

HOMEWORK2 PART1

The architecture of my CV verification system is based on a modular design with a Large Language Model and other tools integrated using the Model Context Protocol. To ensure accurate identity verification, I have also integrated a "Nearest Profile" rule where university and major employer information is prioritized over potentially noisy information like city locations and job titles. The verification process begins with a broad search on LinkedIn to fetch candidate IDs. It then takes a "Deep Dive" into individual profiles to verify educational qualifications and professional history.

```
SYSTEM_PROMPT = """You are a highly analytical CV Verification Agent designed for recruitment compliance and KYC (Know Your Customer). Your goal is

### I. MANDATORY GUIDING PRINCIPLES (IA QA COMPLIANT):
1. **The "Nearest Profile" Rule**: Every CV is derived from a real profile in the database. You MUST find the profile that shares the most core
2. **Prioritize Hard Facts**:
    - High Weight: University names, Degree levels (BSc/PhD), and Employer/Company names[cite: 153].
    - Low Weight (Noise-Prone): Specific city locations, exact Job Titles, and Skill names[cite: 118, 119].
3. **No Pre-Verification Rejection**: Do NOT reject a CV based on internal inconsistencies (e.g., impossible locations or overlapping dates) before it

### II. VERIFICATION WORKFLOW:
1. **Broad Identity Search**:
    - Start by searching the candidate's name using `search_linkedin_people` without location or industry filters to avoid missing profiles due to
    - Use `fuzzy=True` if an exact name search returns no results[cite: 259].
2. **Detailed Profile Analysis**:
    - Iterate through the top 3-5 profile IDs using `get_linkedin_profile`[cite: 271].
    - Match profiles based on the **School Name** and **Major Employers** listed on the CV.
3. **Social Presence & Network Strength**:
    - Use `search_facebook_users` to cross-verify personal details such as `hometown` or `original_name`[cite: 161, 191].
    - Optionally use `get_linkedin_interactions` to assess if the candidate has a realistic professional network[cite: 317].
4. **Discrepancy Detection**:
    - Compare degrees (e.g., CV claims PhD, but MCP shows BSc)[cite: 154].
    - Check timelines for logical impossibilities (e.g., two full-time "Senior" roles in different countries simultaneously).

### III. SCORING & REPORTING LOGIC:
- **RELIABILITY_SCORE > 0.5 (PASS)**: The candidate exists. Discrepancies are minor (typos in cities, varied job titles, or unconventional degree names).
- **RELIABILITY_SCORE <= 0.5 (FAIL)**: Clear evidence of fabrication, such as claiming non-existent high-level degrees, false employers, or complete fabrication.

### IV. OUTPUT FORMAT:
1. **Verification Summary**: List what matched and what didn't.
2. **Flagged Issues**: Highlight major red flags (e.g., Degree mismatch).
3. **Final Conclusion**: You MUST end with exactly this format:
RELIABILITY_SCORE: [float between 0.0 and 1.0]
"""


```

The decision-making process is carried out according to a systematic workflow. First, it fetches key information from the PDF CV using MarkItDown. It then utilizes the SocialGraph MCP server to cross-check this information with LinkedIn and Facebook data. The agent is programmed to look for specific discrepancies like a candidate claiming a PhD when they only have a BSc or working full-time in different countries. The final score is then computed according to the weight of these findings. A score below 0.5 is achieved if there is major fabrication.

```
=====  
Processing: CV_4.pdf  
=====  
Agent is thinking...  
Calling: search_linkedin_people | Args: {'q': 'Rahul Sharma'}  
→ Result: [{"id":4,"name":"Rahul Sharma","headline":"Education Professional","industry":"Education","location"...}  
Calling: get_linkedin_profile | Args: {'person_id': 7}  
→ Result: {"id":7,"name":"Rahul Sharma","headline":"Legal Professional","city":"Sha Tin","country":"Hong Kong"...}  
Calling: get_linkedin_profile | Args: {'person_id': 91}  
→ Result: {"id":91,"name":"Rahul Sharma","headline":"Legal Professional","city":"Cebu","country":"Philippines"...
```

```
Finished CV_4.pdf  
Score: 0.4  
Report Snippet: Verification Summary:  
* **Name:** Rahul Sharma - Matched on LinkedIn (Profile ID 91) and Facebook (Profile ID 100).  
* **Education:**  
* CV: P...
```

```
=====  
Processing: CV_5.pdf  
=====  
Agent is thinking...  
Calling: search_linkedin_people | Args: {'q': 'Rahul Sharma'}  
→ Result: [{"id":4,"name":"Rahul Sharma","headline":"Education Professional","industry":"Education","location"...}  
Calling: get_linkedin_profile | Args: {'person_id': 95}  
→ Result: {"id":95,"name":"Rahul Sharma","headline":"AI Professional","city":"Kowloon","country":"Hong Kong","...}  
Calling: get_linkedin_profile | Args: {'person_id': 552}  
→ Result: {"id":552,"name":"Rahul Sharma","headline":"AI Professional","city":"Seattle","country":"USA","indus...}  
Calling: get_linkedin_profile | Args: {'person_id': 12}  
→ Result: {"id":12,"name":"Rahul Sharma","headline":"Logistics Professional","city":"London","country":"UK","i...}  
Calling: search_facebook_users | Args: {'q': 'Rahul Sharma'}  
→ Result: [{"id":4,"display_name":"Rahul Sharma","city":"Berlin","country":"Germany","match_type":"exact"}, {"i...
```

```
Finished CV_5.pdf  
Score: 0.3  
Report Snippet: Verification Summary:
```

The effectiveness of the system was also validated using the sample CVs provided. In the case of Rahul Sharma, the agent correctly identified discrepancies in education and professional history. Therefore, it gave a low reliability score. In the case of Wei Zhang, the agent correctly verified a perfect match between the CV and online footprint. Therefore, it gave a high reliability score. The automated process saves significant manual labor in recruitment compliance and KYC verification.

== Evaluation Result ==

```
'decisions': [1, 1, 1, 0, 0], 'correct': 5, 'total': 5, 'final_score': 1.0}
```