FTEC5660 Homework2 CV Verification System Report

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This report documents the design and implementation of an agentic AI system for automated CV verification against social media profiles. The system leverages MCP (Model Context Protocol) tools to access LinkedIn and Facebook data, employs Gemini 2.5 Flash for natural language understanding, and implements a three-stage verification pipeline. Tested on 5 sample CVs, the system achieved 100% accuracy in correctly identifying genuine and fabricated CVs, with detailed reasoning provided for each case. The system architecture separates concerns between data acquisition, intelligent analysis, and user presentation, ensuring modularity and transparency throughout the verification process.

1 System Architecture and Design Decisions

The CV Verification System is built on a three-layer agentic architecture that separates concerns between data acquisition, intelligent analysis, and user presentation. This design was chosen to maximize modularity, allowing each layer to be developed, tested, and improved independently. The architecture is also designed to be extensible, enabling future integration of additional social media platforms or verification tools without disrupting the core workflow.

1.1 Layer 1: MCP Tool Integration Layer

The foundation of the system is the connection to a SocialGraph MCP (Model Context Protocol) server, which provides standardized access to social media data without requiring custom API integrations or handling authentication complexities. The MCP protocol abstracts away the underlying implementation details of each social media platform, presenting a uniform interface to the agent. This design decision was critical for maintaining focus on the verification logic rather than data acquisition plumbing.

The system utilizes six MCP tools throughout the verification process. The primary tools are search_linkedin_people and get_linkedin_profile, which handle professional background verification. Secondary tools include search_facebook_users and get_facebook_profile for personal information verification, along with get_facebook_mutual_friends for social connection validation and get_linkedin_interactions for professional engagement assessment. The agent establishes a single connection to the MCP server at startup and maintains a dictionary of available tools for efficient access throughout the verification pipeline.

1.2 Layer 2: Core Agent Logic Layer

The agent implements a three-stage verification pipeline that progressively builds confidence in the verification result. This staged approach was designed to balance thoroughness with efficiency, performing lightweight filtering before committing to more computationally expensive analysis.

Stage 1: Structured Information Extraction

The first stage uses Gemini 2.5 Flash to parse unstructured CV text into a structured JSON format. This is critical because raw CV text varies widely in formatting, and structured data enables precise comparison with LinkedIn profiles. Using an LLM for extraction rather than regex or rule-based parsing provides robustness against formatting variations. The prompt is carefully crafted to instruct the model to return ONLY valid JSON without markdown wrapping, ensuring clean parsing. The extracted structure includes full name, location, education history with degrees and institutions, work experience with companies and dates, and skills.

Stage 2: Weighted Profile Matching

The second stage implements a heuristic-based matching algorithm that scores potential LinkedIn profiles against the extracted CV data. Rather than relying solely on LLM judgment for initial filtering, the system uses explicit weighting based on the distinctiveness of different types of information. Companies receive the highest weight at three points because employment history is the strongest identifier of professional identity. Schools receive two points as they are also highly distinctive but slightly less so than companies. Location receives one point as supporting evidence but is the least distinctive, as many people share locations.

The algorithm examines the top five search results from search_linkedin_people, retrieves full profiles via get_linkedin_profile, and computes match scores. This approach balances thoroughness with efficiency, as checking all twenty-plus results would be too time-consuming, while checking only five captures the most relevant matches. For each profile, the system compares companies and schools from the CV against those in the LinkedIn profile, and checks for location alignment. The total match score determines which profile proceeds to deep analysis.

Stage 3: Human-Like LLM Analysis

After identifying the best matching profile, the system engages Gemini for deep discrepancy analysis. This stage is designed to emulate how a human recruiter would evaluate a CV against a LinkedIn profile. The analysis follows a structured step-by-step process examining education, work experience, location and industry, before synthesizing an overall human judgment.

A key design decision was to include explicit scoring guidelines in the prompt that forbid defaulting to 0.5. This forces the model to make nuanced judgments across seven distinct score bands. Scores of 0.95 to 1.00 represent perfect matches with all key information aligning exactly. Scores of 0.85 to 0.94 indicate excellent matches with only minor, insignificant differences. Scores of 0.70 to 0.84 represent good matches with some small discrepancies but core information matching. Scores of 0.60 to 0.69 indicate fair matches with noticeable discrepancies but still probably the same person. Scores of 0.40 to 0.59 represent mixed matches with significant discrepancies where identity is uncertain. Scores of 0.20 to 0.39 indicate poor matches with major discrepancies suggesting different individuals. Scores below 0.19 represent complete mismatches where the profiles clearly belong to different people.

1.3 Layer 3: Visualization and Reporting Layer

A distinctive feature of this system is its real-time process visualization. Every step of the verification process is printed with clear formatting, including ASCII box diagrams that organize information hierarchically. This design choice was motivated by the importance of transparency in agentic AI systems. By showing exactly what the system is doing at each step, users can verify the reasoning behind each score and debug any issues that arise.

The reporting system generates a comprehensive Markdown document that includes a summary table with scores and verdicts, detailed analysis for each CV including the complete LLM reasoning process, and a final scores list ready for submission. This report serves as both documentation of the verification results and as a deliverable for the homework assignment.

2 Agent Workflow and Tool Usage Strategy

2.1 Step-by-Step Workflow

The agent follows a systematic six-step workflow that mirrors human investigation while leveraging automation for speed and consistency. Each step is designed to maximize information gain while minimizing unnecessary API calls.

Step 1: CV Information Extraction

The process begins with the agent receiving raw CV text and sending it to Gemini 2.5 Flash with a prompt specifying the required JSON structure. The prompt explicitly forbids markdown wrapping to ensure clean parsing. This separation of concerns keeps CV parsing, a language understanding task, with the LLM while delegating data retrieval to specialized MCP tools.

Step 2: LinkedIn Search

With structured data available, the agent searches for matching LinkedIn profiles using the candidate's full name without location filtering to maximize recall. The search tool is called with three parameters: the full name as the query, a limit of thirty for comprehensive coverage, and fuzzy matching enabled to handle spelling variations and typos.

Step 3: Profile Evaluation

For the top five search results, the agent retrieves complete profiles using get_linkedin_profile with the person ID from each result. This step is computationally intensive but critical, as search results contain only basic information while full profiles provide the detailed history needed for verification.

For each retrieved profile, the agent extracts companies from LinkedIn work experience and compares them against CV companies, records school matches by comparing institutions, and checks location alignment. A weighted match score is calculated with companies contributing three points per match, schools contributing two points per match, and location contributing one point if aligned.

Step 4: Best Match Selection

The agent selects the profile with the highest match score, with ties resolved by choosing the first encountered as search results are relevance-ordered. Preliminary verdicts are generated based on score thresholds: scores of four or higher indicate strong matches, scores between two and four indicate partial matches, and scores below two indicate weak matches suggesting different individuals.

Step 5: Deep Discrepancy Analysis

This step represents the core of agent intelligence. The LLM performs structured analysis comparing education institutions, degrees, and years, examining work experience companies, titles, dates, and current status, evaluating location and industry alignment, and synthesizing all factors into an overall human judgment. The prompt includes explicit scoring guidelines across seven bands and requires separate lists for matches and discrepancies, ensuring transparent reasoning.

Step 6: Report Generation

Finally, the agent compiles findings into a comprehensive report with summary tables for quick reference and detailed analysis for each CV including complete LLM reasoning, match and discrepancy lists, and final verdicts with scores.

2.2 Tool Usage Patterns

The system demonstrates three distinct tool usage patterns. Sequential tool chaining connects search_linkedin_people to multiple get_linkedin_profile calls before final analysis. Conditional tool selection skips deep LLM analysis when match scores are very low, saving API calls. Mixed tool types combine MCP tools for data retrieval with direct LLM invocation for analysis and extraction.

3 Sample Verification Results

To evaluate the system's performance, we tested it on five sample CVs provided in the homework assignment. These CVs included a mix of genuine and fabricated documents, allowing us to assess the system's ability to correctly identify discrepancies and assign appropriate consistency scores. The ground truth labels for these five CVs were provided, with the first three being genuine documents and the last two containing fabricated information. The system processed each CV through the complete three-stage pipeline described in previous sections, generating both quantitative scores and qualitative analysis for each case.

3.1 Generated Report Sample

After processing all CVs, the system automatically generates a comprehensive Markdown report. Figure 1 below shows a sample of this generated report, which includes a summary table of all results followed by detailed analysis for each CV. The report format is designed to be both human-readable and suitable for submission as part of the homework deliverables.

````
### CV 1: CV_1.pdf - John Smith

**Final Score:** 0.65
**Human Verdict:** probably_same_person

**LLM Reasoning Process:**
```
1.  **Name Comparison:** The full name 'John Smith' matches perfectly on both documents. This is a strong initial indicator of the same person.
2.  **Location Comparison:** The location 'Singapore, Singapore' on the CV matches the city and country 'Singapore' on LinkedIn. This is a perfect match.
3.  **Education Comparison:** The institution 'McGill University' matches exactly. The degree 'Bachelor of Science (BSc) in Marketing' on the CV is fully consistent with
'BSc' and 'Marketing' on LinkedIn. The graduation year '2009' also matches perfectly. This section is a perfect match.
4.  **Work Experience Comparison:** The company 'ByteDance', title 'Engineer', and start year '2020' all match perfectly. However, the CV states 'Present' for the end
date, implying current employment, while LinkedIn explicitly states `is_current: false`. This is a critical and direct contradiction. A human recruiter would view this as
a significant discrepancy regarding the individual's current employment status.
5.  **Skills Comparison:** All three listed skills ('Content Creation', 'SEO', 'Social Media') are present on both documents, indicating consistency in reported
abilities.
6.  **Overall Judgment:** While there are numerous strong matches across name, location, education, skills, and the core details of the work experience (company, title,
start year), the direct contradiction regarding current employment at ByteDance is a major red flag. It suggests either an outdated CV or an attempt to misrepresent
current employment. Despite this significant discrepancy, the sheer volume of other matching data points makes it highly probable that it is the same person, but with a
critical inconsistency that would require immediate clarification. This falls into the 'Fair match' category.
```

**✅ What Matches:**
- Full Name: John Smith
- Location: Singapore, Singapore
- Education Institution: McGill University
- Education Degree: Bachelor of Science (BSc) in Marketing (substantially matching)
- Education End Year: 2009
- Work Experience Company: ByteDance
- Work Experience Title: Engineer
- Work Experience Start Year: 2020
- Skills: Content Creation
- Skills: SEO
- Skills: Social Media

**❌ Discrepancies Found:**
- The CV states 'Present' for the ByteDance work experience end date, while the LinkedIn profile states `is_current: false` for the same role, indicating the person is
not currently employed there. This is a direct contradiction regarding current employment status.
````

Figure1: report screenshot

3.2 Final Scores Summary

The system achieved 100% accuracy on the test set, correctly classifying all five CVs against the ground truth labels. The first three CVs, which were genuine, received scores above the 0.5 threshold (0.65, 0.95, and 0.65 respectively). The last two CVs, which were fabricated, received scores below the 0.5 threshold (0.00 and 0.05 respectively).

Final Scores List for Submission: [0.65, 0.95, 0.65, 0.0, 0.05].

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✅ Accuracy: 100.0% (5/5)

======================================================================
📊 FINAL SCORES FOR SUBMISSION
======================================================================
CV_1.pdf: 0.65 (probably_same_person)
CV_2.pdf: 0.95 (clearly_same_person)
CV_3.pdf: 0.65 (probably_same_person)
CV_4.pdf: 0.00 (unknown)
CV_5.pdf: 0.05 (clearly_different)

📊 Scores List: [0.65, 0.95, 0.65, 0.0, 0.05]
```

Figure 2: final sample results