BrandMate: A Multi-Agent AI Solution for LinkedIn Influencers

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Abstract

LinkedIn influencers struggle with inconsistent brand messaging, keeping up with trends, gaining performance insights, and burnout from manual content creation. `BrandMate`, developed by Aruni Saxena, Paarth Patel, Rishi Barapatre, and Anandita Saolapurkar, is a multi-agent AI system built with LangGraph to address these challenges. It delivers SEO-optimized posts, trend-aware hashtags, automated scheduling, performance tracking, and a feedback dashboard. This document details the problem, solution, deliverables, team contributions, development reflections, project resources, and a deep dive into the Reinforcement Learning (RL) agent's Q-learning mechanism, noting the challenge of RL deployment.

1 Problem Statement

LinkedIn influencers face:

- **Inconsistent Brand Messaging**: Varying tone and style dilute brand identity.
- **Difficulty Keeping Up with Trends**: Rapidly changing trends require constant research.
- **Poor Post Performance Insight**: Limited data hinders strategic improvement.
- **Burnout from Manual Content Creation**: Manual post creation causes fatigue.

2 Multi-Agent AI Solution

`BrandMate` addresses these challenges:

- **Personalized Tone & Trend-Aware Writing**: Extracts tones and integrates trending keywords/hashtags.
- **Specialized Agents Handle Distinct Tasks**: Modular agents streamline content creation.
- **Optimized Content Through Feedback Loops**: RL agent refines strategies.
- **Content Evolves with Performance Data**: Adapts based on engagement data.

Table 1: BrandMate Agent Roles

Agent	Role
`user_interaction_agent`	Extracts tone, target audience, and goal
`brand_identity_agent`	Defines style guide (tone, sentence length, vocabulary)
`content_strategist_agent`	Selects a relevant topic
`seo_agent`	Fetches keywords and hashtags via SerpAPI
`content_generator_agent`	Generates a raw LinkedIn post
`post_editor_agent`	Refines the post and adds branding hashtags
`publishing_agent`	Simulates posting and generates metrics
`rl_feedback_agent`	Updates Q-table and suggests strategies

3 Proposed Solution: BrandMate Architecture

`BrandMate` uses LangGraph to orchestrate eight agents, updating a `BrandMateState` dictionary in a directed acyclic graph (DAG) executed via `app.invoke`. Agent roles are:

The workflow uses:

- ▷ `workflow.add_node(node_id, function)`: Registers agents.
- ▷ `workflow.add_edge(from_node, to_node)`: Defines sequence.
- ▷ `workflow.set_entry_point("user_interaction")`: Sets starting node.
- ▷ `workflow.compile()`: Creates executable `app`.
- ▷ `app.invoke(initial_state)`: Runs the graph.

3.1 Streamlit Deployment Code

The following LangGraph code, integrated with Streamlit, demonstrates the `BrandMate` workflow. This code powers the deployment interface, with screenshots available in the project repository:

```python
import streamlit as st
from langgraph.graph import StateGraph, END
from typing import TypedDict, Dict, Any

class BrandMateState(TypedDict):
    user_input: str
    tone: str
    target: str
    goal: str
    style_guide: Dict[str, str]
    topic: str
    seo_package: Dict[str, Any]
    post: str
    metrics: Dict[str, Any]
    feedback: str
    q_table: Dict[str, Any]

# Placeholder agent functions
def user_interaction_agent(state: BrandMateState) -> BrandMateState:
    state["tone"] = "emotional"
    state["target"] = "women startup founders"
    state["goal"] = "grow followers"
    return state
# ... (other agent functions defined similarly)

# Initialize workflow
workflow = StateGraph(BrandMateState)
workflow.add_node("user_interaction", user_interaction_agent)
workflow.add_node("brand_identity", brand_identity_agent)
workflow.add_node("content_strategist", content_strategist_agent)
workflow.add_node("seo", seo_agent)
workflow.add_node("content_generator", content_generator_agent)
workflow.add_node("post_editor", post_editor_agent)
workflow.add_node("publishing", publishing_agent)
workflow.add_node("rl_feedback", rl_feedback_agent)

# Define edges
workflow.add_edge("user_interaction", "brand_identity")
workflow.add_edge("brand_identity", "content_strategist")
workflow.add_edge("content_strategist", "seo")
workflow.add_edge("seo", "content_generator")
workflow.add_edge("content_generator", "post_editor")
workflow.add_edge("post_editor", "publishing")
workflow.add_edge("publishing", "rl_feedback")
workflow.add_edge("rl_feedback", END)

workflow.set_entry_point("user_interaction")
app = workflow.compile()

# Streamlit interface
st.title("BrandMate: LinkedIn Post Generator")
user_input = st.text_input("Enter your post requirements:")
if st.button("Generate Post"):
    initial_state = {"user_input": user_input}
    result = app.invoke(initial_state)
    st.write("**Generated Post:**", result["post"])
    st.write("**Metrics:**", result["metrics"])
    st.write("**Feedback:**", result["feedback"])
    st.write("**Q-table:**", result["q_table"])
```

Listing 1: LangGraph Workflow with Streamlit Deployment

This code sets up the LangGraph workflow and provides a Streamlit interface for users to input requirements and view outputs, as shown in the deployment screenshots.

4 Final Deliverables

`BrandMate` provides:

01 SEO-Optimized Post Text: Tailored LinkedIn post.

02 Recommended Hashtags: Trend-aware hashtags from `seo_agent`.

03 Schedule-to-Post: Automated scheduling recommendations.

04 Performance Tracker: Real-time metrics (likes, comments, shares).

05 Feedback Dashboard: RL-driven insights and Q-table suggestions.

Table 2: Before and After Using BrandMate

Metric	**Before**	**After**
Time to create a post	∼3–4 hours	< 15 minutes
Post performance insights	Manual brainwork	Real-time metrics + reinforcement learning
SEO optimization	Applied with third-party services / not applied	Automated, dynamic keyword and trend integration
Brand consistency	Inconsistent	Tone/style aligned with goals via strategy agents

5 Before and After Comparison

The table above shows how `BrandMate` transforms content creation, reducing post creation time, automating SEO, providing RL-driven insights, and ensuring brand consistency, enabling influencers to focus on strategy and engagement.

6 Team Contributions

The `BrandMate` project was developed by:

- **Aruni Saxena**: Designed and implemented core agents (`user_interaction_agent`, `brand_identity_agen` `content_strategist_agent`, `content_generator_agent`).
- **Anandita Saolapurkar**: Developed the `seo_agent`, `post_editor_agent`, and `publishing_agent`.
- **Rishi Barapatre**: Engineered the `rl_feedback_agent` with Q-learning.
- **Paarth Patel**: Architected the technical stack, integrating LangGraph and dependencies.

7 Additional Notes or Reflections

7.1 Development Process

Development began with user interviews, followed by a multi-agent design using LangGraph. Aruni and Anandita developed agent logic, Rishi focused on RL, and Paarth integrated the tech stack.

7.2 Challenges and Failed Attempts

- **RL Deployment Challenge**: The `rl_feedback_agent` has not been deployed live. Complex Q-table designs slowed convergence; simplified to `bold_short` and `bold_long`.
- **SEO Agent Integration**: SerpAPI rate limits required mock data fallbacks.
- **State Management**: Inconsistent `BrandMateState` updates were fixed with `TypedDict`.

7.3 Lessons Learned

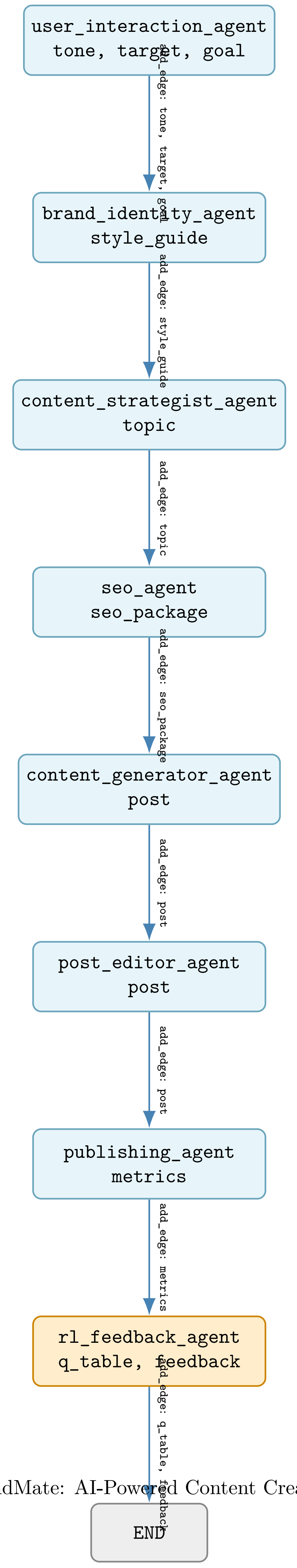
- Modular design needs robust state validation.
- RL requires careful tuning of α and γ.
- API dependencies need fallbacks.

7.4 Planned Fixes

- ▷ **RL Deployment**: Test with real LinkedIn data, expanding Q-table states.
- ▷ **Feedback Dashboard**: Develop a user-facing interface.
- ▷ **SEO Handling**: Implement caching for SerpAPI.

8 Workflow Diagram

The diagram shows the `BrandMate` workflow, with the RL agent highlighted.



BrandMate: AI-Powered Content Creation

9 Reinforcement Learning Agent

The `rl_feedback_agent` uses Q-learning to optimize post strategies.

9.1 Q-Learning Framework

Q-learning updates a Q-table mapping state-action pairs to rewards. States combine tone and post structure (e.g., `bold_short`), with actions mirroring states. The Q-table is in `state["q_table"]` (e.g., `{"bold_short": 0.0, "bold_long": 0.0}`).

The update rule is:

$$Q(s,a) \leftarrow (1-\alpha)Q(s,a) + \alpha\left(r + \gamma \max_{a'} Q(s',a')\right)$$

where:

- ▷ $Q(s,a)$: Q-value for state s and action a.
- ▷ $\alpha = 0.1$: Learning rate.
- ▷ r: Reward from metrics.
- ▷ $\gamma = 0.9$: Discount factor.
- ▷ $\max_{a'} Q(s',a')$: Maximum Q-value for the next state.

9.2 Reward Calculation

The reward is:

$$r = \frac{0.5 \cdot \text{likes} + 1.0 \cdot \text{comments} + 0.7 \cdot \text{shares}}{100}$$

Comments are prioritized (1.0), followed by shares (0.7) and likes (0.5).

9.3 Implementation

The RL agent's code is:

```python
def rl_feedback_agent(state: BrandMateState) -> BrandMateState:
    if "q_table" not in state:
        state["q_table"] = {
            "bold_short": 0.0,
            "bold_long": 0.0
        }
    current_state = f"{state['tone']}_short"
    action = current_state
    metrics = state["metrics"]
    reward = (metrics["likes"] * 0.5 + metrics["comments"] * 1.0 +
       metrics["shares"] * 0.7) / 100
    alpha, gamma = 0.1, 0.9
    state["q_table"][action] = (1 - alpha) * state["q_table"][action]
       + alpha * (reward + gamma * max(state["q_table"].values()))
    best_action = max(state["q_table"], key=state["q_table"].get)
    state["feedback"] = f"Reward: {reward:.2f}. Suggest: Use
       {best_action.replace('_', ' ')} for next post."
    print(f"Feedback: {state['feedback']}")
    print(f"Q-table: {state['q_table']}")
    return state
```

Listing 2: RL Feedback Agent

The agent:

- Initializes the Q-table.
- Forms the state (e.g., `bold_short`).
- Computes the reward from `metrics`.
- Updates the Q-table.
- Suggests the best action and updates `state["q_table"]` and `state["feedback"]`.

9.4 Addressing the Problems

The RL agent tackles:

- **Poor Performance Insight**: Provides metrics analysis and Q-table suggestions.
- **Content Evolution**: Adapts strategies via the feedback dashboard.

10 Example Execution

The workflow is invoked as:

```
initial_state = {
    "user_input": "Create a high-engagement LinkedIn post, emotional
       tone, for women startup founders, to grow followers"
}
result = app.invoke(initial_state)
print("Generated Post:", result["post"])
print("Metrics:", result["metrics"])
print("Feedback:", result["feedback"])
print("Q-table:", result["q_table"])
```

Listing 3: Invoking BrandMate

11 Project Resources and Links

The following resources document the `BrandMate` project:

- **Final Presentation Slides**: Available at `https://www.canva.com/design/DAGobAdE05U/Te5QAhm_Ymb4fe9yFNC8nA/edit`.
- **Demo Link**: The Streamlit deployment is demonstrated through three screenshots, available in the project repository and presentation, showcasing the user interface and outputs.
- **GitHub Code Repository**: Source code, including a `readme.md`, is hosted at `https://github.com/Aruni20p/BrandMate/tree/main`.
- **Video Recording**: A video of the initial deployment on Relevance AI, before transitioning to LangGraph for flexibility, is available at https://drive.google.com/file/d/1D3OgFBFEw5Fj9we0ciY0uifoU
This highlights the shift from a no-code platform to a code-based solution.

12 Conclusion

`BrandMate`, developed by Aruni Saxena, Paarth Patel, Rishi Barapatre, and Anandita Saolapurkar, addresses:

- **Consistent Brand Messaging**: Ensures style via `brand_identity_agent`.
- **Trends**: Integrates keywords via `seo_agent`.
- **Performance Insight**: RL-driven insights via `rl_feedback_agent`.
- **Burnout**: Reduces creation time to <15 minutes.

The deliverables and resources empower influencers, though RL deployment remains a challenge.