact with the company's SQL database using natural language.

You are given a bunch of tools that enable you to perform a variety of tasks. For example, you can transform
the user's question from natural language to SQL code, connect with the company's database and run queries,
get information about each table in the database as well as getting the date today.

No matter what your colleague's question is, you must always call the tool 'get_tables_descriptions' at the start
to understand about the contents of each table in the database.

In queries involving string or text comparisons, you should use the `LIKE` operator for fuzzy matching
and / or the `LOWER` operator for case-insensitive comparisons. In these situations, you should
also first check for a tool that allows you to obtain all unique values in that column. If a tool like this exists,
using it will allow you to identify the range of possible values in that column.

In queries involving company names from the Companies table, you should only use the `LOWER` operator for case-insensitive
comparisons. Never, ever use the `LIKE`operator!

Whenever possible, you should try to use the output of the executed query to answer your colleague's question. If you do
not know the answer, do not fabricate a response. Simply say you do not know.

If your colleague's question is ambiguous, you should get her to clarify what she means. Do not make assumptions.
For example, if your colleague asks who the top 3 customers are, you should ask what she means by top 3 -
is it based on billing amount, number of employees or something else?

You should always be polite and respectful in all of your interactions.

Your colleague's question: {input_question}

Your response:
```

Demo: Which customer from HK used payroll module most frequently last week?

```
> Entering new SQL Agent Executor chain...

Invoking: `get_tables_descriptions` with `Companies, FeatureUsage`


{"AttendanceRecords": "Tracks daily attendance of our customers' employees", "Bonuses": "Contains information about bonuses awarded to our customers' employees", "Companies": "Contai
Invoking: `get_distinct_values_from_companies` with `Country`


List of unique values of the Industry column :
["Energy", "Utilities", "Materials", "Industrials", "Financials", "Consumer Discretionary", "Information Technology", "Real Estate", "Health Care", "Consumer Staples", "Communication
["Direct", "Advertisement", "Referral", "Social Media", "Website"]List of unique values of the Geography column :
["Philippines", "Thailand", "Singapore", "Malaysia", "Hong Kong", "Indonesia"]
Invoking: `get_distinct_values_from_FeatureUsage` with `FeatureName`


List of unique values of the ModuleName column :
["Payroll", "Leave Management", "Performance Review"]List of unique values of the TaskDescription column :
["Edit payroll", "Submit for approval", "Create new leave", "Create payroll notifications", "Delete review", "Submit payroll", "Delete leave submission", "Appeal leave status", "Star
["Not completed", "Completed"]
Invoking: `get_today_date` with ``


2024-05-27
```

Agent follows our instructions in the prompt by first trying to understand the contents of each table

Thinks that the Companies table is relevant

Thinks that the FeatureUsage table is relevant

Uses tool to get today's date because the question involves a date filter

Demo: Which customer from HK used payroll module most frequently last week?

```
Invoking: `sql_db_query_checker` with `{'query': "SELECT c.CompanyName, COUNT(f.FeatureUsageID) as UsageCount \nFROM Companies c \nJOIN FeatureUsage f ON c.CompanyID = f.CompanyID \
```

Agent drafts SQL command and sends it to another LLM to check

```
```sql
SELECT c.CompanyName, COUNT(f.FeatureUsageID) as UsageCount
FROM Companies c
JOIN FeatureUsage f ON c.CompanyID = f.CompanyID
WHERE LOWER(c.Country) = 'hong kong' AND LOWER(f.FeatureName) = 'payroll'
AND f.UsageDate BETWEEN DATE('2024-05-20') AND DATE('2024-05-26')
GROUP BY c.CompanyName
ORDER BY UsageCount DESC
LIMIT 1;
```
Invoking: `sql_db_query` with `{'query': "SELECT c.CompanyName, COUNT(f.FeatureUsageID) as UsageCount \nFROM Companies c \nJOIN FeatureUsage f ON c.CompanyID = f.CompanyID \nWHERE L
```

Agent executes command but receives error response from database

```
Error: (sqlite3.OperationalError) no such column: f.FeatureUsageID
[SQL: SELECT c.CompanyName, COUNT(f.FeatureUsageID) as UsageCount
FROM Companies c
JOIN FeatureUsage f ON c.CompanyID = f.CompanyID
WHERE LOWER(c.Country) = 'hong kong' AND LOWER(f.FeatureName) = 'payroll'
AND f.UsageDate BETWEEN DATE('2024-05-20') AND DATE('2024-05-26')
GROUP BY c.CompanyName
ORDER BY UsageCount DESC
LIMIT 1;]
(Background on this error at: https://sqlalche.me/e/20/e3q8)
Invoking: `sql_db_schema` with `{'table_names': 'FeatureUsage'}`
```

Demo: Which customer from HK used payroll module most frequently last week?

```
CREATE TABLE "FeatureUsage" (
        "UsageID" INTEGER,
        "CompanyID" INTEGER,
        "EmployeeID" INTEGER,
        "ModuleName" TEXT,
        "TaskDescription" TEXT,
        "StartTime" TEXT,
        "EndTime" TEXT,
        "TaskDuration" REAL,
        "CompletionStatus" TEXT,
        "ErrorDetails" TEXT,
        "LastUsedDate" TEXT
)

/*
3 rows from FeatureUsage table:
UsageID CompanyID       EmployeeID      ModuleName      TaskDescription StartTime       EndTime TaskDuration    CompletionStatus        ErrorDetails    LastUsedDate
1       1       9       Payroll Edit payroll    2024-05-14 05:36:23.638602      2024-05-14 06:29:23.638602      53.0    Not completed   Connection timeout      2024-05-08 23:21:00.92
2       1       41      Leave Management        Submit for approval     2024-04-18 10:43:02.478077      2024-04-18 11:21:02.478077      38.0    Not completed   Database error  2024-04
3       1       17      Leave Management        Create new leave        2024-04-23 23:09:30.429753      2024-04-23 23:57:30.429753      48.0    Not completed   Unable to process user
*/
```

Database response indicated that the error lies in FeatureUsage table, so agent decides to get more information about this table

Demo: Which customer from HK used payroll module most frequently last week?

```
Invoking: `sql_db_query_checker` with `{'query': "SELECT c.CompanyName, COUNT(f.UsageID) as UsageCount \nFROM Companies c \nJOIN FeatureUsage f ON c.CompanyID = f.CompanyID \nWHERE LOWER(c.Countr
```

```
```sql
SELECT c.CompanyName, COUNT(f.UsageID) as UsageCount
FROM Companies c
JOIN FeatureUsage f ON c.CompanyID = f.CompanyID
WHERE LOWER(c.Country) = 'hong kong' AND LOWER(f.ModuleName) = 'payroll'
AND f.LastUsedDate BETWEEN DATE('2024-05-20') AND DATE('2024-05-26')
GROUP BY c.CompanyName
ORDER BY UsageCount DESC
LIMIT 1;
```
```

Agent proceeds to draft a revised SQL command

```
Invoking: `sql_db_query` with `{'query': "SELECT c.CompanyName, COUNT(f.UsageID) as UsageCount \nFROM Companies c \nJOIN FeatureUsage f ON c.CompanyID = f.CompanyID \nWHERE LOWER(c.Country) = 'ho
```

```
Error: (sqlite3.OperationalError) no such column: c.Country
[SQL: SELECT c.CompanyName, COUNT(f.UsageID) as UsageCount
FROM Companies c
JOIN FeatureUsage f ON c.CompanyID = f.CompanyID
WHERE LOWER(c.Country) = 'hong kong' AND LOWER(f.ModuleName) = 'payroll'
AND f.LastUsedDate BETWEEN DATE('2024-05-20') AND DATE('2024-05-26')
GROUP BY c.CompanyName
ORDER BY UsageCount DESC
LIMIT 1;]
(Background on this error at: https://sqlalche.me/e/20/e3q8)
Invoking: `sql_db_schema` with `{'table_names': 'Companies'}`
```

Agent executes the command but fails again …

Demo: Which customer from HK used payroll module most frequently last week?

```
CREATE TABLE "Companies" (
        "CompanyID" INTEGER,
        "CompanyName" TEXT,
        "Industry" TEXT,
        "LeadSource" TEXT,
        "CustomerSince" TEXT,
        "Geography" TEXT
)

/*
3 rows from Companies table:
CompanyID       CompanyName     Industry        LeadSource      CustomerSince   Geography
1       Bisnis Indo     Energy  Direct  3/8/21  Philippines
2       CV Nusantara    Utilities       Advertisement   23/2/20 Thailand
3       Perusahaan Indo Materials       Advertisement   9/9/20  Singapore
*/
Invoking: `sql_db_query_checker` with `{'query': "SELECT c.CompanyName, COUNT(f.UsageID) as UsageCount \nFROM Companies c \nJOIN FeatureUsage f ON c.CompanyID = f.CompanyID \nWHERE LOWER(c.Geography) = 'hong
```

Database response indicated that the error lies in Companies table, so agent decides to get more information about this table

```
```sql
SELECT c.CompanyName, COUNT(f.UsageID) as UsageCount
FROM Companies c
JOIN FeatureUsage f ON c.CompanyID = f.CompanyID
WHERE LOWER(c.Geography) = 'hong kong' AND LOWER(f.ModuleName) = 'payroll'
AND f.LastUsedDate BETWEEN DATE('2024-05-20') AND DATE('2024-05-26')
GROUP BY c.CompanyName
ORDER BY UsageCount DESC
LIMIT 1;
```
```

Agent proceeds to draft a revised SQL command

Demo: Which customer from HK used payroll module most frequently last week?

Agent executes revised command and succeeds

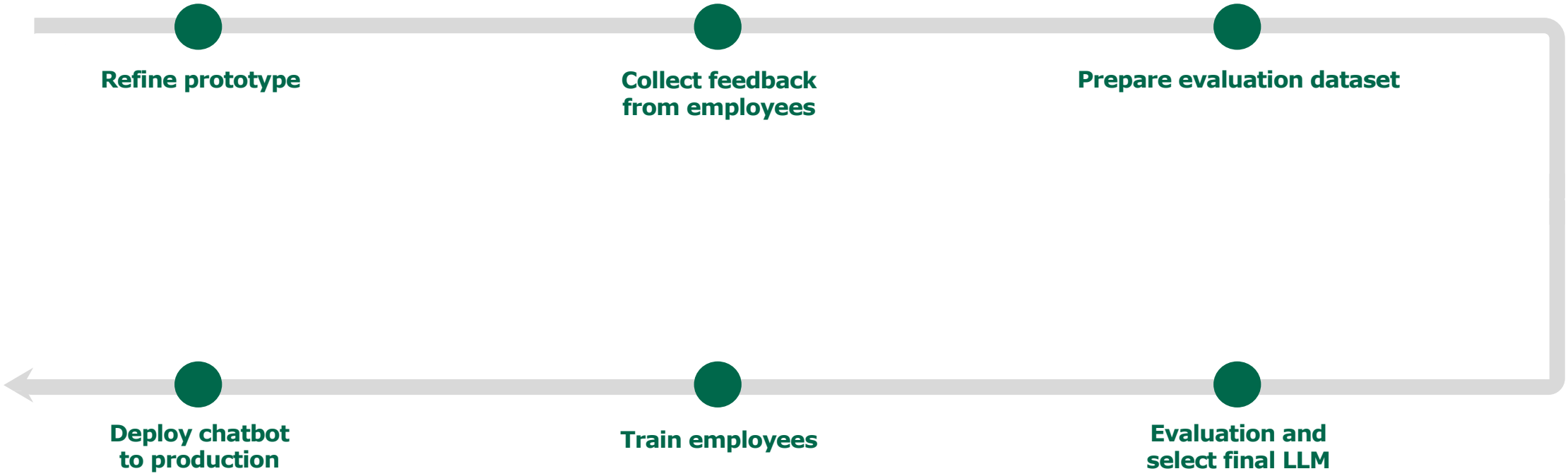
```
Invoking: `sql_db_query` with `{'query': "SELECT c.CompanyName, COUNT(f.UsageID) as UsageCount \nFROM Companies c \nJOIN FeatureUsage f ON c.CompanyID = f.CompanyID \nWHERE LOWER(c.Geography) = 'hong kong' AND LOWER(f.Modu

[('Tulip Industries', 3)]The customer from Hong Kong who used the payroll module most frequently last week is **Tulip Industries**, with a total of 3 usages.
```

Using the results of the query, agent produces a response to the user's question

Rollout plan

Our plan


Refine prototype
Collect feedback from employees
Prepare evaluation dataset
Deploy chatbot to production
Train employees
Evaluation and select final LLM

Stages and milestones

Stage	Tasks	Milestones	Duration
Refine prototype	• Build web interface for users to interact with chatbot • Set up logging system to record all conversations in next stage	Full-fledged web app approved	~ 1 day
Collect feedback from employees	• Conduct user interviews with a test group of employees across different departments • Allow them to interact with chatbot freely and only give them a basic idea of the chatbot's purpose • Observe their interaction patterns with the chatbot and ask them about their experience / needs • Log all messages exchanged with chatbot • Make refinements to chatbot using feedback obtained	All interviews completed App revisions approved	~ 2 weeks
Prepare evaluation dataset	• Prepare a list of 100 questions for evaluation • List should include a diverse range of questions with varying degrees of complexity • Potential sources: chatbot conversations from previous stage, past data requests made by employees, self-generated questions • Data analysts to prepare the correct answer to all questions by generating the correct SQL commands	Evaluation dataset approved	~ 3 days

Stages and milestones

Stage	Tasks	Milestones	Duration
Evaluation and select final LLM	• For each model, generate responses to all questions in evaluation dataset • Compare results across different models in terms of accuracy, cost and latency • Select winning model • Ensure that accuracy of winning model is 100%	Final LLM approved 100% accuracy on evaluation dataset	~ 1 week
Train employees	• Conduct in-person / virtual sharing sessions for all employees that will be using the chatbot • Provide examples of use cases based on department	Sharing sessions completed	~ 3 days
Deploy chatbot to production	• Ensure that chatbot has read permissions only • Customize chatbot for different departments so that each department only has access to selected data (optional)	QA completed and approved	~ 3 days

Post-deployment

Monitoring chatbot performance and measuring success

After deployment, we want to **closely monitor the chatbot's performance**

- Log all user questions and chatbot responses
- Collect a sample at regular intervals and measure accuracy of the chatbot's responses
- Over time, as we have more confidence in the chatbot, we can reduce the sample size

We will **measure success by measuring how often employees can rely on the chatbot for their data needs**

- *Success metric: number of data requests per employee per week*
- We hope to observe a significant reduction in the number of data requests to the data team
- In addition, we will start to track the proportion of employees who use the chatbot per week and we hope to see a much higher level of adoption compared to existing dashboards

We should continue to explore **how we can further improve performance of our agent**:

- Replace LLM with newer, improved models that can improve accuracy and reduce cost
- Regularly collect feedback from users to understand their evolving needs
- Adding tools that enable the chatbot to provide a variety of responses (in addition to text), e.g. tool that allows agent to execute Matplotlib operations and generate visualizations for the user

Estimated project value

	Description	Assumptions	Annual impact
Labour cost savings	• Value of the time data analysts currently spend responding to data requests and maintaining analytics dashboards	• 4 data analysts in the company • Annual comp of each data analyst: USD70k • % of time spent on these tasks: 40%	**~ USD110k**
Subscription fee savings	• Savings arising from the reduction in subscription fees to BI software providers (eg Tableau)	• Current # of Tableau Viewer subscriptions: 50 • Annual cost of each Tableau Viewer subscription: USD180 • Estimated # of subscriptions we can reduce: 40	**~ USD7k**
Cost of running chatbot	• Cost of inference for GPT 4o	• Estimated cost per chatbot interaction: ~USD0.05 (based on OpenAI's current pricing policy for GPT 4o and the estimated average token usage per interaction) • # of employees given access to chatbot: 70 • # of chatbot interactions per employee per month: 50	**~ USD2k (-)**
			~ USD115k

Beyond direct cost savings …

We believe that the **indirect value of this project is far greater than the direct cost savings**

- Giving employees instant access to accurate and relevant data would enable them to make informed decisions quickly, resulting in **higher productivity and improved decision-making**
- Creating an environment of data transparency and empowering team members with the tools to access data independently can **improve employee engagement, leading to a more motivated workforce**
- By helping employees gain more access to data, they can develop a deeper and more holistic understanding of the business and may be **better positioned to produce innovative ideas** that can create value for the organization

What we are most excited about though, is how this can **propel us in our journey to becoming an AI-first organization**

The learnings that we gain from taking this first step will be invaluable in building future agentic systems across other functions, and can potentially **unlock multi-agent workflows that can perform complex, multifaceted tasks**

Example of multi-agent collaboration

Customer support agent that resolves customer queries