# Gaurav Tuli – Applied ML Portfolio (Projects 17–26, Concise 2025)

## 1. Preface

Dr. Gaurav Tuli is a national award-winning Data & AI expert with a PhD in applied machine learning and network science. Over the last decade he has guided technical teams to transform innovative ideas into production-ready solutions. His work includes deploying ML pipelines for health agencies and leading teams in classical, generative, and agentic AI. He has collaborated with organizations like Meta and Google on projects in patient profiling and privacy. He has published over 30 research papers (PNAS, ICDM) and been featured in media such as *Wired* and the *BBC*.

## 2. Project 17: Multi-Agent System – MOTL-based ISR Supervision (MAS-1)

### 2.1 At a Glance

* Investigated a “Man-On-The-Loop” approach for supervising autonomous agent teams in an ISR mission.
* Used high-level cultural parameters (e.g., risk aversion, individualism) as global control inputs.
* Demonstrated that adjusting these group traits significantly influenced collective behavior and mission success.

### 2.2 The Problem

* Individual oversight of large agent teams is impractical in time-critical ISR scenarios.
* Direct micromanagement cannot scale, creating the need for new high-level control methods.
* No existing method allowed indirect influence on group behavior via global parameter tuning.

### 2.3 The Solution

* Built a custom agent-based simulation to test the MOTL concept in a surveillance mission.
* Modeled two cultural dimensions (uncertainty avoidance and individualism) affecting all agents’ decisions.
* Provided a user interface for adjusting trait sliders and observing group performance in real time.

### 2.4 Architecture Overview

* Simulated a team of autonomous agents on a mission with adjustable cultural parameters.
* Implemented a supervisory console where the operator could adjust global trait values.
* Tracked group and individual performance metrics to evaluate each trait configuration.
* Agents followed utility-based norms that enabled cooperative, group-oriented behavior.
* A front-end dashboard visualized updated state metrics as parameters changed.

### 2.5 Results and Impacts

* Small trait adjustments caused significant shifts in team behavior and mission outcomes.
* Validated the MOTL approach: global parameter changes steered agents effectively without low-level commands.
* Operators learned trait–outcome relationships and tuned parameters to improve coordination.

### 2.6 Skills and Tools Used

| Technique/Skill | Tools/Implementation |
| --- | --- |
| Multi-agent simulation | Custom testbed development |
| Cultural modeling | Hofstede cultural dimensions |
| Optimization analysis | Utility theory, Pareto rules |
| Data analysis | Statistical analysis of simulation outputs |
| Research and collaboration | Academic writing (IEEE publication) |

### 2.7 Cross-Project Capabilities

* Introduced the MOTL supervision concept, which shaped later multi-agent control research (MAS-2).
* Developed agent-based modeling techniques applied to other domains (human factors, robotics).
* Combined AI with social science modeling, an interdisciplinary approach reused in other projects.

### 2.8 Published Papers/Tools

* *Influencing Agent Group Behavior by Adjusting Cultural Trait Values* (IEEE Trans. SMC-B, 2010).
* Prototype multi-agent simulation platform for MOTL experiments (USAF-funded research tool).

## 3. Project 18: Multi-Agent System – MOTL Paradigm for Control Systems (MAS-2)

### 3.1 At a Glance

* Proposed and validated a “Man-On-The-Loop” paradigm for human supervision of large agent networks.
* Embedded socio-psychological models to let a human set global rules instead of issuing individual commands.
* Showed that indirect, high-level policy changes can shape system-wide behavior and reduce workload.

### 3.2 The Problem

* Direct micromanagement of large, fast agent systems is unsustainable and leads to cognitive overload.
* Complex systems needed a framework where a human could guide outcomes without controlling each component.
* It was unclear if altering global social rules could effectively direct overall system dynamics.

### 3.3 The Solution

* Built a general agent-based simulation embedding social and cultural parameters for agents.
* Defined global policy variables that a human supervisor could adjust to influence all agents collectively.
* Implemented scenarios comparing direct control (issuing individual commands) versus the indirect MOTL approach.

### 3.4 Architecture Overview

* Large-scale multi-agent simulation environment with configurable rules and objectives.
* Global policy parameters modeled a supervisor’s macro-level influence on all agents.
* Agents followed global norms and adapted behavior when those norms were changed.
* Conducted experimental scenarios: no intervention, direct commands, and indirect MOTL control.
* Monitored system efficiency and coordination, comparing MOTL performance to expected human organizational patterns.

### 3.5 Results and Impacts

* Validated MOTL: human policy tweaks led to measurable changes in collective agent behavior.
* Showed that indirect control can guide agents and reduce the need for constant oversight.
* Supervisors using MOTL managed large systems without overload, improving overall coordination.

### 3.6 Skills and Tools Used

| Technique/Skill | Tools/Implementation |
| --- | --- |
| Theoretical modeling | AI + social science concept development |
| Agent-based simulation | Custom simulation platform |
| Comparative analysis | Statistical comparison of scenarios |
| Human–machine interface | Paradigm design, peer-reviewed writing |
| Interdisciplinary research | Journal publication (JETAI 2009) |

### 3.7 Cross-Project Capabilities

* Provided conceptual groundwork applied in MAS-1 (ISR scenario) and later work.
* Demonstrated interdisciplinary modeling (psychology + AI) used in later healthcare analytics.
* Established the design philosophy of embedding high-level human influence in AI systems.

### 3.8 Published Papers/Tools

* *Natural Human Role in Supervising Complex Control Systems* (Journal of Experimental & Theoretical AI, 2009).
* Simulation framework for MOTL vs direct control (research prototype for experimentation).

## 4. Project 19: Patient Experience – US Longitudinal Study (1)

### 4.1 At a Glance

* Collected and analyzed 2.76 million patient experience tweets (2013–2017) from across the US.
* Found that patient sentiment became less negative nationwide over time, with distinct urban-rural and daily patterns.
* Demonstrated that Twitter can serve as a real-time, large-scale barometer of patient healthcare experiences.

### 4.2 The Problem

* Existing surveys are infrequent, biased, and lack real-time nationwide patient feedback.
* Healthcare providers needed timely insights into patient satisfaction and concerns.
* Without alternate data, shifts in patient sentiment could remain undetected by stakeholders.

### 4.3 The Solution

* Collected 27.3 million tweets (2013–2017) via Twitter’s API using patient experience keywords.
* Built an automated pipeline with a tweet classifier, geolocation engine, and sentiment analyzer.
* Filtered 2.76 million relevant patient-experience tweets and geolocated ~32% to US states.

### 4.4 Architecture Overview

* Used continuous tweet ingestion with keyword filters (excluding URLs for relevance).
* Classified tweets with an SVM-based model to identify patient experience content.
* Geolocated tweets to states using profile text and Google Maps API.
* Performed sentiment analysis (positive/neutral/negative) on each relevant tweet.
* Aggregated data into a dashboard for temporal and geographic visualization.

### 4.5 Results and Impacts

* Nationwide, ~36% of patient-experience tweets were negative, ~28% positive (2013–2017).
* Observed that overall sentiment became less negative over four years; night-time tweets were more negative than daytime.
* Found urban-area tweets showed more extreme sentiment (higher negativity) than rural tweets.

### 4.6 Skills and Tools Used

| Technique/Skill | Tools/Implementation |
| --- | --- |
| Big data processing | Twitter GNIP API (27 million tweets) |
| Natural language processing | NLTK/SVM for tweet classification, sentiment analysis |
| Crowdsourced annotation | Amazon Mechanical Turk labeling |
| Geospatial analysis | Google Maps API for state-level mapping |
| Statistical analysis | Regression, significance testing on trends |

### 4.7 Cross-Project Capabilities

* Twitter data pipeline and sentiment methods were reused in subsequent patient experience projects.
* Crowdsourced ML labeling approach (MTurk) was also used in the Gun Violence curation project.
* Geolocation and mapping techniques paralleled those in the Gun Violence platform.

### 4.8 Published Papers/Tools

* “Using Twitter to Examine Web-Based Patient Experience Sentiments in the United States: Longitudinal Study” (J. Med. Internet Res. 2018).
* Code suite for tweet classification, geolocation, and sentiment analysis (developed for this study).

## 5. Project 20: Patient Experience – US Hospital Sentiment via Twitter (2)

### 5.1 At a Glance

* Analyzed 404,065 tweets @-mentioned to 2,349 US hospitals (2012), identifying ~34.7K patient experience posts.
* Found Twitter feedback covered diverse aspects of care and provided immediate patient insights.
* Twitter sentiment only weakly matched traditional survey results, indicating it is mainly a supplemental indicator.

### 5.2 The Problem

* Formal patient experience surveys have long delays and low response rates, missing timely feedback.
* Hospitals lacked immediate, unfiltered patient feedback outside official channels.
* It was unclear if social media sentiment could reliably complement established quality measures.

### 5.3 The Solution

* Collected 404,065 tweets (2012) directed at official hospital Twitter accounts.
* Used a machine learning classifier to filter ~34,725 patient experience tweets.
* Performed sentiment analysis and manually coded topics for a sample of patient-feedback tweets.

### 5.4 Architecture Overview

* Aggregated all @-mention tweets to official hospital accounts via API.
* Machine learning model filtered patient experience-related tweets from general mentions.
* Applied NLP for sentiment scoring and manually categorized sample tweets by topic.
* Merged Twitter results with hospital quality datasets (HCAHPS survey scores, readmission rates).
* Conducted statistical analysis comparing social media feedback to hospital performance.

### 5.5 Results and Impacts

* Only about 10% of tweets at US hospitals were patient-experience related.
* These patient-feedback tweets covered diverse aspects of care, reflecting varied real-time concerns.
* Hospital Twitter sentiment was only weakly related to formal quality measures.

### 5.6 Skills and Tools Used

| Technique/Skill | Tools/Implementation |
| --- | --- |
| Social media mining | Twitter API to capture hospital mentions |
| Text classification | ML classifier to isolate experience tweets |
| Sentiment analysis and coding | NLP plus manual content coding |
| Data integration | Merged Twitter data with hospital metrics |
| Statistical analysis | Correlation and regression analysis |

### 5.7 Cross-Project Capabilities

* Built on prior methods of combining social media with formal data (from the longitudinal study).
* Refined tweet classification and sentiment techniques that informed the racial disparities analysis.
* Engaging hospital stakeholders with data parallels engaging policymakers in other projects.

### 5.8 Published Papers/Tools

* A BMJ *Quality & Safety* paper (2016) documented this hospital Twitter analysis.
* Developed a dataset of hospital-related tweets and a survey instrument for hospital social media practices.

## 6. Project 21: Patient Experience – Racial Disparities in Experience Sentiment (3)

### 6.1 At a Glance

* Analyzed ~852K patient experience tweets (2013–2016) to examine racial/ethnic sentiment trends and ACA impact.
* Verified that Twitter’s user race distribution closely matches the U.S. population, allowing robust group comparisons.
* Found all groups’ sentiment improved over time; Hispanic/Latino users had the largest gain and Black users the largest post-ACA boost.

### 6.2 The Problem

* Minority patient experiences are underrepresented in surveys, masking disparities in feedback.
* Without inclusive data, health systems struggle to identify patient experience gaps in minority communities.
* Policymakers lacked timely tools to evaluate if reforms like the ACA reduced care disparities.

### 6.3 The Solution

* Filtered and analyzed 851,973 geolocated patient experience tweets (2013–2016) with inferred user race/ethnicity.
* Verified Twitter’s racial composition (r²=0.99 with Census) to confirm validity.
* Classified tweets by inferred race/ethnicity and computed yearly average sentiment per group with regression analysis to detect trends and ACA effects.

### 6.4 Architecture Overview

* Extracted tweets from users with identifiable race/ethnicity and US location.
* Applied algorithms to infer each user’s racial/ethnic group (validated against Census data).
* Used previously labeled tweet sentiments (positive/neutral/negative) for analysis.
* Aggregated sentiment per group per year and applied regression to measure changes pre- vs post-ACA.

### 6.5 Results and Impacts

* Twitter’s racial/ethnic distribution mirrored the U.S. population, confirming data representativeness.
* All groups’ average sentiment became more positive from 2013 to 2016.
* Hispanic/Latino users’ sentiment improved the most (1.5× the gain of White users); post-ACA, Black users’ sentiment rose 2.2× more than White users’.
* These findings suggest ACA implementation coincided with improved experiences for minority patients.

### 6.6 Skills and Tools Used

| Technique/Skill | Tools/Implementation |
| --- | --- |
| Demographic inference | Algorithms to assign race/ethnicity to users |
| Statistical modeling | Regression analysis of sentiment trends |
| Public policy analysis | Interpreting ACA impact through data |
| Big data handling | Processing nearly 1M tweets with multiple attributes |
| Collaborative research | Work with epidemiologists; journal publication |

### 6.7 Cross-Project Capabilities

* Built on the earlier patient experience pipeline, demonstrating scalability to demographic analysis.
* Combining social data with demographic inference is a model for evaluating policy impacts in other domains.
* Emphasized equity-focused analytics, aligning with other projects targeting vulnerable groups.

### 6.8 Published Papers/Tools

* *Racial and Ethnic Disparities in Patient Experiences in the United States: 4-Year Content Analysis of Twitter* (J. Med. Internet Res. 2020).
* Developed an analytical framework for social media-based health disparity research.
* Shared findings with public health stakeholders to inform ACA evaluation.

## 7. Project 22: Social Contagion – Smoking Behavior Structured Resistance Model

### 7.1 At a Glance

* Introduced a multi-stage contagion model for smoking that incorporates addiction and resistance.
* Found that addiction creates a “structured resistance,” making smoking persist longer.
* Explained the slow decline in smoking rates by showing that once endemic, eradication becomes very difficult.

### 7.2 The Problem

* Standard epidemic models predicted quick smoking eradication, contrary to real slow declines.
* Real-world data show smoking rates fell only gradually over decades.
* Existing models ignored nicotine addiction, failing to capture persistent smoking dynamics.

### 7.3 The Solution

* Extended the classic SIS epidemic model with multi-level addiction and resistance states.
* Created a “structured resistance” model where quitting raises an individual’s susceptibility to relapse.
* Validated the model with simulations on longitudinal social network data (Framingham Heart Study).

### 7.4 Architecture Overview

* Multi-level contagion model with multiple Susceptible (S1…Sn) and Infected (I1…In) states by addiction level.
* Quitting raises an individual’s susceptibility tier, reflecting higher relapse risk after quitting.
* Sustained abstinence can slowly lower susceptibility over time, modeling gradual recovery.

### 7.5 Results and Impacts

* The model exhibits backward bifurcation: once smoking is endemic, it is very hard to eradicate.
* Simulated smoking trends closely matched the empirically observed slow historical decline.
* Concluded that ending the smoking epidemic requires substantially greater effort due to addiction effects.

### 7.6 Skills and Tools Used

| Technique/Skill | Tools/Implementation |
| --- | --- |
| Network epidemic modeling | Custom contagion models with addiction levels |
| Social network simulation | Framingham longitudinal data simulation |
| Mathematical analysis | Epidemic threshold and bifurcation theory |
| Data interpretation | Matching model output to public health trends |

### 7.7 Cross-Project Capabilities

* Developed a multi-level contagion framework applicable to other addiction-like behaviors.
* Insights on threshold dynamics informed intervention strategy designs in later projects.
* Provided groundwork for targeted network interventions (edge-removal methods) in subsequent work.

### 7.8 Published Papers/Tools

* *Addiction Dynamics May Explain the Slow Decline of Smoking Prevalence* (LNCS, 2012).
* Introduced the Structured Resistance Model concept for “policy-resistant” problems.
* Integrated findings into social simulation platforms for public health policy experimentation.

## 8. Project 23: Social Contagion – Smoking Contagion Online Exposure and Estimation

### 8.1 At a Glance

* Analyzed Twitter data to quantify teens’ exposure to pro-tobacco messages, finding substantial underage visibility.
* Built a scalable pipeline to collect and classify smoking-related tweets and infer user age.
* Estimated that underage users saw multiple pro-smoking posts per day from key influencers.

### 8.2 The Problem

* Social platforms hide user age, making it hard to identify teen users on Twitter.
* Massive, noisy tweet streams make isolating meaningful exposure signals difficult.
* The effect of online pro-smoking content on teen smoking behavior remains unclear.

### 8.3 The Solution

* Built a Twitter data pipeline to collect and classify smoking-related tweets at scale.
* Used machine learning to infer users’ ages (under 18 vs. adult) from tweet patterns.
* Modeled teen tweet-reading behavior to estimate how many pro-tobacco posts they see daily.

### 8.4 Architecture Overview

* Scalable data ingestion archived targeted tweets and user metadata via Twitter APIs.
* NLP and feature extraction cleaned text and prepared data for classification.
* “Happy Birthday” tweets were used in an age classifier to identify under-18 users (~80% accuracy).
* A probabilistic model (Poisson process) estimated the probability that teens see key tweets.

### 8.5 Results and Impacts

* Estimated that about 36% of key influencers’ direct followers were likely under age 18.
* Underage followers saw a median of ~2.2 pro-tobacco tweets per day from these accounts.
* Revealed significant adolescent exposure to tobacco content online, prompting calls for social media oversight.

### 8.6 Skills and Tools Used

| Technique/Skill | Tools/Implementation |
| --- | --- |
| Social media mining | Twitter API for large-scale data collection |
| Natural language processing | Text cleaning and feature engineering |
| Machine learning | SVM and Random Forest for tweet/age classification |
| Network statistics | Probabilistic modeling of information exposure |
| Systems integration | Designed end-to-end data pipeline |

### 8.7 Cross-Project Capabilities

* Developed a reusable social media analysis pipeline, later applied to e-cigarette studies.
* Age inference methods generalize to finding vulnerable groups in any online contagion.
* Integration of ML and network analysis here informed later projects on community and hotspot identification.

### 8.8 Published Papers/Tools

* PhD Thesis: *Exposure of a Vulnerable Population to Smoking-Related Messaging on Twitter*.
* Custom Twitter surveillance pipeline (data collection, classification, visualization software).
* Recommendations for linking social media exposure with behavior, guiding future research.

## 9. Project 24: Social Contagion – E-cig Online Exposure and Hotspots

### 9.1 At a Glance

* Identified geographic hotspots of e-cigarette–related tweets across the US.
* Found that most hotspots had high pro-vaping sentiment and many underage participants.
* Highlighted West Coast regions where youth engagement with vaping messages was particularly high.

### 9.2 The Problem

* Earlier e-cigarette Twitter studies had small samples and missed broader patterns.
* No prior work had spatially mapped e-cig tweet clusters to find significant hotspots.
* Differentiating genuine public tweets from overwhelming commercial promotions was challenging.

### 9.3 The Solution

* Collected two years of geotagged e-cigarette tweets (~83,000) nationwide.
* Removed commercial spam via machine learning classifiers to focus on genuine user content.
* Applied spatiotemporal scan statistics to detect clusters with unusually high e-cig tweet volumes.
* Analyzed each hotspot’s sentiment (pro vs. anti vaping) and fraction of underage users.

### 9.4 Architecture Overview

* Twitter Streaming API captured a 1% sample of geotagged tweets (Oct 2012–Oct 2014).
* Filtered by e-cigarette keywords, yielding 62,894 US geotagged e-cig tweets.
* Used an SVM classifier to separate non-commercial e-cig tweets from advertising content.
* Employed SaTScan-like spatiotemporal scanning to find statistically significant hotspots.
* Computed sentiment scores and age metrics for each detected cluster.

### 9.5 Results and Impacts

* Discovered multiple e-cigarette tweet hotspots, mostly on the US West Coast.
* About 75% of hotspots had above-average pro-vaping sentiment and higher youth participation.
* Identified regions with intense pro-vaping influence among youth, underscoring need for targeted monitoring.

### 9.6 Skills and Tools Used

| Technique/Skill | Tools/Implementation |
| --- | --- |
| Geospatial analysis | Spatiotemporal scan statistics (hotspot detection) |
| Big data processing | Twitter streaming and filtering (~83K tweets) |
| Machine learning | Text classification to filter commercial posts |
| Sentiment and demographic analysis | NLP plus age inference for user demographics |
| Data visualization | Mapping hotspots and trends on dashboards |

### 9.7 Cross-Project Capabilities

* Adapted the flexible Twitter surveillance pipeline to a new topic (e-cigarettes).
* Applied spatial analysis of social data, a technique transferable to other public health signals.
* Content filtering methods here (distinguishing organic vs. commercial posts) informed other contagion analyses.

### 9.8 Published Papers/Tools

* PhD Thesis (Chapter 5): *Find and Analyze Hotspots of E-cigarette-related Tweets*.
* Developed spatiotemporal hotspot detection and analysis tools for social media data.
* Produced the first spatial analysis of vaping discourse, cited in later health social media studies.

## 10. Project 25: Social Contagion – Blocking Contagion via Edge Removal

### 10.1 At a Glance

* Studied how to stop contagion spread by cutting network links (edges).
* Proved key edge-removal problems are NP-hard and developed a novel edge-removal heuristic.
* Showed the heuristic significantly improves containment of both simple and complex contagions.

### 10.2 The Problem

* Selecting an optimal set of edges to delete for maximum containment is NP-hard.
* For complex contagions (requiring multiple exposures), edge removal has no constant-factor approximation.
* Prior research mostly focused on node removal or ignored outbreak-specific contagion dynamics.

### 10.3 The Solution

* Formulated edge removal as optimization problems under various constraints (budgets, targeted closures).
* Proved new hardness results for complex contagions and identified special tractable cases.
* Developed an “edge-covering” heuristic to select edges to cut in weighted and unweighted networks.
* Simulated contagion spread on large real networks to compare the heuristic against existing methods.

### 10.4 Architecture Overview

* Combined graph-theoretic edge cover and cut models with contagion dynamics (independent cascade and threshold models).
* Analyzed computational complexity of edge removal versus node removal strategies.
* Used a simulation framework on real networks (e.g., contact and social graphs) to test interventions.
* Heuristic algorithm considered edge weights, directions, and outbreak source information to prioritize cuts.

### 10.5 Results and Impacts

* The edge-removal heuristic outperformed prior strategies, blocking more contagion spread in 12 test scenarios.
* Confirmed that while optimal solutions are intractable, a scalable heuristic achieves strong containment.
* Compared node vs. edge removal: cutting specific links often contained outbreaks more cost-effectively.
* Methods informed follow-up research and have been applied to other network intervention scenarios.

### 10.6 Skills and Tools Used

| Technique/Skill | Tools/Implementation |
| --- | --- |
| Graph algorithms and theory | NP-completeness proofs, approximation limits |
| Heuristic design | Edge-blocking algorithm (implementation) |
| Network simulation | Contagion diffusion on large graphs |
| Data analysis | Comparative evaluation on real networks |
| Interdisciplinary approach | Algorithms + epidemiology for interventions |

### 10.7 Cross-Project Capabilities

* Edge-cutting techniques integrate with community-based blocking by isolating cross-community links.
* Developed general methods handling both simple and complex contagions for a versatile intervention toolkit.
* Established large-scale simulation and evaluation practices used across other contagion projects.

### 10.8 Published Papers/Tools

* *Blocking Simple and Complex Contagion by Edge Removal* – IEEE ICDM 2013.
* Released an edge-blocking heuristic code, validated on real social networks (e.g., Montgomery County network).
* Findings cited in later network science research and integrated into contagion simulation platforms.

## 11. Project 26: Social Contagion – Blocking Contagion via Community Structure

### 11.1 At a Glance

* Created a hybrid contagion-blocking strategy using community detection and targeted inter-community links.
* This approach outperformed purely structural or dynamic methods, especially for complex contagions.
* Demonstrated that combining network structure and contagion dynamics yields better containment.

### 11.2 The Problem

* Pure structural (proactive) blocking can fail to stop spread, especially for complex contagions.
* Pure dynamics-based (reactive) methods are effective but slow and require detailed model data.
* Little prior work addressed blocking contagions that require multiple confirmations (complex contagions).

### 11.3 The Solution

* Developed a cluster-based algorithm: partition the network into communities, then focus blocking on inter-community connections.
* Assumed contagion spreads quickly inside communities, so prioritized preventing cross-community transmission.
* Implemented a hybrid node selection approach combining structural metrics and contagion simulations.
* Tested on multiple networks, showing this hybrid method outperformed purely centrality- or simulation-based strategies.

### 11.4 Architecture Overview

* Used a progressive threshold model (complex contagion) for simulations (nodes require ≥2 infected neighbors to activate).
* Applied community detection (e.g., modularity clustering) to divide the network into dense clusters.
* Identified all edges between communities as potential “choke points” for contagion crossing.
* Applied reactive blocking on these boundary regions: after limited spread, froze a minimal set of boundary nodes to stop transmission.

### 11.5 Results and Impacts

* The community-based hybrid method contained complex contagions more effectively than degree-based interventions.
* It matched or surpassed the performance of state-of-the-art simulation-only methods, validating the hybrid approach.
* Tested on three real networks, demonstrating the strategy’s scalability and generality.
* Provided an effective strategy for complex contagions, influencing later contagion intervention research.

### 11.6 Skills and Tools Used

| Technique/Skill | Tools/Implementation |
| --- | --- |
| Community detection | Graph clustering (modularity algorithms) |
| Complex contagion simulation | Threshold model testing and refinement |
| Hybrid algorithm design | Combined structural metrics with simulation feedback |
| Empirical evaluation | Contagion diffusion code and statistical analysis |
| Multi-domain insight | Combined social network analysis with contagion modeling |

### 11.7 Cross-Project Capabilities

* Community-based blocking complements edge removal by focusing on cross-community links as critical cuts.
* Approach applies to other domains (e.g., immunization or cybersecurity) that can leverage community structure.
* Hybrid proactive-reactive concept influenced integrated strategies across contagion projects, showing combined methods yield better results.

### 11.8 Published Papers/Tools

* *Blocking Complex Contagions Using Community Structure* – AAMAS Workshop 2013.
* Developed the Community-based Node Selection (CNS) hybrid blocking algorithm.
* Extended results in a journal submission, with this work incorporated into broader contagion intervention studies.