Accelerating Criminal Investigations with TRACY

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Abstract. Effective investigation of criminal cases increasingly depends on the ability to correlate both content data (e.g., call audio, text messages, or email bodies) and non-content data (NCD)—metadata such as subscriber details, traffic/logs, and location information—with supporting evidence like surveillance footage and witness testimonies. This reliance aligns with and is underscored by the European Commission's ongoing efforts to regulate and study the retention of NCD, recognizing its critical role in law enforcement and public safety. A primary challenge for Law Enforcement Agencies (LEAs) is processing the massive volumes of data lawfully obtained from Communication Service Providers (CSPs). Even when constrained in time and space (e.g., a 4-hour window within a 2×2km area), mobile signaling records can exceed one million entries. To address this, we propose TRACY, a framework that scans large-scale signaling communication logs to identify terminals located near key evidence points during a crime, relying solely on encrypted terminal identifiers. We propose three core analytical methods within TRACY: (Method-1) scoring individuals based on spatiotemporal proximity to evidence, (Method-2) detection of co-located individuals within short time intervals to infer potential coordination, and (Method-3) network analysis of communication data to assess individual influence and connectivity. These methods are combined through a final scoring mechanism that robustly ranks suspects by integrating both spatial-temporal and behavioral indicators. To further enhance suspect discovery, TRACY Canvas, an in-house developed tool, provides an interactive platform to visualize suspect relationships and explore supporting evidence. It allows investigators to interpret data-driven findings more intuitively and investigate connections between individuals identified through TRACY's analytical pipeline. We deployed the integration on realistic data and evaluated it through two synthetic case studies: (1) a demo robbery in Athens and (2) a Zurich drug-related scenario involving three suspects from ROXANNE Simulated Data (ROXSD). Results show that combining spatial-temporal inference and communication behavior significantly improves detection rates, revealing suspects initially missed by physical presence inference alone. The system demonstrates high hit rates in identifying true suspects and accelerates investigations while complying with European privacy regulations.

Keywords: TRACY · Non-Content data · Law Enforcement Agencies · Suspect Detection· Mobile Signaling Data · ROXANNE

1 Introduction

The rapid growth of digital communications has significantly transformed the landscape of criminal investigations. Law Enforcement Agencies (LEAs) can nowadays lawfully request and access vast amounts of data (for a limited time) from Communication Service Providers (CSPs), which offers new opportunities for more effective investigation of criminal cases [5]. However, the large volume and complexity of this data present a substantial challenge. Investigators are tasked with sifting through massive datasets that include Call Detail Record (CDR): including metadata about phone calls (CALLs) or messages (SMS), and Data Usage Detail Record (DDR): metadata about mobile data sessions, such as internet usage, app activity, and IP sessions over mobile networks. Both CDR and DDR can be used to track a terminal's overall communications activity (voice and data) and location patterns based on cell tower information, allowing to uncover meaningful patterns of behavior and lead to suspect identification. The motivation for this paper stems from the need to speed up criminal investigations by considering both content and non-content communication data, and correlating it with additional surveillance evidence such as Closed-Circuit Television (CCTV) footage and witness testimonies. Specifically, our focus is on addressing the complexities of processing large amounts of data that is both time and location-restricted —often limited to small windows of time and specific geographic areas (e.g., a 4-hour window within a $2 \times 2\,\mathrm{km}$ area surrounding a crime scene) [21].

In this context, TRACY [1] (A bigdata analyTics from base-stations Registrations And Cdrs e-evidence sYstem) stands out as a solution that analyzes mobile signaling datasets to pinpoint devices that were located near crime scenes at the time of the incident. It operates without needing access to call content, instead utilizing encrypted terminal identifiers and mobile network topology to draw insights. By processing massive amounts of non-content CDR and DDR metadata, TRACY significantly speeds up the process of identifying relevant (and potentially suspect) terminals during criminal investigations.

Although content is unavailable, valuable metadata such as cell ID, timestamp, and tower geolocation is retained. For privacy preservation, this information is aggregated into $2 \times 2, \mathrm{km}$ spatial grid cells. The dataset is dominated by DDR signaling records (approximately 95%), with CDR (CALL and SMS) contributing 5%. To quantify the terminal's relevance to a case, we introduce

[1] https://www.tracy-project.eu/

a scoring mechanism based on evidence intervals-time windows as reported by LEAs when the crime is believed to have occurred. An evidence point is a specific location and time where a key event occurred or was captured (e.g., crime scene, CCTV footage). It helps track when and where something happened and can be marked as critical or non-critical based on its importance.

Prior work in behavioral analysis and mobile data mining has explored the use of geo-positional and communication patterns to understand human behavior [18, 4, 20]. However, our work stands apart by integrating spatial-temporal heuristics with behavioral scoring in a unified system aimed at real-world criminal investigation scenarios.

We propose three core methods within the TRACY framework to identify and rank suspects from large-scale mobile signaling data collected near crime events. TRACY Method-1 scores individuals based on their spatio-temporal proximity to key evidence points—locations and times where a crime-related event occurred (e.g., crime scenes, CCTV detections). This method identifies terminals frequently or closely present at these evidence points during the critical window. Following the individual-level suspect scoring of TRACY Method-1, TRACY Method-2 [17] shifts the focus to relational analysis—identifying concurrent pairs of individuals who appear together at the same location within a one-minute interval, using synthetic terminal data. Such patterns help infer possible coordination or group activity among individuals. TRACY Method-3 builds on the successful application of network analysis features from the ROXANNE [2] project on real content data [23], [24], evaluating each terminal's connectivity and influence within the broader communication graph. Building upon the AUTOCRIME [13] platform developed under the ROXANNE project, we also present TRACY Canvas [12], a visualization tool developed entirely using open-source technologies to render complex communication networks. Through dynamic filtering, visual timelines, and geospatial mapping, TRACY Canvas helps bridge the gap between raw metadata and investigative reasoning. Investigators can visualize clusters of co-located individuals, inspect communication patterns, and cross-reference metadata with external evidence such as surveillance video timestamps. Together, these methods enable a comprehensive ranking mechanism that integrates spatial, temporal, and behavioral signals to prioritize individuals for investigation. The final suspect list is not only based on presence near evidence points, but also on their behavioral proximity to others involved, and their strategic position in the communication network. This fusion of physical and digital traces enables more robust suspect identification compared to traditional spatial-only filtering approaches.

Due to the inherent sensitivity and restricted access of real-world data related to criminal scenarios, the use of synthetic data has become indispensable in contemporary forensic research [7, 14, 13, 17, 3]. All data processing within the TRACY project is conducted in strict adherence to European privacy regulations, thereby ensuring both legal compliance and the ethical handling of per-

[2] https://www.roxanne-euproject.org/

sonal information in the context of criminal investigations. Notably, our study relies exclusively on synthetic non-content data to uphold these standards.

In this paper, we evaluated TRACY through synthetic case studies that simulate real-world investigative scenarios. These case studies, derived from the ROXANNE Simulated Dataset (ROXSD) [14], demonstrate how TRACY surfaces suspects overlooked by traditional spatiotemporal filters alone. In both scenarios—a street robbery in Athens and a drug trafficking case in Zurich—TRACY achieved high detection accuracy, successfully correlating location, co-presence, and behavioral indicators to identify suspects. These results underscore TRACY's potential to enhance digital investigations by accelerating suspect triage while preserving data privacy and regulatory compliance.

2 Prior Work

Mobile phone data has been widely used to analyze human behavior across land use, public health, transportation, and social networks [9, 1, 25, 11]. Since 2010, location-sharing apps like Foursquare, Yelp, and Gowalla have enabled users to check-in, promote venues, and express identity through location [19, 6].

Trajectory records are also used for pathfinding and travel recommendations based on GPS/WiFi data [25]. Co-occurrence in movement patterns often reflects latent social or contextual links. Such geolocation corpora have also supported synthetic mobility data generation [1, 9].

Smartphones act as rich forensic evidence sources, offering data across multiple sensors [16]. Leveraging this data, ML techniques applied to sensor data (e.g., accelerometer, gyroscope) show potential in classifying criminal activity [15]. However, such methods require physical access to devices, which is often infeasible in daily law enforcement.

Alternatively, mobile metadata offers valuable insight into population dynamics and criminal behavior. Cell tower logs and CDRs have been used to forecast crimes using models like random forests and regression, linking mobility patterns to crime rates [22, 2].

Nevertheless, access to real-world law enforcement data is restricted due to legal and privacy concerns [8, 10], hindering large-scale validation. Hence, synthetic data are essential in recent research. It mimics real-world complexity without exposing sensitive information and allows the design of scalable forensic tools.

Notably, Rangappa *et al.* [17] emphasize tracing suspect movements using Non-Content Data (NCD), integrating multiple sources. The TRACY project's use of synthetic NCD supports scalable, privacy-compliant investigation pipelines aligned with real evidence.

3 Problem Statement

3.1 Background and Motivation

Understanding human behavior in urban areas is key to urban planning and safety. Previous work has used mobile phone metadata to study this across cities and times [9, 11]. Despite dataset differences, the main challenge remains: how to analyze human presence and movement from coarse spatio-temporal data?

3.2 Limitations of Existing Approaches

Suspect identification often uses historical signaling records but faces issues:

1. **Spatial Resolution**: Location is approximated by CELL IDs, causing uncertainty from hundreds of meters near towers to kilometers in rural zones.
2. **Temporal Constraints**: Sparse and irregular signaling events hinder accurate mobility reconstruction.
3. **Prior Investigations**: Projects like TRACY show potential for criminal analysis but struggle to narrow suspects due to data imprecision.

3.3 The Challenge

We study a crime in a 2×2 km urban area with an initial suspect list from filtering. Refinement is needed within spatial (2 km) and narrow temporal bounds around the event.

How to accurately identify suspects using coarse mobile signaling data constrained by spatial and temporal proximity?

This is critical in urban surveillance, where millions interact with infrastructure continuously.

3.4 Spatio-temporal Evidence and Simulation Scenario

Identifying suspects near a crime scene using geolocated timestamps is key. We simulate this with four evidence points tagged by location and time.

Given millions of potential paths taken by individuals (simplified as black lines in Figure 1), the core objective is to identify suspects or potential perpetrators whose movement paths intersect with the reported evidence points, both spatially and temporally. For example, the green path corresponds to a suspect intersecting all four evidence points, while the red path intersects only two, suggesting varying levels of suspicion.

This problem extends further into:

1. Detecting and ranking suspects based on how closely their movement paths align with evidence points during the specified time intervals.
2. Enhancing spatial-temporal analysis with behavioral signals (e.g., call logs, device metadata) to improve identification through multimodal correlation.
3. Visualizing terminal networks and mobility graphs to detect interaction zones, frequently visited places, and possible accomplice links.

Our work proposes a framework to simulate, visualize, and analyze such scenarios, laying the groundwork for scalable, automated suspect identification systems in real-world surveillance contexts.

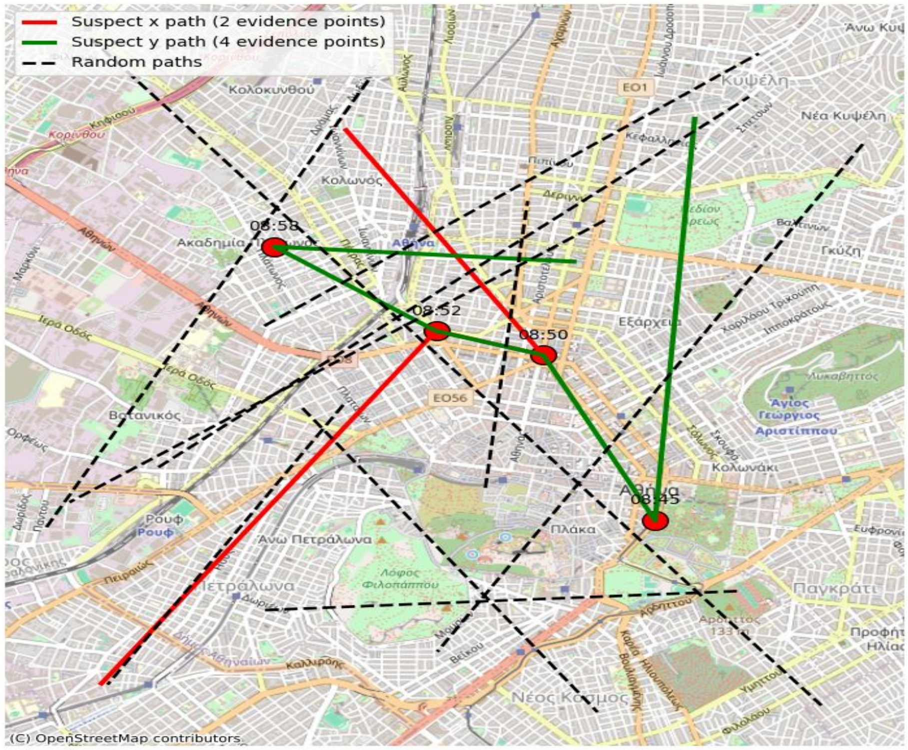

Fig. 1. Paths of mobile terminals as 2D (geolocation) and time sequences. We plot paths of random and suspected terminals.

4 Legal

The operational use of TRACY brings forth important legal considerations related to data retention, access, and the scope of data requests. Law enforcement agencies (LEAs) may need to request large amounts of data to identify relevant devices, and the main legal issue is whether national laws allow such broad access, especially for live data. National laws also govern the procedure, including safeguards like judicial approval or emergency access through prosecutors. An important consideration is what types of crimes justify requesting location data, as the Court of Justice of the European Union (CJEU) has ruled that such data can reveal private information and should be limited to serious crimes or national security cases. National laws vary in interpreting this rule, which involves both targeted data retention and access. TRACY could also be useful for reviewing past cases, meaning access to historical data is important. A practical challenge is the lack of standard formats for data provided by operators, which can delay LEAs in using the data efficiently.

5 Dataset Description

5.1 Non-content Data (NCD)

NCD refers to metadata related to communication events, excluding actual content. It includes:

- **Subscriber Data**: Identifiers like name, address, phone number.
- **Traffic Data**: Communication type, time, and participants.
- **Location Data**: E.g., Cell ID, used to infer geographic position via:
  - *OpenCelliD*: Public global cell tower database.
  - *CellMapper*: Crowd-sourced mobile infrastructure mapping.

5.2 Realistic Dataset (Athens)

Collected during a pilot in Athens on Jan 27, 2025 (13:00–16:00), this dataset includes 1,156 call/SMS/data events from 46 anonymized users. Though GPS is unavailable, cell-ID-based location tracking enables spatial-temporal analysis.

5.3 Synthetic Dataset: Athens (SAEX1)

Simulated data from July 28, 2023, spans 6.9M events from 32,485 terminals in a 2 km x 2 km area over 4 hours. After filtering for activity near Kerameikos, 1.5M records from 30,703 users remained. Records are categorized as:

- **CDR**: Voice/SMS, includes start/end times (calls), Cell ID (caller only).
- **DDR**: Internet usage, with start time and Cell ID.

Ground truth includes crime details (e.g., perpetrator ID: 5000000), CCTV sightings, and primary suspect IDs.

5.4 Synthetic Dataset: Zurich

This dataset simulates 9,000 terminals over 8 hours using Swiss open-access antenna data. Terminals and antennas are used to generate mobility paths (filtered via haversine distance). Events include 10% calls, 5% SMS, and 85% DDR, close to realistic durations.

Three additional suspect paths were manually created (linked to ROXSD), ensuring overlaps in antenna connections and CDR events. Ground truth includes a reported drug transaction and multiple eyewitness and CCTV observations. Primary suspect IDs: `ru05M_T`, `ru06F_T`, `cs04M_T`.

6 TRACY Workflow

TRACY uses heuristics and machine learning to make ongoing predictions, flagging terminals that exhibit behavioral patterns similar to those observed in case analyses. In this section, we describe how TRACY processes large volumes of data, identifies suspects, and extracts key insights through a combination of spatial, temporal, and network-based methods.

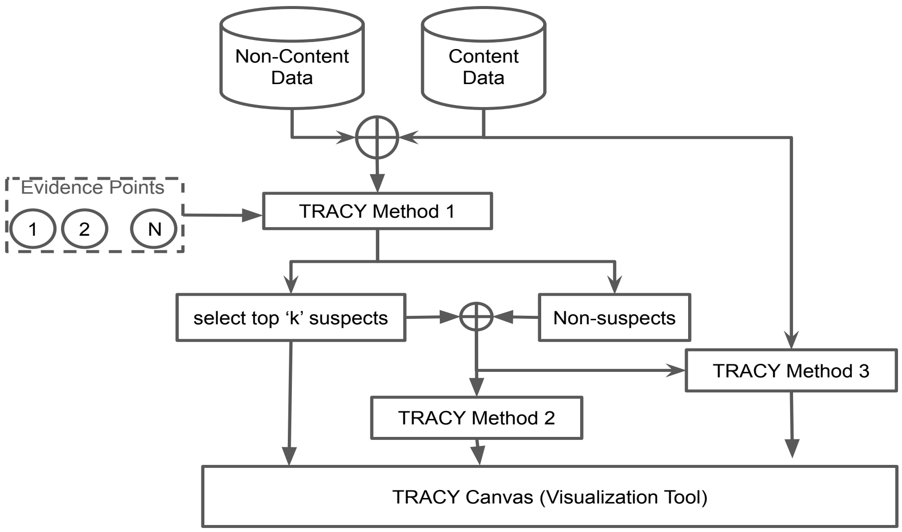

Fig. 2. System architecture illustrating the workflow of TRACY.

6.1 System Architecture

Figure 2 represents the workflow of TRACY, which integrates content and non-content data along with evidence points to identify potential suspects. TRACY Method 1 scores individuals based on their proximity to evidence-related locations and corresponding time intervals. The top-k candidates are then examined by TRACY Method 2, which detects concurrent pairs—individuals who co-occur within a one-minute window across sites—revealing possible coordination. In parallel, TRACY Method 3 performs graph analytics on the communication network, combining PageRank, degree centrality, and a frequency-weighted interaction score into a Network Analysis (NA) score. The outputs from all methods feed into the TRACY Canvas, a visualization tool for interpreting suspect rankings. More details of the methods and the visualization tool are discussed in the subsequent sections.

- **Data Sources**
  The system ingests two main categories of data: *Non-Content Data* and *Content Data*.
- **Evidence Points**
  Evidence points are defined by a specific location and time interval, indicating where and when a key event occurred—such as a crime scene, the time a crime took place, or the availability of CCTV footage. These points serve as reference anchors to identify suspects in the data.
- **TRACY Method 1**
  The TRACY Method 1 is the core analytical engine that takes both the merged data (Content + Non-Content) and the evidence points as input. A

set of *Evidence Points*, indexed from 1 to N, is provided as an additional input to the TRACY Method 1. Scoring the individuals are based on spatiotemporal proximity to evidence. More details are discussed in 6.2
- **Suspect Selection**
  Based on the output from the TRACY Method 1, we select the top-k most relevant or suspicious entities. These are considered potential suspects for further investigation or visualization.
- **Non-Suspects and Integration**
  The remaining entities classified as *non-suspects* are not discarded but are instead routed to the Autocrime Platform. This ensures that even non-suspects are preserved for contextual understanding or secondary analysis.
- **TRACY Canvas**
  The final results, including both the selected suspects and insights from the Autocrime Platform, are compiled and visualized. This enables LEA's or downstream systems to interpret the findings and make informed decisions.

6.2 TRACY Method 1

The summary of TRACY Method 1 is as follows:

- **Input Dataset:** Contains person IDs, latitude/longitude, and timestamps; loaded into a dataframe.
- **Grouping by Terminal ID:** Data is organized per terminal to enable focused analysis.
- **Evidence Points:** Time-bound events reported by police, serving as query points.
- **Time Window Extraction:** Time frames are derived from evidence entries.
- **Matching and Scoring:** Terminal records overlapping with evidence windows are scored.
- **Suspect List Generation:** Terminals are ranked based on scores and returned.

6.3 TRACY Method 2: Concurrent Pair Detection

Building on TRACY Method 1, Method 2 focuses on identifying pairs of individuals co-located within the same area during a one-minute interval using synthetic terminal data. A concurrent pair is defined as two terminals present at the same cell location within this short window.

Expanding on prior work [17], we applied a spatio-temporal co-occurrence approach using TRACY's synthetic dataset, which includes person IDs, cell coordinates, and timestamps. The timeline was divided into 1-minute slots, and individuals at each location were grouped into all possible pairs to detect colocation events.

For each pair, we tracked meeting frequency, shared locations, and cumulative distance traveled—computed using the Haversine formula for geographic distance estimation. This process, repeated across all time slots (e.g., 240 between 08:00 and 12:00), produced a dictionary of co-occurring pairs sorted by total joint distance, helping to reveal strong physical meeting edges.

6.4 TRACY Method 3

TRACY Method 3 performs graph analytics on the communication network by combining PageRank, degree centrality, and a frequency-weighted interaction score into a Network Analysis (NA) score. The details of TRACY Method 3 are provided after the introduction of the network analysis section (see Section 7.3).

7 Interpretation of Evidence

This section explains how evidence derived from TRACY Method 1 and Method 2 is interpreted and presented using visual techniques. It focuses on the analysis of CDR and DDR data through graph-based methods. We also introduce the TRACY Canvas, an open-source visualization tool developed to support and enhance network-based analysis. The key components are described in below sub-sections.

7.1 TRACY Canvas: Visualization through the Network

As part of the TRACY project, we developed the TRACY Canvas, an open-source visualization tool designed to interpret results from TRACY methods. Building upon the ROXANNE project, more technical details are available in the accompanying report[3].

Call Detail Records (CDR) are visualized as networks, where nodes represent terminal IDs and edges indicate communication (calls or SMS). Device Detection Records (DDR), lacking terminal-to-terminal links, do not form meaningful networks. TRACY Method 1 annotates the CDR network with crime scene presence per terminal. TRACY Method 2 adds co-location data to support analysis of physical proximity.

Figure 3 shows the **Network of Terminals**, where:

- Nodes = terminals; red = suspects, grey = others.
- Edges = communication events: grey (calls), orange (SMS).

Arrows show direction, edge color indicates type. This helps reveal clusters, suspect interactions, and potential collaborators.

Figure 4 shows the **Network of Individuals with Physical Concurrent Edge**, combining communication with co-location (green edges). These concurrent edges, derived from Method 2, highlight overlapping physical presence, revealing potential in-person meetings and coordinated activity.

7.2 Network Analysis

While the TRACY Canvas primarily serves as a tool for visualizing the outcomes of the TRACY Method 1 and Method 2, network analysis adds an essential layer

[3] See technical report for full details.

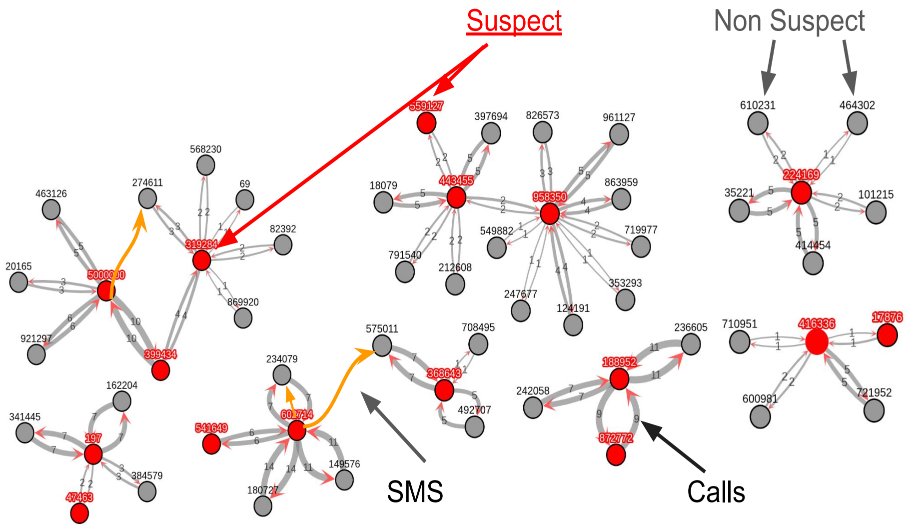

Fig. 3. Network of Terminals

of interpretation on top of these visualizations. It does more than just display the data—it helps uncover hidden patterns and relationships within large-scale CDR. By applying unsupervised methods based on graph structure, we extract insights such as:

– Visualizing CALL and SMS links between terminals in a clear, structured graph
– Identifying cohesive groups that are not easy to see from big CDRs files (e.g., main network and their clans).
– Focusing on more influential node (terminal) and its interacting neighbors.
– Spotting outliers—nodes with little or unusual activity
– This analytical layer transforms the TRACY Canvas from a static visual display into a powerful investigative tool for LEA.

7.3 TRACY Method 3: Scoring Based on Network and Communication Patterns

TRACY Method 3 applies network analysis to the call detail records (CDR) graph, incorporating metrics like PageRank and degree centrality to assess the influence and connectivity of individuals. It also computes a communication-based score to capture suspicious behavioral patterns.

A directed graph is constructed where each node represents a phone number and edges indicate suspicious interactions, weighted by base suspicion scores. Two primary graph-based features are used:

– **Degree Centrality (DC):** Measures how strongly a node influences others through outgoing weighted edges.

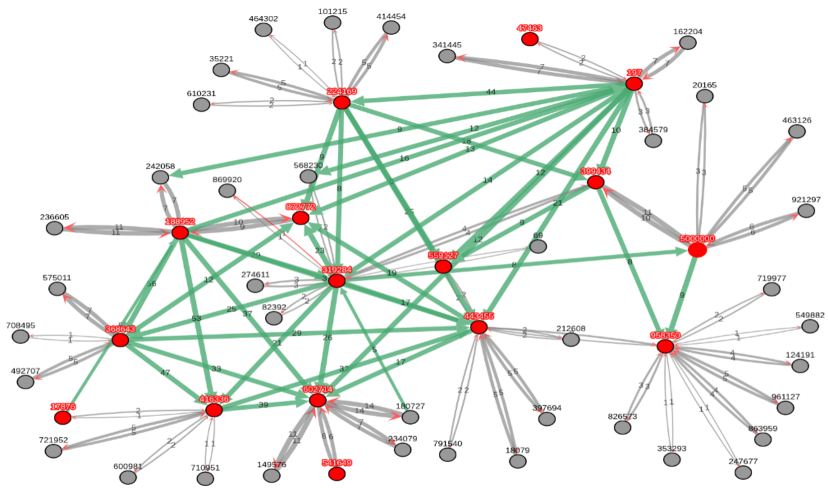

Fig. 4. Network of Individuals with Physical Concurrent Edge

– **PageRank (PR):** Reflects both direct and indirect influence based on the overall network structure.

For the communication score (CS), features such as number of calls near the crime scene, call durations, and call counts are normalized using Min-Max scaling. The final communication score is a weighted sum of these normalized features:

$$\text{Communication Score} = \sum_{i=1}^{n} w_i \cdot x_i, \quad \text{where} \quad \sum_{i=1}^{n} w_i = 1,\ w_i \geq 0 \tag{1}$$

The TRACY Method 3 score is then computed as a weighted combination of the three components:

$$\text{TRACY\_Method\_3\_Score} = \beta_1 \cdot \text{PR} + \beta_2 \cdot \text{DC} + \beta_3 \cdot \text{CS} \tag{2}$$

with constraints:

$$\beta_1 + \beta_2 + \beta_3 = 1, \quad \beta_i \geq 0 \tag{3}$$

This score effectively integrates both network structure and communication behavior to enhance suspect identification.

8 Evaluation of TRACY Methods

To evaluate the performance of the proposed TRACY methods, we calculate the 'Hit Rate'. It measures the number of true suspects that appear in the top-k

ranked predictions. A "hit" occurs when a ground-truth suspect is found within the top-k list.

Table 1 reports the Top-k suspect identification hit rates for various feature sets across different platforms (TRACY Method 1, TRACY Method 3 and TRACY Final score). The hit rate at a particular threshold k where k is defined as the number of unique ground-truth suspects correctly identified within the top-k ranked predictions, divided by the total number of ground-truth suspects. A prediction is considered a hit if a suspect from the ground-truth set

Table 1. Suspect Identification Rate for Different Features Across Various Top-k Thresholds Across Platforms. This measures the Top-k Suspect Identification Rates Across Platforms and Feature Categories

Scoring Systems	Category of Features	Normalised Feature	Hit Rate @1	Hit Rate @5	Hit Rate @10	Hit Rate @20
TRACY Method 1	Evidence Based	Spatio Temporal	0.00	0.33	0.33	0.67
TRACY Method 3	Network Based	Degree Centrality (N1)	0.00	0.33	0.33	0.67
		Page Rank (N2)	0.00	0.00	0.33	0.67
		N1 + N2	0.00	0.00	0.67	0.67
	Call Based	Calls Near Crime (A1)	0.00	0.33	0.67	0.67
		Avg Call Duration (A2)	0.00	0.00	0.00	0.33
		Distance To Evidence (A3)	0.33	0.67	1.00	1.00
		A1 + A2 + A3	0.00	0.33	0.67	1.00
TRACY Final	Graph Based	N1 + N2	0.000	0.33	0.67	0.67
	Call Based	A1 + A2 + A3	0.00	0.33	0.67	1.00

appears in the top-k list sorted by feature-based scores. The ranking scores are computed as weighted combinations of different feature values (e.g., degree centrality, call proximity to crime, call duration), and multiple weight configurations are evaluated. This approach allows measuring how effectively each feature or combination of features helps surface true suspects early in the ranked list. Notably, features like Distance to Evidence and combinations such as A1 + A2 + A3 show consistently higher hit rates, especially at broader thresholds (e.g., Top-10 or Top-20), indicating strong discriminatory power.

9 Visualization of Suspects

Figure 5 shows the network after applying the TRACY Method 1. Each **node** represents an individual, with **edges** indicating communication interactions, including content and non-content data. Red nodes mark suspects, while gray nodes are non-suspects. Edge **thickness** reflects interaction frequency—thicker edges mean more frequent communications or physical contact.

Two areas stand out: region **(a)** features suspect node `5000000` with many strong connections, indicating a central role, while region **(b)** shows non-suspect

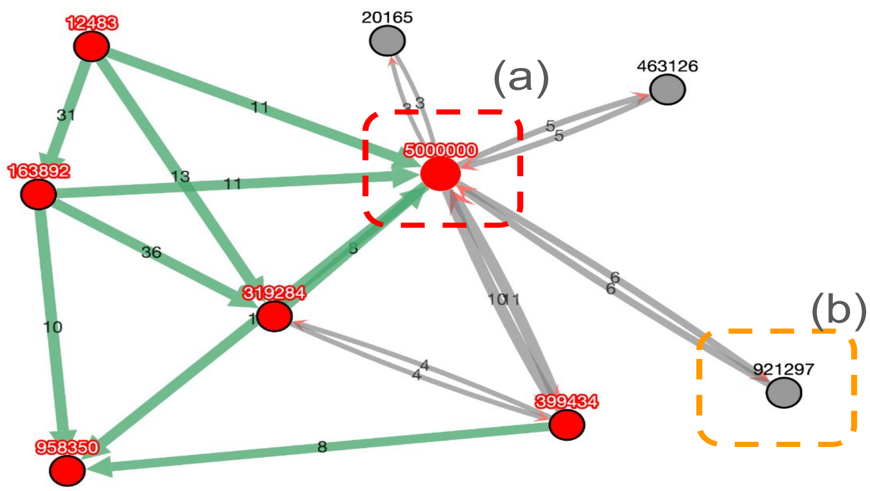

Fig. 5. Spotlight Visualization of CDR for terminal 500000 from TRACY Canvas

node `921297` with fewer, weaker ties. This highlights TRACY's effectiveness in identifying key suspicious individuals within the network.

10 Conclusions

In this paper, we present TRACY, a significant advancement in leveraging non-content communication data to support criminal investigations. By integrating spatial-temporal proximity analysis, co-location detection, and network analysis into a unified scoring system, TRACY effectively identifies and prioritizes suspects. The three proposed core methods are combined into a comprehensive scoring mechanism: Method-1, assesses individual proximity to evidence points; Method-2, detects co-located pairs to infer coordination; and Method-3, employs network analysis to evaluate influence and connectivity. This robust approach enables investigators to prioritize suspects based on both physical movement and digital communication patterns. Complementing these analytical methods, the TRACY Canvas visualization tool provides an intuitive platform for exploring suspect relationships and integrating multiple evidence views, thereby facilitating easier interpretation and decision-making. Evaluation results on synthetic case studies demonstrate that TRACY reliably detects true suspects with high accuracy, with detection rates significantly improving when multiple features are combined. Overall, TRACY proves to be a practical and effective solution that accelerates investigative processes while respecting legal privacy standards.

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