Intro to Agents and ADK

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Outline

1. Introduction

2. Implementation

YHK

Introduction

What Makes an AI Agent Different?

- Unlike LLMs that just respond to prompts, agents are autonomous
- Can look at their environment and analyze the situation
- Make comprehensive plans to achieve specific goals
- Actually take action to execute those plans
- Agents bridge the gap between answering and doing

Welcome to AI Agents

- AI agents represent one of the most exciting frontiers in AI
- Not just everyday chatbots - systems that reason, plan, and take action
- Move beyond AI that just answers questions to AI that does things
- Can take on complex multi-step tasks autonomously
- The core promise: AI that accomplishes goals independently
- Technology is advancing rapidly from conversational to agentic AI

Meet Suresh - The Impossible Job

- Suresh's boss tasks him with planning a massive get-together
- Must research a huge guest list and plan fancy menu
- Needs to find entertainment for the event
- A simple chatbot cannot handle these complex requirements
- Suresh needs an AI agent - not just responses, but actions
- Perfect example of why we need more than conversational AI

Introduction to AI Agents

- 2025 is expected to be the year of AI agents.
- AI agents combine multiple components to solve complex problems.
- Shifting from monolithic models to compound AI systems.
- Compound AI systems use system design for better problem solving.
- AI agents improve with reasoning, acting, and memory components. (ReAct = Reasoning + Acting)

The Evolution of AI Capabilities

- **Traditional Programming:** Needed code to operate
- **Traditional ML:** Needed feature engineering
- **Deep Learning:** task-specific model
- **ChatGPT (2022):** Many tasks single model
  - Zero-shot learning (no examples needed)
  - In-context learning (understands from instructions)
- **Agents (2024 . . .):** Can actually **do things**, not just talk

Why Does "Taking Action" Matter?

- In 2022, ChatGPT was revolutionary because AI felt conversational
- By 2024, people wanted more than conversation, they wanted **execution**
- Examples of what users now expect:
  - Instead of listing leads ? **email them directly**
  - Instead of summarizing docs ? **file and create workflow tasks**
  - Instead of suggesting products ? **customize landing pages**
- This shift from **information** to **action** defines the agent era

How Agents Work?

- Agent acts, take you from one state to the other state, provides value by workflow automation. (ReAct paper: Reasoning and Action), it can plan and make decisions.
- Agents have access to tools (ToolFormer paper) e.g. Search APIs, booking, send email etc.
- Interacting of external environment and other Agents, etc.
- Memory to keep the history of conversations/actions done so far.
- May have human-in-loop to keep it sane in the wild-world.
- Agents were there from 1950's but they are effective because of LLMs.
- Agents are systems where LLMs dynamically direct their own processes and tool usage
- Can operate autonomously over extended periods using various tools
- Distinct from workflows: agents have dynamic control vs. predefined code paths
- Essential component in modern AI systems with varying degrees of autonomy

The Agent's Fundamental Game Loop

- Not a one-and-done action, but a continuous reasoning loop
- Similar to a programming while loop that keeps iterating
- **Thought**: Analyzes situation and plans next step
- **Action**: Calls specific tools to execute the plan
- **Observation**: Examines results of the action taken
- Cycle repeats: Thought → Action → Observation
- Continues until the task is completely accomplished
- This loop enables continuous adaptation and problem-solving

Agent's Inner Monologue

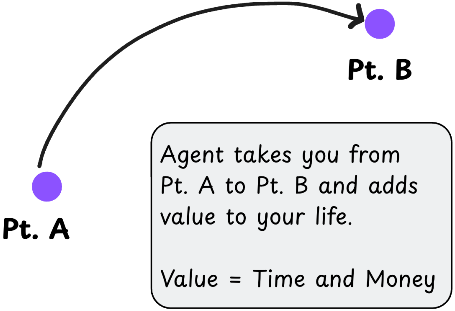
- Agents have visible thought processes before taking action
- Example: "User wants weather in New York. I have a tool for that."
- "My first move is to call the weather API"
- Internal planning step makes agents more than reactive programs
- Reasoning through problems before execution
- This deliberation distinguishes agents from simple scripts
- Shows intelligent decision-making rather than blind execution

How Do Agents Take Action?

- The magic lies in **tools** and **function calling**
- Agents are paired with APIs, plugins, or external systems
- Instead of just text responses, LLMs output structured commands:
  - ”Call the send_email() function with these inputs...”
  - ”Fetch records from CRM using this query...”
  - ”Schedule a meeting for Tuesday at 2PM...”
- **Mental model:** LLM = brain, Tools = hands
- Without tools, agents just talk. With tools, they act.

Defining AI Agents with an example

- Planning a trip involves many complex tasks
- Point A: Just discussing the trip
- Point B: All bookings and itinerary ready
- AI Agents aim to take you from A to B
- First idea: Agent adds value by saving time/money



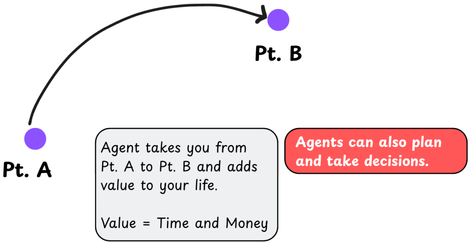
Agent takes you from Pt. A to Pt. B and adds value to your life.

Value = Time and Money

(Ref: Vizuara AI Agents Bootcamp)

Evolving Definition of Agents

- Not all tools from A to B are agents (e.g., cars)
- Agents must plan and make decisions
- Second definition includes decision-making ability
- Example: Choosing flights based on budget
- Planning daily itinerary needs contextual judgment



Agent takes you from Pt. A to Pt. B and adds value to your life.

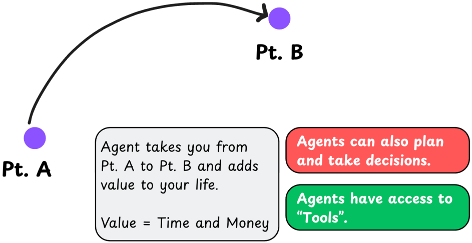
Value = Time and Money

Agents can also plan and take decisions.

(Ref: Vizuara AI Agents Bootcamp)

Agents Need Tools

- Even self-driving cars plan but are not agents
- Agents need access to external tools
- Tools = Access to services (e.g., Gmail, Booking)
- Agents perform tasks using these tools
- Third definition adds tool access to capabilities



Agent takes you from Pt. A to Pt. B and adds value to your life.

Value = Time and Money

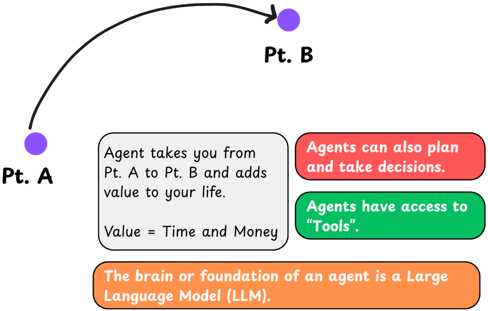
Agents can also plan and take decisions.

Agents have access to "Tools".

(Ref: Vizuara AI Agents Bootcamp)

Rise of LLMs in Agents

- Transformers (2017) enabled powerful LLMs
- LLMs understand and generate human language
- Agents use LLMs for reasoning and planning
- LLMs enable understanding of webpages and writing emails
- Fourth definition: Agents are LLMs with tools and planning ability



Agent takes you from Pt. A to Pt. B and adds value to your life.

Value = Time and Money

Agents can also plan and take decisions.

Agents have access to “Tools”.

The brain or foundation of an agent is a Large Language Model (LLM).

(Ref: Vizuara AI Agents Bootcamp)

What Is an Agent? (Technical Definition)

- Agent acts and takes you from one state to another, providing value through workflow automation
- Based on ReAct paradigm: **Reasoning + Acting**
- Key capabilities:
  - Can plan and make decisions
  - Has access to tools (search APIs, booking, email, etc.)
  - Interacts with external environments and other agents
  - Maintains memory of conversations and actions
  - May include human-in-the-loop for safety
- Agents existed since the 1950s but are now effective because of LLMs

Two Ways to Define Agents

Technical View:

- LLM (brain)
- + Tools (hands)
- + Planning (strategy)
- + Memory (context)
- + State management

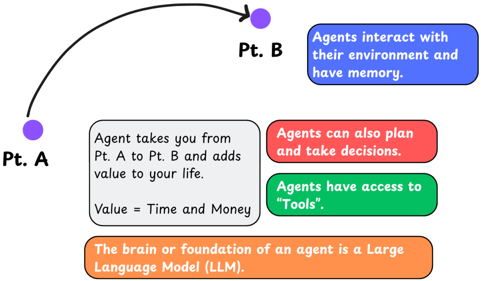
Business View:

- Systems that complete tasks end-to-end
- Focus on outcomes, not components
- Solve real-world problems
- Provide measurable value

Important: Today's agents are **engineering wrappers** around AI models, the intelligence comes from the LLMs, agents help act on that intelligence.

Final Definition of Agents

- Agents can learn from feedback and environment
- Agents interact with tools, humans, and websites
- They improve with experience (memory)
- Fifth definition: LLMs + Tools + Planning + Learning
- Agents evolve over time via memory and feedback



Agents interact with their environment and have memory.

Agent takes you from Pt. A to Pt. B and adds value to your life.

Value = Time and Money

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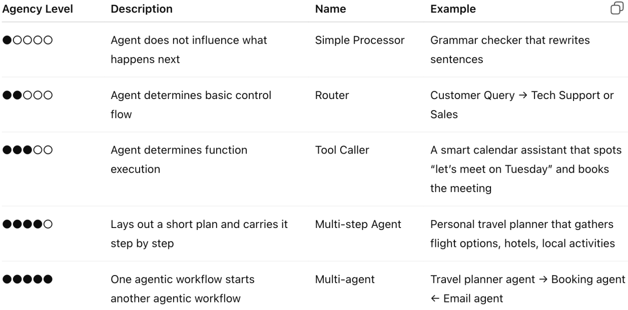
(Ref: Vizuara AI Agents Bootcamp)

Understanding Agency

- Agency = Level of autonomy an agent has
- Low agency → less value
- High agency → high value
- More autonomous agents can handle complex tasks
- Agency is key to measuring agent usefulness



Agency Level	Description	Name	Example
●○○○○	Agent does not influence what happens next	Simple Processor	Grammar checker that rewrites sentences
●●○○○	Agent determines basic control flow	Router	Customer Query → Tech Support or Sales
●●●○○	Agent determines function execution	Tool Caller	A smart calendar assistant that spots "let's meet on Tuesday" and books the meeting
●●●●○	Lays out a short plan and carries it step by step	Multi-step Agent	Personal travel planner that gathers flight options, hotels, local activities
●●●●●	One agentic workflow starts another agentic workflow	Multi-agent	Travel planner agent → Booking agent ← Email agent

(Ref: Vizuara AI Agents Bootcamp)

Tools: The Agent's Hands

- LLM is the agent's brain; tools are its hands
- Tools are functions agents call to interact with the world
- Can search web, run calculations, or query databases
- Bridge between thinking and doing in the real world
- Enable agents to move from planning to execution
- Without tools, agent thoughts would be useless
- Tools provide the interface to external systems and data

Two Ways Agents Use Tools

- **JSON Agent**: Writes structured work orders for other systems
- JSON approach requires external system to read and execute
- **Code Agent**: Directly writes and runs code blocks
- Code approach is more direct and powerful
- Code is naturally more expressive than JSON
- Can handle complex logic like loops and conditionals
- Modular, easier to debug, and taps into existing libraries
- Code agents can access thousands of APIs directly

Code Agent in Action

- Alfred needs a gala menu - agent has ”suggest_menu” tool
- Agent doesn’t just make up suggestions randomly
- Generates and runs actual code to call the specific tool
- Gets real results from the tool execution
- Super direct, efficient, and powerful way to take action
- Code generation enables precise tool interaction
- Results are based on actual tool capabilities, not hallucination

Advanced Pattern: Agentic RAG

- Traditional RAG: Retrieval Augmented Generation fetches info before answering
- Agentic RAG supercharges this with intelligent multi-step processes
- Turns retrieval itself into an agent-driven task
- Like having a master researcher on staff
- Doesn't just do one search - runs complete research processes
- Rewrites queries for better results and runs multiple searches
- Uses findings to inform next searches and validates accuracy
- Pulls from both private data and public web sources

Multi-Agent Systems: Digital Teams

- Complex problems like finding the missing Batmobile need teams
- Single agents can't handle web searches, calculations, and visualization
- Solution: Build teams of specialized agents
- Manager agent acts as project lead breaking down big tasks
- Delegates work to specialist agents with specific skills
- Web agent handles online searching while manager coordinates
- Manager focuses on big picture and final integration
- Digital division of labor for complex problem solving

The GAIA Benchmark Reality Check

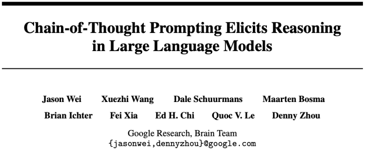
- GAIA benchmark tests real-world multi-step problems
- Measures how well systems handle tricky, complex tasks
- Results are eye-opening and show current limitations
- Humans solve these tasks with 92% accuracy
- Today's most advanced AI models: only 15% accuracy
- Massive 77% gap between human and AI performance
- This gap is exactly what agentic systems aim to close
- Shows the enormous potential for improvement

The Fundamental Shift

- Moving from conversational AI to agentic AI era
- Old paradigm: Ask questions, get answers
- New paradigm: State goals, systems plan and accomplish them
- Represents fundamental change in human-computer interaction
- Technology for building personal AI assistants advancing rapidly
- Not a question of ”if” but ”when” this becomes reality
- The future Alfred is closer than we think
- Prepare for AI that can handle ”impossible” complex tasks

Papers that Shaped AI Agents

- Core research papers laid the foundation
- Introduced key frameworks and architectures
- Sparked recent boom in agent development
- Include Transformer and Agentic frameworks
- Major driving force in LLM-based agent systems



Chain-of-Thought Prompting Elicits Reasoning in Large Language Models

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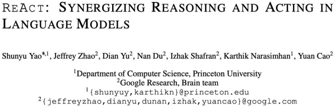

REACT: SYNERGIZING REASONING AND ACTING IN LANGUAGE MODELS

Shunyu Yao*[,1], Jeffrey Zhao[2], Dian Yu[2], Nan Du[2], Izhak Shafran[2], Karthik Narasimhan[1], Yuan Cao[2]

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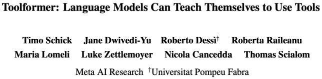
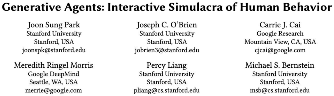


Toolformer: Language Models Can Teach Themselves to Use Tools

Timo Schick Jane Dwivedi-Yu Roberto Dessì† Roberta Raileanu
Maria Lomeli Luke Zettlemoyer Nicola Cancedda Thomas Scialom
Meta AI Research †Universitat Pompeu Fabra



Generative Agents: Interactive Simulacra of Human Behavior

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(Ref: Vizuara AI Agents Bootcamp)

When to Use Agents?

- Best suited for tasks requiring flexibility and model-driven decision-making
- Consider tradeoffs: agents increase latency and cost for better task performance
- Recommended for open-ended problems with unpredictable steps
- Simple solutions preferred - single LLM calls with retrieval often sufficient

Future AI Applications

- What are future AI applications like?
  - **Generative:** Generate content like text and images
  - **Agentic:** Execute complex tasks on behalf of humans
- How do we empower every developer to build them?
  - **Co-Pilots:** Human-AI collaboration
  - **Autonomous:** Independent task execution
- 2024 is expected to be the year of AI agents

The Big Question

- Agentic AI technology is moving incredibly fast
- Personal AI assistants will soon be capable of complex tasks
- Think beyond simple queries to multi-step accomplishments
- Consider what ”impossible” tasks you want to delegate
- What complex, party-of-the-century level challenge will you tackle?
- The era of AI that truly does rather than just discusses
- Prepare for AI assistants that can handle your biggest challenges

Google ADK (Agent Development Kit)

Introduction to ADK Framework

- ADK (Agent Development Kit) is Google's framework for building sophisticated AI agents and agentic applications
- Official documentation available at: `https://google.github.io/adk-docs/`
- Designed for production-ready agentic systems with focus on scalability and reliability
- Supports multi-agent systems, tool integration, and flexible deployment options
- Built on Google's Gemini models with support for multiple LLM providers
- Framework emphasizes type safety, async operations, and enterprise-grade features

Key Components

- **Agents:** Core building blocks with instructions, tools, and model configuration
- **Tools:** Functions that agents can call to interact with external systems and APIs
- **Sessions:** Manage conversation context and state across multiple interactions
- **Runners:** Execute agent logic with support for streaming and async operations
- **Memory:** Store and retrieve conversation history and context
- **Multi-Agent Support:** Coordinate multiple specialized agents working together
- **Deployment:** Built-in support for FastAPI and serverless deployment

ADK Architecture Levels

- **Basic Agents:** Single agent with tools and instructions
- **Stateful Agents:** Agents with session management and memory
- **Multi-Agent Systems:** Multiple specialized agents collaborating
- **Agentic Workflows:** Complex orchestration with control flow
- **Production Systems:** Deployed services with monitoring and scaling
- Each level provides additional capabilities for building sophisticated AI applications

Key Features - Model Support & Flexibility

- **Gemini Integration:** Native support for Google's Gemini models (1.5 Pro, 2.0 Flash)
- **Multi-Provider:** Works with OpenAI, Anthropic, and other LLM providers
- **Type Safety:** Full TypeScript/Python type annotations for reliability
- **Async-First:** Built on async/await for high-performance concurrent operations
- **Streaming Support:** Real-time response streaming for better UX
- **Tool Calling:** Native function calling with structured input/output
- **Production Ready:** Built-in FastAPI integration and deployment patterns

Advanced Capabilities - Grounding & Multi-Modal

- **Google Search Grounding:** Connect agents to real-time web search results
- **Multi-Modal Input:** Support for text, images, audio, and video
- **Code Execution:** Built-in code interpreter for dynamic computation
- **Vertex AI Integration:** Enterprise features like RAG and vector search
- **Function Calling:** Structured tool execution with automatic parameter extraction
- **Safety Filters:** Built-in content safety and harm prevention

Enterprise Features - State & Deployment

- **Session Management:** Persistent conversation state across interactions
- **Cloud Integration:** Native support for Google Cloud services
- **Structured Output:** Pydantic models for type-safe responses
- **Error Handling:** Robust retry logic and error recovery
- **Monitoring:** Integration with Cloud Logging and Tracing
- **Authentication:** Built-in OAuth and API key management
- **Scalability:** Designed for high-throughput production workloads

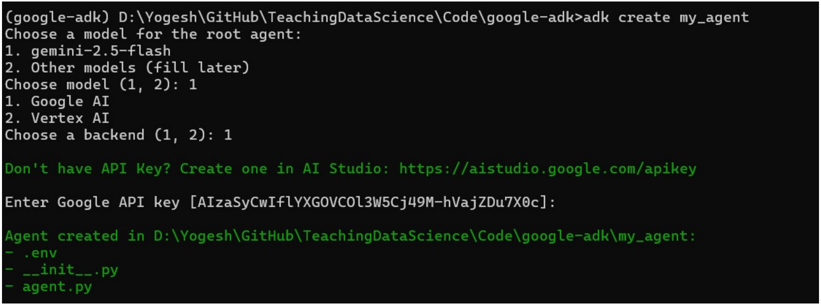
Installation & Setup

- **Simple Installation:** Install via pip with minimal dependencies
- **CLI Tools:** Built-in commands for project creation and management
- **Project Generation:** Automatic scaffolding with best practices
- **API Key Creation:**Get the API key from `https://aistudio.google.com/api-keys`
- **API Key Setup:** Configure Gemini API key via environment variable
- **Quick Start:** Start building agents immediately after installation

```
pip install google-adk
pip install google-adk --use-deprecated=legacy-resolver

# Create a new agent project
adk create my_agent

# Set API key in .env file
echo 'GOOGLE_API_KEY="YOUR_API_KEY"' > my_agent/.env # write your API key into an .env

```

Use CLI not VS code

Use Anaconda prompt with Admin permissions.



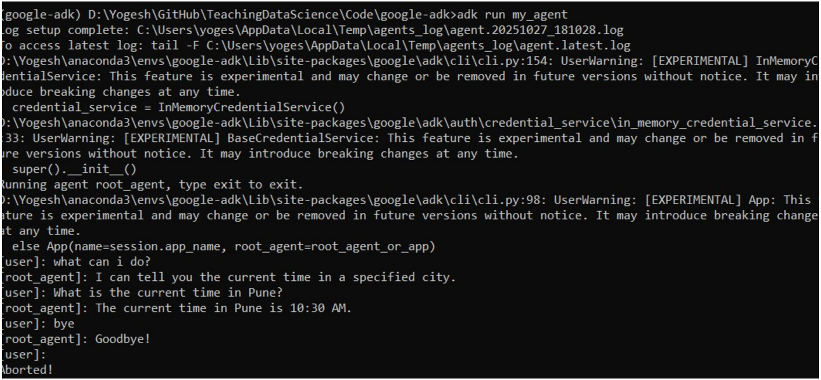
```
(google-adk) D:\Yogesh\GitHub\TeachingDataScience\Code\google-adk>adk create my_agent
Choose a model for the root agent:
1. gemini-2.5-flash
2. Other models (fill later)
Choose model (1, 2): 1
1. Google AI
2. Vertex AI
Choose a backend (1, 2): 1

Don't have API Key? Create one in AI Studio: https://aistudio.google.com/apikey

Enter Google API key [AIzaSyCwIflYXGOVCOl3W5Cj49M-hVajZDu7X0c]:

Agent created in D:\Yogesh\GitHub\TeachingDataScience\Code\google-adk\my_agent:
- .env
- __init__.py
- agent.py
```

Explore the agent project

- The created agent project has the following structure, with the agent.py file containing the main control code for the agent.
- The agent.py file contains a root_agent definition which is the only required element of an ADK agent. You can also define tools for the agent to use. Update the generated agent.py
- Run your agent using the adk run command-line tool.
- The ADK framework provides web interface you can use to test and interact with your agent.

```
my_agent/
    agent.py      # main agent code
    .env          # API keys or project IDs
    __init__.py

adk run my_agent

adk web --port 8000 my_agent
```

Wrong time!!



```
(google-adk) D:\Yogesh\GitHub\TeachingDataScience\Code\google-adk>adk run my_agent
Log setup complete: C:\Users\yoges\AppData\Local\Temp\agents_log\agent.20251027_181028.log
To access latest log: tail -F C:\Users\yoges\AppData\Local\Temp\agents_log\agent.latest.log
D:\Yogesh\anaconda3\envs\google-adk\Lib\site-packages\google\adk\cli\cli.py:154: UserWarning: [EXPERIMENTAL] InMemoryC
dentialService: This feature is experimental and may change or be removed in future versions without notice. It may in
oduce breaking changes at any time.
  credential_service = InMemoryCredentialService()
D:\Yogesh\anaconda3\envs\google-adk\Lib\site-packages\google\adk\auth\credential_service\in_memory_credential_service.
:33: UserWarning: [EXPERIMENTAL] BaseCredentialService: This feature is experimental and may change or be removed in f
ure versions without notice. It may introduce breaking changes at any time.
  super().__init__()
Running agent root_agent, type exit to exit.
D:\Yogesh\anaconda3\envs\google-adk\Lib\site-packages\google\adk\cli\cli.py:98: UserWarning: [EXPERIMENTAL] App: This
ature is experimental and may change or be removed in future versions without notice. It may introduce breaking change
at any time.
  else App(name=session.app_name, root_agent=root_agent_or_app)
[user]: what can i do?
[root_agent]: I can tell you the current time in a specified city.
[user]: What is the current time in Pune?
[root_agent]: The current time in Pune is 10:30 AM.
[user]: bye
[root_agent]: Goodbye!
[user]:
Aborted!
```

Basic Agent Example - Simple Setup

- Create a basic agent with Gemini 2.0 Flash model
- Define tools using Python functions with type hints
- Agent automatically handles function calling and response generation
- Clean separation between tool definition and agent logic
- Synchronous execution for simple use cases

```python
from adk import Agent
from adk.models import GeminiModel
import yfinance as yf

def get_stock_price(symbol: str) -> dict:
    """Get current stock price for a given symbol."""
    # Implementation using yfinance or similar
    stock = yf.Ticker(symbol)
    return {"symbol": symbol, "price": stock.info.get('currentPrice')}

agent = Agent(
    model=GeminiModel(model_name="gemini-2.0-flash-exp"),
    tools=[get_stock_price],
    instructions="You are a helpful financial assistant. Use tools when needed."
)

response = agent.run("What is NVIDIA's current stock price?")
print(response.text)
```

Agent with Multiple Tools

- Define multiple specialized tools for the agent with docstring
- Agent selects appropriate tools based on dcostring and user query

```python
from adk import Agent
from adk.models import GeminiModel
import yfinance as yf

def get_stock_price(symbol: str) -> float:
    """Get current stock price."""
    return yf.Ticker(symbol).info.get('currentPrice', 0)

def get_company_info(symbol: str) -> dict:
    """Get company information."""
    ticker = yf.Ticker(symbol)
    return {"name": ticker.info.get('longName'),
            "sector": ticker.info.get('sector'),
            "summary": ticker.info.get('longBusinessSummary')}

def get_analyst_recommendations(symbol: str) -> str:
    """Get analyst recommendations."""
    return yf.Ticker(symbol).recommendations.to_string()

agent = Agent(model=GeminiModel(model_name="gemini-2.0-flash-exp"),
    tools=[get_stock_price, get_company_info, get_analyst_recommendations],
    instructions="Provide detailed financial analysis using available tools.")

for chunk in agent.run_stream("Write a report on NVIDIA stock"):
    print(chunk.text, end="", flush=True)
```

Agent with Session Management

- Sessions maintain conversation history and context
- Enable multi-turn conversations with memory
- Store and retrieve previous interactions
- Support for persistent storage backends

```python
from adk import Agent, Session
from adk.models import GeminiModel
from adk.storage import InMemoryStorage
import yfinance as yf

def get_stock_price(symbol: str) -> float:
    """Get current stock price."""
    return yf.Ticker(symbol).info.get('currentPrice', 0)

def get_company_info(symbol: str) -> dict:
    """Get company information."""
    ticker = yf.Ticker(symbol)
    return {"name": ticker.info.get('longName'),
            "sector": ticker.info.get('sector'),
            "summary": ticker.info.get('longBusinessSummary')}

# Create storage for session history
storage = InMemoryStorage()

agent = Agent(
    model=GeminiModel(model_name="gemini-2.0-flash-exp"),
    tools=[get_stock_price, get_company_info],
    instructions="You are a financial advisor. Remember previous conversations."
)
```

Agent with Session Management

```python
# Create a session for this conversation
session = Session(
    agent=agent,
    storage=storage,
    session_id="user-123"
)

# Multi-turn conversation
response1 = session.run("What's NVIDIA's stock price?")
print(response1.text)

# Agent remembers previous context
response2 = session.run("How about their competitor AMD?")
print(response2.text)

# Session history is maintained
response3 = session.run("Compare both companies")
print(response3.text)

```

Agent with Google Search Grounding

- Google Search grounding provides real-time web information
- Automatically cites sources in responses
- Reduces hallucination with factual grounding
- Requires Vertex AI setup for production use

```
from adk import Agent
from adk.models import GeminiModel
from adk.extensions import GoogleSearchGrounding

agent = Agent(
    model=GeminiModel(
        model_name=”gemini−2.0−flash−exp”,
        extensions=[GoogleSearchGrounding()]
    ),
    instructions=”Provide well−researched answers with citations.”
)

response = agent.run(
    ”What are the latest developments in AI semiconductor technology?”
)
print(response.text)
# Response will include citations from search results

```

Structured Output with Pydantic

- Define expected output schema using Pydantic models
- Ensures type-safe and structured responses
- Automatic validation of agent outputs
- Ideal for integration with downstream systems

```python
from adk import Agent
from adk.models import GeminiModel
from pydantic import BaseModel, Field

def get_stock_price(symbol: str) -> float:
    :

def get_company_info(symbol: str) -> dict:
    :


class StockAnalysis(BaseModel):
    symbol: str = Field(description="Stock ticker symbol")
    current_price: float = Field(description="Current stock price")
    recommendation: str = Field(description="Buy/Hold/Sell recommendation")
    reasoning: str = Field(description="Analysis reasoning")

agent = Agent(
    model=GeminiModel(model_name="gemini-2.0-flash-exp"),
    tools=[get_stock_price, get_company_info],
    output_schema=StockAnalysis,
    instructions="Analyze the stock and provide structured recommendation."
)

result: StockAnalysis = agent.run("Analyze NVIDIA stock")
print(f"Symbol: {result.symbol}")
print(f"Price: ${result.current_price}")
```

Multi-Agent System - Architecture

- **Specialized Agents:** Each agent focuses on specific domain expertise
- **Orchestration:** Coordinator agent manages task delegation
- **Parallel Execution:** Multiple agents can work simultaneously
- **Result Aggregation:** Combine outputs from multiple agents
- **Scalable Design:** Handle complex workflows through collaboration

Multi-Agent Implementation - Part 1

```python
from adk import Agent
from adk.models import GeminiModel

def web_search(query: str) -> str:
    """Search the web for information."""
    # Implementation using search API
    pass

def get_stock_data(symbol: str) -> dict:
    """Get comprehensive stock data."""
    import yfinance as yf
    ticker = yf.Ticker(symbol)
    return {
        "price": ticker.info.get('currentPrice'),
        "recommendations": ticker.recommendations.tail(5).to_dict()
    }

web_agent = Agent(
    name="Web Agent",
    model=GeminiModel(model_name="gemini-2.0-flash-exp"),
    tools=[web_search],
    instructions="Search the web and provide sourced information."
)

finance_agent = Agent(
    name="Finance Agent",
    model=GeminiModel(model_name="gemini-2.0-flash-exp"),
    tools=[get_stock_data],
    instructions="Analyze financial data and present in clear tables."
)
```

Multi-Agent Implementation - Part 2

- Coordinator agent orchestrates multiple specialized agents
- Delegates tasks to appropriate agents based on requirements
- Aggregates and synthesizes results from multiple sources

```python
from adk import Agent, MultiAgentOrchestrator
from adk.models import GeminiModel

orchestrator = MultiAgentOrchestrator(
    agents=[web_agent, finance_agent],
    coordinator=Agent(
        model=GeminiModel(model_name="gemini-2.0-flash-exp"),
        instructions="""You coordinate a team of specialized agents.
        - Use Web Agent for market news and trends
        - Use Finance Agent for stock data and analysis
        - Synthesize their outputs into comprehensive reports.""" ))

# Run multi-agent workflow
result = orchestrator.run(
    "Provide a comprehensive analysis of AI semiconductor companies "
    "including market outlook and financial performance")

print(result.text)

# Access individual agent outputs
for agent_name, agent_result in result.agent_outputs.items():
    print(f"\n{agent_name} output:")
    print(agent_result.text)
```

FastAPI Deployment

Deploy agents as REST APIs using FastAPI

```
from fastapi import FastAPI, HTTPException
from fastapi.responses import StreamingResponse
from adk import Agent, Session
from adk.models import GeminiModel
from pydantic import BaseModel
import uvicorn

app = FastAPI(title=”ADK Agent API”)

agent = Agent(
    model=GeminiModel(model_name=”gemini−2.0−flash−exp”),
    tools=[get_stock_price, get_company_info],
    instructions=”You are a financial assistant API.”
)

class QueryRequest(BaseModel):
    message: str
    session_id: str
```

FastAPI Deployment

```python

@app.post("/chat")
async def chat(request: QueryRequest):
    session = Session(agent=agent, session_id=request.session_id)
    response = await session.run_async(request.message)
    return {"response": response.text}

@app.post("/chat/stream")
async def chat_stream(request: QueryRequest):
    session = Session(agent=agent, session_id=request.session_id)

    async def generate():
        async for chunk in session.run_stream_async(request.message):
            yield chunk.text

    return StreamingResponse(generate(), media_type="text/plain")

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

Vertex AI Integration

```
from adk import Agent
from adk.models import VertexAIModel
from adk.extensions import VertexAIVectorSearch
from google.cloud import aiplatform

# Initialize Vertex AI
aiplatform.init(project=”your—project—id”, location=”us—central1”)

# Create agent with Vertex AI backend
agent = Agent(
    model=VertexAIModel(
        model_name=”gemini—2.0—flash—exp”,
        project=”your—project—id”,
        location=”us—central1”
    ),
    extensions=[
        VertexAIVectorSearch(
            index_endpoint=”your—index—endpoint”,
            deployed_index_id=”your—index—id”
        )
    ],
    instructions=”Answer questions using both your knowledge and the vector store.”
)

response = agent.run(”What are our company policies on remote work?”)
print(response.text)
```

Error Handling & Reliability

```python
from adk import Agent
from adk.models import GeminiModel
from adk.exceptions import ToolExecutionError, ModelError
import logging
import yfinance as yf
logging.basicConfig(level=logging.INFO)
logger = logging.getLogger(__name__)

def safe_tool_wrapper(func):
    """Decorator for safe tool execution with fallback."""
    def wrapper(*args, **kwargs):
        try:
            return func(*args, **kwargs)
        except Exception as e:
            logger.error(f"Tool {func.__name__} failed: {e}")
            return {"error": str(e), "fallback": True}
    return wrapper

@safe_tool_wrapper
def get_stock_price(symbol: str) -> dict:
    """Get stock price with error handling."""
    return {"price": yf.Ticker(symbol).info['currentPrice']}

```

Error Handling & Reliability

```
agent = Agent(
    model=GeminiModel(
        model_name="gemini-2.0-flash-exp",
        max_retries=3,
        timeout=30
    ),
    tools=[get_stock_price],
    instructions="Handle errors gracefully and inform users."
)

try:
    response = agent.run("What's the price of NVDA?")
    print(response.text)
except ModelError as e:
    logger.error(f"Model error: {e}")
    print("Sorry, I'm having trouble processing your request.")
```

Framework Comparison: LangGraph vs Agno vs ADK

Feature	LangGraph	Agno	ADK
Primary Focus	Graph-based workflows	Multi-agent systems	Enterprise AI agents
Developer	LangChain AI	Agno (ex-phidata)	Google
Architecture	State machines & graphs	Agent teams	Agent orchestration
Model Support	100+ providers	23+ providers	Gemini + multi-provider
Learning Curve	Steep (graph concepts)	Moderate	Moderate
Setup Time	Complex	Minutes	Minutes
Performance	Good	3μs instantiation	Optimized for Gemini
State Management	Built-in (checkpoints)	Session storage	Session & Cloud
Memory	Memory modules	Built-in drivers	In-memory & Cloud
Multi-Agent	Via subgraphs	Native teams	Orchestrator pattern
Workflow Control	Explicit graphs	Coordinate mode	Coordinator agent
Streaming	Yes	Yes	Yes (native async)
RAG Support	Vector stores	20+ vector DBs	Vertex AI Search
Deployment	Custom	FastAPI built-in	FastAPI + Cloud Run
Monitoring	LangSmith	agno.com	Cloud Console
Production Ready	Yes	Yes	Yes (enterprise)
Best For	Complex workflows	Fast prototyping	Google Cloud users
Unique Feature	Graph visualization	6.5KB/agent memory	Search grounding

Best Practices

- **Start Simple:** Begin with basic agents before adding complexity
- **Clear Instructions:** Provide specific, actionable instructions to agents
- **Tool Design:** Keep tools focused and well-documented with type hints
- **Error Handling:** Always implement proper error handling and retries
- **Testing:** Test agents thoroughly before production deployment
- **Monitoring:** Implement logging and monitoring for production systems
- **Security:** Validate inputs and sanitize outputs
- **Cost Management:** Monitor API usage and implement rate limiting

Getting Started - Next Steps

- **Documentation:** Explore comprehensive guides at `https://google.github.io/adk-docs/`
- **Examples Repository:** Check out example projects and templates
- **Community:** Join Google Cloud community for support
- **Start Building:** Begin with simple agents and iterate
- **Cloud Integration:** Leverage Google Cloud services for production
- **Vertex AI:** Explore enterprise features for advanced use cases
- **Monitoring:** Use Cloud Console for production monitoring

Resources & References

- **Official Documentation:** `https://google.github.io/adk-docs/`
- **GitHub Repository:** `https://github.com/google/adk`
- **Gemini API:** `https://ai.google.dev/`
- **Vertex AI:** `https://cloud.google.com/vertex-ai`
- **Google Cloud:** `https://cloud.google.com/`
- **Community Support:** Google Cloud Community forums

Thanks . . .

- Search **”Yogesh Haribhau Kulkarni”** on Google and follow me on LinkedIn, GitHub, Medium
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- yogeshkulkarni at yahoo dot com
- Call + 9 1 9 8 9 0 2 5 1 4 0 6

(https://medium.com/@yogeshharibhaukulkarni)

(https://www.linkedin.com/in/yogeshkulkarni/)

(https://www.github.com/yogeshhk/)

Pune AI Community (PAIC)

- Two-way communication:
  - Website puneaicommunity dot org
  - Email puneaicommunity at gmail dot com
  - Call + 9 1 9 8 9 0 2 5 1 4 0 6
  - LinkedIn: https://linkedin.com/company/pune-ai-community
- One-way Announcements:
  - Twitter (X) @puneaicommunity
  - Instagram @puneaicommunity
  - WhatsApp Community: Invitation Link https://chat.whatsapp.com/LluOrhyEzuQLDr25ixZ
  - Luma Event Calendar: puneaicommunity
- Contribution Channels:
  - GitHub: Pune-AI-Community and puneaicommunity
  - Medium: pune-ai-community
  - YouTube: @puneaicommunity

Website

Pune AI Community (PAIC) QR codes

Website

Medium Blogs

Twitter-X

LinkedIn Page

Github Repository

WhatsApp Invite

Luma Events

YouTube Videos

Instagram