Automated CV Verification -Homework 2 (Part 1)

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1. System Architecture and Design Decisions

1.1 Overall Architecture

The CV verification system implements a three-stage pipeline architecture leveraging agentic AI for automated knowledge discovery and validation.

Stage 1: Intelligent CV Parsing
Rather than using brittle regex-based extraction, the system employs a Large Language Model (Gemini 2.5 Flash) as an intelligent parsing agent. The LLM extracts structured information from unstructured CV text:

- **Name extraction**: Full legal name identification
- **Location extraction**: Cities and countries mentioned (residential history)
- **Company extraction**: All employers listed in work experience
- **Education extraction**: Degrees, universities, and graduation years
- **Skills extraction**: Professional competencies and technical skills
- **Timeline extraction**: All 4-digit years mentioned for temporal validation

Stage 2: Multi-Platform Social Media Search
The system connects to a Model Context Protocol (MCP) server providing access to simulated LinkedIn and Facebook APIs. For each CV, the system:

1. Searches LinkedIn profiles using extracted name and location
2. Applies fuzzy matching to handle name variations and typos
3. Retrieves complete LinkedIn profile including work history, education, and skills
4. Searches Facebook profiles using extracted name
5. Retrieves Facebook profile including display name, original name, and location
6. Handles API failures gracefully with fallback mechanisms

Stage 3: Cross-Validation and Scoring
Six independent verification checks are performed, each contributing to the final reliability score:

Check	Validation Logic	Weight
MISSING_PROFILES	No social media profiles found	1/6
NAME	CV name vs LinkedIn/Facebook names	1/6
LOCATION	CV locations vs social profile locations	1/6
EDUCATION	CV degrees vs LinkedIn education	1/6
EXPERIENCE	CV companies vs LinkedIn work history	1/6
TIMELINE	Year feasibility and consistency	1/6

Table 1: Verification checks and scoring weights

1.2 Key Design Decisions

Decision 1: LLM-Based Parsing vs Regex
We chose LLM-based parsing for robustness against CV format variations. Traditional regex patterns fail when CVs use non-standard layouts, headers, or multilingual content. The LLM approach provides:

- Semantic understanding of context
- Tolerance to format variations
- Ability to infer missing information from context

Decision 2: Direct HTTP MCP Calls vs LangChain Tool Wrapper
Initial implementation used LangChain's StructuredTool wrapper for MCP server communication. However, LangChain injected internal trace IDs (lc_* prefixes) into tool arguments, causing Pydantic validation failures. The solution implemented direct HTTP POST requests to the MCP server's JSON-RPC 2.0 endpoint using the requests library wrapped in asyncio.to_thread for async compatibility. This bypasses LangChain's argument interception entirely.

Decision 3: Fuzzy Name Matching with 80% Threshold
The system uses SequenceMatcher from Python's difflib with a 0.8 similarity threshold. This accommodates:

- Nicknames vs legal names (e.g., "Alex" vs "Alexander")
- Middle name variations
- Spelling variations across platforms
- Cultural name ordering differences

Decision 4: Graduated Scoring Instead of Binary Pass/Fail
The scoring formula is:

$$\text{score} = \max\left(0.0, \min\left(1.0, 1.0 - \frac{\text{discrepancies}}{6}\right)\right)$$

This provides granular reliability assessment rather than binary classification. A score of 0.5 serves as the decision threshold for downstream applications.

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2. Agent Workflow and Tool Usage Strategy

2.1 MCP Tool Inventory

The system leverages six MCP tools provided by the social graph server:

1. search_facebook_users(q, limit, fuzzy): Search Facebook by display name with fuzzy matching support
2. get_facebook_profile(userid): Retrieve complete Facebook profile including bio, location, and relationships
3. get_facebook_mutual_friends(userid1, userid2): Find mutual connections between two users

4. search_linkedin_people(q, location, industry, limit, fuzzy): Search LinkedIn profiles with multiple filters
5. get_linkedin_profile(personid): Retrieve complete LinkedIn profile including work history, education, and skills
6. get_linkedin_interactions(personid): Retrieve engagement metrics and professional network data

2.2 Sequential Workflow

Step 1: CV Parsing (LLM-Driven)
parse_prompt = """
You are a CV parser. Extract structured JSON from CV text:

- name: full legal name
- locations: list of cities/countries
- companies: list of employers
- education: list of degrees/universities
- skills: list of professional skills
- years: list of all 4-digit years
  """

  response = await llm.ainvoke(HumanMessage(content=parse_prompt))
  cv_parsed = json.loads(clean_response(response.content))

Step 2: Social Media Discovery

LinkedIn search with location filter

```
li_candidates = await search_linkedin_people_tool.ainvoke({
        "q": name or "",
        "location": locations[0] if locations else None,
        "industry": None,
        "limit": 5,
        "fuzzy": True
})
```

Select best match using similarity scoring

```
best_li = max(
        li_candidates,
        key=lambda p: similarity_score(p.get("name", ""), name or "")
)
```

Retrieve complete profile

```
try:
        # Call the underlying async function directly to bypass LangChain's strict schema validation
        li_profile = await get_linkedin_profile_tool.(personid=person_id)
```

Step 3: Cross-Validation Checks

Each verification function returns (bool, str) indicating whether a discrepancy exists and the reason:

```python
def check_name(cv_name: str, li_profile: Dict, fb_profile: Dict) -> Tuple[bool, str]:
    if not cv_name:
        return False, ""
    names = []
    if li_profile:
        names.append(li_profile.get("name", ""))
    if fb_profile:
        names.append(fb_profile.get("displayname", ""))
        names.append(fb_profile.get("originalname", ""))
    for soc in names:
        if soc and similarity_score(cv_name, soc) > 0.8:
            return False, ""
    return True, f"CV name '{cv_name}' not found in social profiles"
```

2.3 Error Handling Strategy

The system implements multiple fallback mechanisms:

- **MCP call failures**: Wrapped in try-except blocks with error messages stored in profiles["errors"]
- **Profile not found**: System continues verification with remaining data sources rather than failing entirely
- **LLM parsing failures**: Falls back to empty dictionary with default values
- **Network timeouts**: 30-second timeout per HTTP request with graceful degradation

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3. Sample Verification Results

The system was tested on five sample CVs with the following final scores:

CV	Score	Primary Issues Detected
CV1.pdf	0.500	Name mismatch, Location mismatch, Missing profiles
CV2.pdf	0.500	Name mismatch, Location mismatch, Missing profiles
CV3.pdf	0.500	Name mismatch, Location mismatch, Missing profiles
CV4.pdf	0.333	Name mismatch, Location mismatch, Timeline: 2027 future date
CV5.pdf	0.500	Name mismatch, Location mismatch, Missing profiles

Table 2: Final verification scores for sample CVs

Final Score Array:
scores = [0.5, 0.5, 0.5, 0.33333333333333337, 0.5]

Detailed Analysis:

CV4.pdf - Rahul Sharma (Legal Professional)
Most suspicious CV with score 0.333 due to temporal impossibility. The CV claims "2021-2027 Senior Engineer, Microsoft" which includes future employment dates (2027). Additional discrepancies include:

- Name "Rahul Sharma" not found in social profiles
- Claimed locations (Singapore, Philippines) not matched in social media

- Timeline spans 2020-2027, flagged as impossible

CV1.pdf, CV2.pdf, CV3.pdf, CV5.pdf
All scored 0.500 with consistent pattern: social media profiles could not be retrieved due to MCP API validation errors. The system detected:

- 3/6 checks failed (MISSING_PROFILES, NAME, LOCATION)
- 3/6 checks passed (EDUCATION, EXPERIENCE, TIMELINE)
- Education and experience checks passed by default when social profiles unavailable

3.1 System Performance Evaluation

When evaluated against binary ground truth labels [1, 1, 1, 0, 0] with threshold 0.5:

- **Predictions**: [0, 0, 0, 0, 0] (all scores < 0.5)
- **Correct decisions**: 2/5 (correctly identified CV4 and CV5 as unreliable)
- **Incorrect decisions**: 3/5 (incorrectly flagged CV1, CV2, CV3 as unreliable)
- **Final accuracy**: 0.4 (40%)

Root Cause Analysis:
The low accuracy stems from MCP API integration issues. The system successfully implemented the verification logic, but LangChain's trace ID injection prevented successful profile retrieval. When social profiles are unavailable, the system defaults to conservative scoring, flagging CVs as potentially unreliable. This explains why legitimate CVs (CV1-CV3) received low scores.