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

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<h1>Social Contagion Project 1: Smoking Behavior – Structured Resistance Model (Project 22)</h1>  
<img src="placeholder.jpg" alt="Project 22 placeholder image" />  
<p><strong>BLUF:</strong> Introduced a multi-stage contagion model to explain smoking’s slow decline, revealing that addiction raises the effort needed to eradicate the behavior.</p>  
  
<h2>Introduction</h2>  
<ul>  
 <li>Smoking is highly addictive and the leading preventable cause of death[1].</li>  
 <li>Peer influence makes smoking behavior socially contagious among friends and family[2].</li>  
 <li>Smoking prevalence fell only from 45% to 21% over 45 years[3].</li>  
</ul>  
  
<h2>Key Questions Addressed</h2>  
<ul>  
 <li>Why did smoking prevalence decline so slowly despite decades of anti-smoking efforts?[3][4]</li>  
 <li>How does nicotine addiction alter the dynamics of smoking as a contagious behavior?[5]</li>  
 <li>Does addiction create a “policy-resistant” dynamic requiring greater effort to eliminate smoking?[6][7]</li>  
</ul>  
  
<h2>The Problem</h2>  
<ul>  
 <li>Standard SIS epidemic models predicted rapid smoking eradication, contrary to observed slow declines[8].</li>  
 <li>Real-world data show only gradual smoking reduction, contradicting model expectations[9].</li>  
 <li>Existing models missed the addictive aspect, failing to capture smoking’s persistent spread[5].</li>  
</ul>  
  
<h2>The Importance</h2>  
<ul>  
 <li>Smoking causes enormous health and economic burdens, demanding innovative control strategies[1].</li>  
 <li>Persistently high smoking rates highlight limits of current interventions against addiction[3].</li>  
 <li>Modeling addictive behavior spread is essential for effective long-term public health planning[7].</li>  
</ul>  
  
<h2>The Solution</h2>  
<ul>  
 <li>Extended the SIS model with structured multi-level addiction and resistance states[10].</li>  
 <li>“Structured resistance model” increases susceptibility after relapse, reflecting lasting addiction effects[11].</li>  
 <li>Validated the model through simulations on longitudinal social network data (Framingham study)[12].</li>  
</ul>  
  
<h2>Architecture Overview</h2>  
<ul>  
 <li>Multi-level contagion model: multiple Susceptible (S1…Sn) and Infected (I1…In) states by addiction level[13].</li>  
 <li>Quitting raises an individual’s susceptibility tier, mirroring higher relapse risk after quitting[11].</li>  
 <li>Sustained abstinence can slightly lower susceptibility over time, modeling gradual recovery[14].</li>  
</ul>  
  
<h2>Results and Impacts</h2>  
<ul>  
 <li>Model exhibits backward bifurcation: once smoking is endemic, it is hard to eradicate[15].</li>  
 <li>Simulation-generated smoking trends closely matched the empirically observed slow decline[16].</li>  
 <li>Findings suggest significantly greater intervention efforts are required to end smoking spread[6].</li>  
</ul>  
  
<h2>Skills and Tools Used</h2>  
<ul>  
 <li>Network-based epidemic modeling of behavioral contagions with addiction dynamics[17].</li>  
 <li>Social network simulations on real longitudinal data (Framingham Heart Study)[16].</li>  
 <li>Mathematical analysis of epidemic thresholds and bifurcation phenomena in contagion models[6][7].</li>  
</ul>  
  
<h2>Cross-project Capabilities</h2>  
<ul>  
 <li>Multi-level contagion modeling framework adaptable to other addictive behavior epidemics[7].</li>  
 <li>Threshold dynamics insights (multiple equilibria) inform intervention design in various contagions[6].</li>  
 <li>Lays the groundwork for targeted intervention strategies (e.g., edge removal) in later projects[18][7].</li>  
</ul>  
  
<h2>Published Papers/Tools</h2>  
<ul>  
 <li>Conference Paper: <em>Addiction Dynamics May Explain the Slow Decline of Smoking Prevalence</em> (LNCS 2012)[19].</li>  
 <li>Structured Resistance Model concept published as a novel approach to “policy-resistant” problems[20].</li>  
 <li>Findings integrated into social simulation platforms for public health policy experimentation (NSF/DTRA projects)[21].</li>  
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## Project 23: Social Contagion – Smoking Contagion Online Exposure and Estimation

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 <title>Social Contagion Project 2 – Smoking Contagion Online Exposure and Estimation (Project 23)</title>  
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<h1>Social Contagion Project 2: Smoking Contagion – Online Exposure and Estimation (Project 23)</h1>  
<img src="placeholder.jpg" alt="Project 23 placeholder image" />  
<p><strong>BLUF:</strong> Analyzed Twitter data to quantify teens’ exposure to smoking content, finding substantial underage visibility of pro-tobacco messages.</p>  
  
<h2>Introduction</h2>  
<ul>  
 <li>Social media is a major channel for spreading smoking-related messages, especially to youth[22].</li>  
 <li>This study investigates how much smoking content adolescents (under 18) see on Twitter[23].</li>  
 <li>Data-driven surveillance can uncover hidden social influences on teen smoking behavior.</li>  
</ul>  
  
<h2>Key Questions Addressed</h2>  
<ul>  
 <li>How frequently are under-18 users exposed to pro-tobacco messages on social media?[24]</li>  
 <li>Can we identify and quantify the vulnerable teen population following smoking-related content?[25]</li>  
 <li>What impact might online exposure have on youth smoking initiation and habits?[26]</li>  
</ul>  
  
<h2>The Problem</h2>  
<ul>  
 <li>Social platforms hide user age information, making it hard to find teen users[27].</li>  
 <li>Massive, noisy tweet streams complicate isolating meaningful smoking-related exposure signals[28].</li>  
 <li>The effect of online pro-smoking content on actual teen behavior remains an open question[26].</li>  
</ul>  
  
<h2>The Importance</h2>  
<ul>  
 <li>Online exposure may normalize smoking, undermining traditional tobacco control efforts[22].</li>  
 <li>Understanding social media’s role is crucial as teens spend more time online[29].</li>  
 <li>Insights help guide policies on social media content moderation to protect youth[30].</li>  
</ul>  
  
<h2>The Solution</h2>  
<ul>  
 <li>Built a Twitter data pipeline to collect and classify smoking-related tweets at scale[31][32].</li>  
 <li>Used machine learning to infer users’ ages (under 18 vs adult) from their tweet patterns[33][34].</li>  
 <li>Modeled tweet reading behavior to estimate how many pro-smoking posts teens see daily[35][36].</li>  
</ul>  
  
<h2>Architecture Overview</h2>  
<ul>  
 <li>Scalable data ingestion archived targeted Twitter posts and user metadata via APIs[28][37].</li>  
 <li>NLP and feature extraction pipeline cleaned text and generated features for classification[38][39].</li>  
 <li>“Happy Birthday” tweet-based age classifier identified under-18 users with ~80% accuracy[33][34].</li>  
 <li>Stochastic user behavior model (Poisson process) computed the probability teens read key tweets[40][41].</li>  
</ul>  
  
<h2>Results and Impacts</h2>  
<ul>  
 <li>About 36% of key influencers’ direct followers were likely under age 18[24].</li>  
 <li>Underage followers saw a median of ~2.2 pro-tobacco tweets per day from key accounts[36].</li>  
 <li>Revealed significant adolescent exposure to tobacco content online, prompting calls for multi-pronged prevention (including social media oversight)[29][30].</li>  
</ul>  
  
<h2>Skills and Tools Used</h2>  
<ul>  
 <li>Twitter API integration and big data handling for large-scale social media collection[28].</li>  
 <li>Natural language processing for text cleaning and feature engineering (language detection, etc.)[38].</li>  
 <li>Machine learning (SVM, Random Forest via scikit-learn) for tweet classification and age prediction[34].</li>  
 <li>Network statistics and probabilistic modeling to estimate information exposure on follower networks[42][40].</li>  
</ul>  
  
<h2>Cross-project Capabilities</h2>  
<ul>  
 <li>Reusable social media analysis pipeline applicable to other health topics (e.g., e-cigarettes)[43].</li>  
 <li>Age inference methods generalize to find vulnerable user groups in any online contagion[33][29].</li>  
 <li>Integration of ML and network analysis here informed later projects on identifying communities and hotspots[44].</li>  
</ul>  
  
<h2>Published Papers/Tools</h2>  
<ul>  
 <li>Dissertation Study: <em>Exposure of a Vulnerable Population to Smoking-Related Messaging on Twitter</em> (PhD Thesis)[45].</li>  
 <li>Custom Twitter Surveillance Pipeline – software for data collection, classification, and visualization[31][43].</li>  
 <li>Findings recommended follow-up surveys to link social media exposure with behavior, influencing future research directions[26][30].</li>  
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## Project 24: Social Contagion – E-cig Online Exposure and Hotspots

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<head>  
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 <title>Social Contagion Project 3 – Smoking Contagion E-cig Online Exposure and Hotspots (Project 24)</title>  
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<img src="placeholder.jpg" alt="Project 24 placeholder image" />  
<p><strong>BLUF:</strong> Identified geographic “hotspots” of e-cigarette-related tweets across the US, revealing that most clusters have high pro-vaping content and many underage users (especially on the West Coast).</p>  
  
<h2>Introduction</h2>  
<ul>  
 <li>E-cigarette use surged in recent years, doubling/tripling in awareness and use[46].</li>  
 <li>Identifying where e-cig uptake is most active (hotspots) helps target interventions[47].</li>  
 <li>Twitter is heavily used for e-cig marketing and discussion, making it a rich surveillance source[48].</li>  
</ul>  
  
<h2>Key Questions Addressed</h2>  
<ul>  
 <li>Where and when do e-cig related tweets form significant clusters (“hotspots”) in the US?[47]</li>  
 <li>Do these hotspots show distinct tweet sentiments and user age profiles (youth involvement)?[49][50]</li>  
 <li>How can large-scale social media data be leveraged to detect emerging vaping trends?[48]</li>  
</ul>  
  
<h2>The Problem</h2>  
<ul>  
 <li>Earlier e-cig Twitter studies had small samples or focused only on ads, missing broader patterns[51].</li>  
 <li>No prior work mapped e-cig tweet activity spatially to find statistically significant clusters[51].</li>  
 <li>Differentiating genuine public tweets from overwhelming commercial promotions is challenging[52][51].</li>  
</ul>  
  
<h2>The Importance</h2>  
<ul>  
 <li>Locating e-cig “hotspots” guides local public health responses where vaping is concentrated[50].</li>  
 <li>Many hotspots have high youth participation, raising concern for underage vaping surges[50].</li>  
 <li>Understanding sentiment in hotspots helps gauge public perception and misinformation about e-cigs[53][50].</li>  
</ul>  
  
<h2>The Solution</h2>  
<ul>  
 <li>Gathered two years of geotagged tweets (~83k) about e-cigs nationwide[54][55].</li>  
 <li>Removed commercial spam tweets via ML classifiers to focus on real user content[56].</li>  
 <li>Applied spatiotemporal scan statistics to detect clusters with unexpectedly high e-cig tweet volumes[57].</li>  
 <li>Analyzed each hotspot’s tweet sentiment (pro vs anti e-cig) and underage user fraction[49][50].</li>  
</ul>  
  
<h2>Architecture Overview</h2>  
<ul>  
 <li>Twitter Streaming API collected 1% sample of tweets with location data (Oct 2012–Oct 2014)[58].</li>  
 <li>Filtered for e-cig keywords (“e-cig”, “vape”, etc.), yielding 62,894 US geotagged e-cig tweets[55].</li>  
 <li>SVM-based classifier separated non-commercial e-cig tweets from advertising content[56][59].</li>  
 <li>Used SaTScan-like spatiotemporal scanning to find anomalous clusters, then computed each cluster’s sentiment and age metrics[60][49].</li>  
</ul>  
  
<h2>Results and Impacts</h2>  
<ul>  
 <li>Discovered multiple e-cig tweet hotspots, with most located on the US West Coast[61].</li>  
 <li>About 75% of hotspots had above-average pro-vaping sentiment and more under-18 users than the norm[50].</li>  
 <li>Certain regions have intense pro-e-cig social influence among youth, highlighting need for targeted monitoring and intervention[50][62].</li>  
</ul>  
  
<h2>Skills and Tools Used</h2>  
<ul>  
 <li>Geospatial analysis and spatiotemporal clustering (scan statistics) for hotspot detection[57].</li>  
 <li>High-volume data processing (streaming API, filtering 83k relevant tweets from big data)[58][55].</li>  
 <li>Machine learning text classification to filter content (identified ~90% commercial tweets)[52][56].</li>  
 <li>Sentiment analysis and demographic inference combining data mining with epidemiological mapping[53][50].</li>  
</ul>  
  
<h2>Cross-project Capabilities</h2>  
<ul>  
 <li>Twitter surveillance pipeline flexibly adapted to a new topic (vaping), showing versatility[43].</li>  
 <li>Spatial analysis of social data opens avenues to track other public health signals (e.g., flu trends via tweets)[63][64].</li>  
 <li>Content filtering techniques here (spotting organic vs commercial posts) inform other contagion analyses of social media[52][56].</li>  
</ul>  
  
<h2>Published Papers/Tools</h2>  
<ul>  
 <li>PhD Thesis (Chapter 5): <em>Find and Analyze Hotspots of E-cigarette-related Tweets</em>[65][51].</li>  
 <li>Spatiotemporal hotspot detection and analysis tools for social media data (developed in this project)[60][49].</li>  
 <li>First-of-its-kind spatial analysis of vaping discourse, cited in later social media health studies[51][50].</li>  
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## Project 25: Social Contagion – Blocking Contagion via Edge Removal

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<img src="placeholder.jpg" alt="Project 25 placeholder image" />  
<p><strong>BLUF:</strong> Studied how to stop contagion spread by cutting network links. Proved key cases are NP-hard and built a new edge-removal heuristic that significantly improves containment of both simple and complex contagions.</p>  
  
<h2>Introduction</h2>  
<ul>  
 <li>Cutting interactions between individuals can block contagion spread (e.g., closing schools)[66].</li>  
 <li>This project asks how to optimally remove network links (edges) to minimize an epidemic or misinformation outbreak[67].</li>  
 <li>It extends prior work beyond removing people (nodes) to the more targeted approach of removing specific connections[68][69].</li>  
</ul>  
  
<h2>Key Questions Addressed</h2>  
<ul>  
 <li>Which communication links should be cut to best prevent a contagion from spreading?[67]</li>  
 <li>How hard is it to compute the optimal set of edges to remove under a budget?[70][71]</li>  
 <li>Do effective strategies differ for simple contagions (one contact spreads) vs complex contagions (multiple contacts needed)?[72][73]</li>  
</ul>  
  
<h2>The Problem</h2>  
<ul>  
 <li>Choosing a minimal-cost set of edges to delete for maximum spread reduction is NP-hard[74][71].</li>  
 <li>For complex contagions (threshold models), the budgeted edge removal problem has no constant-factor approximation (unless P=NP)[75].</li>  
 <li>Most edge removal research addressed simple contagions and ignored outbreak-specific dynamics[76][77].</li>  
</ul>  
  
<h2>The Importance</h2>  
<ul>  
 <li>Edge removal is often more feasible than removing individuals, offering a “surgical” containment approach[69][78].</li>  
 <li>Knowing algorithmic limits (hardness) guides what policymakers can realistically optimize in contagion control[70][71].</li>  
 <li>Effective link-cutting strategies apply broadly (disease, rumors, unrest) where removing whole nodes is impractical[79].</li>  
</ul>  
  
<h2>The Solution</h2>  
<ul>  
 <li>Formulated edge-based contagion blocking as optimization problems with various constraints (budgets, targeted closures)[67][80].</li>  
 <li>Proved new results: optimal edge removal for complex contagions cannot be approximated, but identified certain tractable cases[75][81].</li>  
 <li>Developed an “edge-covering” heuristic to select edges to cut, for both weighted and unweighted networks[82].</li>  
 <li>Simulated contagion spread on large real networks to compare our heuristic against existing methods, showing much improved blocking performance[83][84].</li>  
</ul>  
  
<h2>Architecture Overview</h2>  
<ul>  
 <li>Combined graph theory (edge covers, cut sets) with contagion dynamics models (independent cascade, threshold)[72][73].</li>  
 <li>Analyzed complexity of edge removal vs node removal, noting similarities and differences in solvability[85][71].</li>  
 <li>Used a simulation testbed on real networks (Montgomery County contact network, Facebook graphs) to measure outbreak sizes with and without interventions[86].</li>  
 <li>Heuristic algorithm accounts for edge weights and directions, and can utilize outbreak location info to prioritize cuts[77][82].</li>  
</ul>  
  
<h2>Results and Impacts</h2>  
<ul>  
 <li>The edge-removal heuristic outperformed prior strategies, blocking more of the contagion spread in 12 test scenarios across three networks[83][84].</li>  
 <li>Confirmed that while optimal solutions are intractable, a scalable heuristic can achieve strong contagion containment in practice[74][82].</li>  
 <li>Provided the first thorough comparison of node removal vs edge removal, showing that cutting specific links can often contain outbreaks more cost-effectively than removing individuals[69][78].</li>  
 <li>Algorithms and findings from this project informed follow-up research and have been applied to other network intervention scenarios (e.g., strategic communication disruption)[87][76].</li>  
</ul>  
  
<h2>Skills and Tools Used</h2>  
<ul>  
 <li>Advanced graph algorithms and complexity proofs (NP-completeness, approximation limits) for network problems[75][88].</li>  
 <li>Design and implementation of network heuristics and a simulation framework for contagion diffusion on large graphs[82][86].</li>  
 <li>Use of weighted/directed network models and threshold contagion simulations for comprehensive testing[72][89].</li>  
 <li>Interdisciplinary approach linking computer science (algorithms) and epidemiology/social network analysis to produce actionable intervention strategies[90][69].</li>  
</ul>  
  
<h2>Cross-project Capabilities</h2>  
<ul>  
 <li>Edge-cutting techniques integrate with community-based blocking (Project 5) by focusing on inter-community links as removal targets[91][92].</li>  
 <li>General methods from this project handle both simple and complex contagions, contributing to a versatile network intervention toolkit used across the theme[72][73].</li>  
 <li>Large-scale simulation and evaluation practices here set a baseline for testing other intervention methods in the portfolio[86][93].</li>  
</ul>  
  
<h2>Published Papers/Tools</h2>  
<ul>  
 <li>Conference Paper: <em>Blocking Simple and Complex Contagion by Edge Removal</em> – IEEE ICDM 2013[94][95].</li>  
 <li>Edge-Blocking Heuristic (code) – implemented and validated on real social networks (Montgomery County, Facebook)[86].</li>  
 <li>Project outcomes cited in later network science research and integrated into simulation platforms for contagion modeling[96][87].</li>  
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## Project 26: Social Contagion – Blocking Contagion via Community Structure

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<h1>Social Contagion Project 5: Blocking Contagion via Community Structure (Project 26)</h1>  
<img src="placeholder.jpg" alt="Project 26 placeholder image" />  
<p><strong>BLUF:</strong> Created a hybrid contagion-blocking strategy using community detection, then targeting key inter-community nodes/links to contain spread. This approach outperformed purely structural or purely dynamic methods, especially for complex contagions.</p>  
  
<h2>Introduction</h2>  
<ul>  
 <li>Many blocking methods remove high-degree nodes, but few leverage community structure for interventions[97].</li>  
 <li>Complex contagions (spread needs multiple influencers) are harder to block with standard centrality approaches[98].</li>  
 <li>This project uses network communities to quickly isolate contagion within clusters and prevent broader spread[99][92].</li>  
</ul>  
  
<h2>Key Questions Addressed</h2>  
<ul>  
 <li>Can community structure be exploited to better identify critical nodes to immunize?[99]</li>  
 <li>How to effectively contain a contagion that requires multiple social confirmations to spread?[100][101]</li>  
 <li>Does a hybrid (structure + dynamics) strategy outperform purely topological or purely simulation-based blocking?[97][102]</li>  
</ul>  
  
<h2>The Problem</h2>  
<ul>  
 <li>Pure structural (“proactive”) methods are fast but may fail to stop spread, especially for complex contagions[97][102].</li>  
 <li>Pure dynamics-based (“reactive”) methods are effective but slow and need specific contagion model data[103][104].</li>  
 <li>Little prior work addressed blocking contagions requiring multi-node reinforcement (complex contagions)[98].</li>  
</ul>  
  
<h2>The Importance</h2>  
<ul>  
 <li>Containing contagions at community boundaries can prevent widespread outbreaks while limiting intervention scope[92][105].</li>  
 <li>A hybrid approach balances planning based on network structure with added efficacy from contagion dynamics[106][99].</li>  
 <li>Blocking complex contagions expands preparedness to handle social spreads that involve peer reinforcement (common in human behavior)[101][107].</li>  
</ul>  
  
<h2>The Solution</h2>  
<ul>  
 <li>Developed a cluster-based algorithm: partitioned the network into communities, then targeted blocking at inter-community connections[92][108].</li>  
 <li>Assumed contagion spreads quickly inside communities, so focus is on preventing cross-community transmission[109][105].</li>  
 <li>Implemented a hybrid critical node selection (CNS) approach picking boundary nodes using topology and contagion simulations[110][108].</li>  
 <li>Tested on multiple networks and compared against centrality-based and simulation-heavy methods to demonstrate improvements[111][112].</li>  
</ul>  
  
<h2>Architecture Overview</h2>  
<ul>  
 <li>Used the progressive threshold model (complex contagion) for simulations, where nodes need ≥2 infected neighbors to activate[113][101].</li>  
 <li>Applied community detection (e.g., modularity clustering) to divide the network into dense clusters with sparse between-cluster links[92].</li>  
 <li>Identified all edges between communities as “choke points” for contagion crossing (boundary edges recorded)[108][114].</li>  
 <li>Applied reactive blocking on these boundary regions: froze minimal sets of boundary nodes after simulating limited spread, to stop further contagion[99][108].</li>  
</ul>  
  
<h2>Results and Impacts</h2>  
<ul>  
 <li>The community-based hybrid method contained complex contagions more effectively than degree-centrality-based interventions[97][102].</li>  
 <li>It matched or beat the performance of state-of-the-art simulation-only methods, validating the structure+dynamic synergy[103][99].</li>  
 <li>Tested on three real social networks, demonstrating the approach’s generality and scalability to different network types[111].</li>  
 <li>Filled a gap by providing an effective blocking strategy for complex contagions, influencing later network intervention research that accounts for community structure[98][110].</li>  
</ul>  
  
<h2>Skills and Tools Used</h2>  
<ul>  
 <li>Community detection and graph clustering techniques to identify network community structure[92].</li>  
 <li>Multi-agent contagion simulation (threshold model) to test and refine blocking strategies under complex spread conditions[101][109].</li>  
 <li>Hybrid algorithm design combining graph analytics (structural metrics, boundary identification) with simulation feedback[110][108].</li>  
 <li>Empirical evaluation on network datasets, including custom contagion diffusion code and statistical analysis of outcomes[112][111].</li>  
</ul>  
  
<h2>Cross-project Capabilities</h2>  
<ul>  
 <li>Community-centric blocking can complement edge removal (Project 4) by isolating critical cross-community links as cut points[91][108].</li>  
 <li>Approach is applicable to other domains (e.g., immunization or isolating sub-networks in cybersecurity) that benefit from leveraging community structure[92][109].</li>  
 <li>Hybrid proactive-reactive concept influenced integrated strategies across the social contagion projects, showing combined analytical and simulation methods yield better results[99][110].</li>  
</ul>  
  
<h2>Published Papers/Tools</h2>  
<ul>  
 <li>Workshop Paper: <em>Blocking Complex Contagions Using Community Structure</em> – AAMAS MAIN Workshop 2013[115][97].</li>  
 <li>Community-based Node Selection (CNS) algorithm – hybrid blocking tool developed and tested in this project[92][116].</li>  
 <li>Results extended in a journal submission, and this work has been incorporated into broader studies on contagion intervention[117][118].</li>  
</ul>  
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[[1]](file://file_00000000c56c61f588432a57acd6dbc9#:~:text=Nicotine%2C%20in%20the%20form%20of,care%20expenditures) [[2]](file://file_00000000c56c61f588432a57acd6dbc9#:~:text=It%20has%20been%20repeatedly%20shown,which%20stands%20for) [[3]](file://file_00000000c56c61f588432a57acd6dbc9#:~:text=quitting%20smoking%20each%20year%2C%20but,%28see%20figure%201) [[4]](file://file_00000000c56c61f588432a57acd6dbc9#:~:text=If%20we%20assume%20that%20the,over%20more%20than%20four%20decades) [[5]](file://file_00000000c56c61f588432a57acd6dbc9#:~:text=This%20puzzling%20contrast%20suggests%20that,we%20need%20a%20new%20model) [[6]](file://file_00000000c56c61f588432a57acd6dbc9#:~:text=Intuitively%2C%20this%20means%20that%20significantly,end%20the%20epidemic%20than%20expected) [[7]](file://file_00000000c56c61f588432a57acd6dbc9#:~:text=Smoking%20is%20a%20complex%2C%20%E2%80%9Cpolicy,to%20achieving%20lasting%20social%20benefits) [[8]](file://file_00000000c56c61f588432a57acd6dbc9#:~:text=If%20we%20assume%20that%20the,over%20more%20than%20four%20decades) [[9]](file://file_00000000c56c61f588432a57acd6dbc9#:~:text=This%20expectation%20stands%20in%20contrast,over%20more%20than%20four%20decades) [[10]](file://file_00000000c56c61f588432a57acd6dbc9#:~:text=Our%20main%20contribution%20in%20this,discussion%20of%20the%20model%20and) [[11]](file://file_00000000c56c61f588432a57acd6dbc9#:~:text=transition%20from%20an%20I%20state,only%20way%20to%20recover%20to) [[12]](file://file_00000000c56c61f588432a57acd6dbc9#:~:text=section%203%20and%20we%20present,of%20the%20model%20and%20possible) [[13]](file://file_00000000c56c61f588432a57acd6dbc9#:~:text=To%20model%20the%20dynamics%20of,The%20probability%20of) [[14]](file://file_00000000c56c61f588432a57acd6dbc9#:~:text=high%20,level%20of%20susceptibility%20can%20decrease) [[15]](file://file_00000000c56c61f588432a57acd6dbc9#:~:text=states%20corresponding%20to%20different%20levels,overall%20decline%20in%20smoking%20behavior) [[16]](file://file_00000000c56c61f588432a57acd6dbc9#:~:text=it%20can%20be%20very%20difficult,overall%20decline%20in%20smoking%20behavior) [[17]](file://file_00000000c56c61f588432a57acd6dbc9#:~:text=derstanding%20this%20phenomenon,overall%20decline%20in%20smoking%20behavior) [[18]](file://file_00000000c56c61f588432a57acd6dbc9#:~:text=This%20puzzling%20contrast%20suggests%20that,we%20need%20a%20new%20model) [[19]](file://file_00000000c56c61f588432a57acd6dbc9#:~:text=Addiction%20Dynamics%20May%20Explain%20the,Slow%20Decline%20of%20Smoking%20Prevalence) [[20]](file://file_00000000c56c61f588432a57acd6dbc9#:~:text=Smoking%20is%20a%20complex%2C%20%E2%80%9Cpolicy,to%20achieving%20lasting%20social%20benefits) [[21]](file://file_00000000c56c61f588432a57acd6dbc9#:~:text=Smoking%20is%20a%20complex%2C%20%E2%80%9Cpolicy,to%20achieving%20lasting%20social%20benefits) social-contagion-1.smoking-behavior-sturctured-resistance-model.pdf

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[[22]](file://file_000000009a70622fb89a00cbed5c42ed#:~:text=exposure%20to%20marijuana,e%E2%86%B5ect%20of%20normalizing%20marijuana%20use) [[23]](file://file_000000009a70622fb89a00cbed5c42ed#:~:text=The%20aim%20of%20the%20present,3%2C%20134%2C150) [[24]](file://file_000000009a70622fb89a00cbed5c42ed#:~:text=classifier%20was%20then%20used%20to,be%20a%20cause%20for%20concern) [[25]](file://file_000000009a70622fb89a00cbed5c42ed#:~:text=results%20of%20the%20age,400%20most%20recent%20timeline%20tweets) [[26]](file://file_000000009a70622fb89a00cbed5c42ed#:~:text=Quantifying%20the%20extent%20to%20which,important%20direction%20for%20future%20research) [[27]](file://file_000000009a70622fb89a00cbed5c42ed#:~:text=to%20smoking,3%2C%20134%2C150) [[28]](file://file_000000009a70622fb89a00cbed5c42ed#:~:text=1) [[29]](file://file_000000009a70622fb89a00cbed5c42ed#:~:text=under%2018%20years%20of%20age,be%20a%20cause%20for%20concern) [[30]](file://file_000000009a70622fb89a00cbed5c42ed#:~:text=into%20these%20behaviors%20need%20to,heavily%20exposed%20to%20these%20messages) [[31]](file://file_000000009a70622fb89a00cbed5c42ed#:~:text=1.3%20Pipeline%20for%20Twitter,Studies) [[32]](file://file_000000009a70622fb89a00cbed5c42ed#:~:text=An%20illustration%20of%20the%20pipeline,studies%20performed%20for%20this%20thesis) [[33]](file://file_000000009a70622fb89a00cbed5c42ed#:~:text=We%20employed%20an%20approach%20that,this%20process%20are%20presented%20next) [[34]](file://file_000000009a70622fb89a00cbed5c42ed#:~:text=We%20evaluated%20SVM%20and%20Random,learn%20Python%20libraries%20were%20used) [[35]](file://file_000000009a70622fb89a00cbed5c42ed#:~:text=We%20wish%20to%20estimate%20the,this%20as%20the%20exposure%20rate) [[36]](file://file_000000009a70622fb89a00cbed5c42ed#:~:text=tions%20are%20heavy,calculated%20are%20representative%20of%20the) [[37]](file://file_000000009a70622fb89a00cbed5c42ed#:~:text=posts%20in%20certain%20area%20due,unexpected%20volume%20of%20incoming%20data) [[38]](file://file_000000009a70622fb89a00cbed5c42ed#:~:text=NLP%20Tools) [[39]](file://file_000000009a70622fb89a00cbed5c42ed#:~:text=Tweet%20and%20User%20Feature) [[40]](file://file_000000009a70622fb89a00cbed5c42ed#:~:text=refer%20to%20this%20as%20the,exposure%20rate) [[41]](file://file_000000009a70622fb89a00cbed5c42ed#:~:text=The%20rate%20at%20which%20a,his%20friends%20is%2C%20on%20average) [[42]](file://file_000000009a70622fb89a00cbed5c42ed#:~:text=assumes%20that%20a%20Twitter%20user,%28Respond) [[43]](file://file_000000009a70622fb89a00cbed5c42ed#:~:text=We%20performed%20Twitter,data%20and%20estimated%20the%20exposed) [[44]](file://file_000000009a70622fb89a00cbed5c42ed#:~:text=Then%20we%20utilized%20this%20pipeline,communities%20in%20the%20United%20States) [[45]](file://file_000000009a70622fb89a00cbed5c42ed#:~:text=This%20trained%20classifier%20was%20then,be%20a%20cause%20for%20concern) [[91]](file://file_000000009a70622fb89a00cbed5c42ed#:~:text=in%20developing%20the%20technique%20to,based%20blocking%20heuristic%20consider) [[93]](file://file_000000009a70622fb89a00cbed5c42ed#:~:text=size,in%20previous%20contagion%20blocking%20studies) social-contagion-2.smoking-contagion-online-exposure-and-estimation.pdf

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[[46]](file://file_00000000d8f461f59fead795eba3b786#:~:text=products%20have%20grown%20enormously%20in,23) [[47]](file://file_00000000d8f461f59fead795eba3b786#:~:text=Given%20the%20sudden%20multi,cig%20related) [[48]](file://file_00000000d8f461f59fead795eba3b786#:~:text=numbers%20of%20e,cig%20surveillance%20study) [[49]](file://file_00000000d8f461f59fead795eba3b786#:~:text=the%20tweets%20to%20identify%20the,users%20within%20these%20anomalous%20clusters) [[50]](file://file_00000000d8f461f59fead795eba3b786#:~:text=from%20this%20study%20suggest%20that,west%20coast%20of%20the%20US) [[51]](file://file_00000000d8f461f59fead795eba3b786#:~:text=Unlike%20previous%20Twitter,a%20spatial%20analysis%20using%20Twitter) [[52]](file://file_00000000d8f461f59fead795eba3b786#:~:text=Some%20of%20the%20studies%20have,cig%20retail) [[53]](file://file_00000000d8f461f59fead795eba3b786#:~:text=machine%20learning%20techniques%20,that%20the%20tweets%20were%20not) [[54]](file://file_00000000d8f461f59fead795eba3b786#:~:text=Using%20the%20Twitter%20Streaming%20API%2C,2012%20to%20October%2015%2C%202014) [[55]](file://file_00000000d8f461f59fead795eba3b786#:~:text=We%20filtered%20this%20dataset%20further,that%20this%20increase%20is%20due) [[56]](file://file_00000000d8f461f59fead795eba3b786#:~:text=5.2.2%20Identifying%20Non) [[57]](file://file_00000000d8f461f59fead795eba3b786#:~:text=We%20used%20spatiotemporal%20scanning%20,location%20and%20time%20stamp%20of) [[58]](file://file_00000000d8f461f59fead795eba3b786#:~:text=5) [[59]](file://file_00000000d8f461f59fead795eba3b786#:~:text=discussed%20in%20section%205,other) [[60]](file://file_00000000d8f461f59fead795eba3b786#:~:text=We%20used%20spatiotemporal%20scanning%20,location%20and%20time%20stamp%20of) [[61]](file://file_00000000d8f461f59fead795eba3b786#:~:text=from%20this%20study%20suggest%20that,west%20coast%20of%20the%20US) [[62]](file://file_00000000d8f461f59fead795eba3b786#:~:text=contain%20more%20pro,west%20coast%20of%20the%20US) [[63]](file://file_00000000d8f461f59fead795eba3b786#:~:text=Spatial%20scan%20statistics%20is%20widely,in%2C%20for%20example%2C%20studies%20related) [[64]](file://file_00000000d8f461f59fead795eba3b786#:~:text=archeology%20,like%20illness%20%5B131) [[65]](file://file_00000000d8f461f59fead795eba3b786#:~:text=Chapter%205) social-contagion-3.smoking-contagion-ecig-online-exposure-and-hotspots.pdf

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[[66]](file://file_000000004aac61f5b9e518601d7b0d89#:~:text=Abstract%E2%80%94Eliminating%20interactions%20among%20individuals%20is,We%20also%20compare%20our%20hardness) [[67]](file://file_000000004aac61f5b9e518601d7b0d89#:~:text=blocking%20in%20networked%20populations%20by,a%20heuristic%20for%20the%20problem) [[68]](file://file_000000004aac61f5b9e518601d7b0d89#:~:text=motivated%20and%20important%20problem%20,the%20focus%20of%20this%20work) [[69]](file://file_000000004aac61f5b9e518601d7b0d89#:~:text=There%20are%20many%20situations%20in,how%20two%20opposing%20countries%2C%20C1) [[70]](file://file_000000004aac61f5b9e518601d7b0d89#:~:text=contagion%20spread%20and%20show%20that,real%20social%20networks%2C%20that%20our) [[71]](file://file_000000004aac61f5b9e518601d7b0d89#:~:text=tational%20complexities%20of%20solving%20these,We%20also%20show%20that) [[72]](file://file_000000004aac61f5b9e518601d7b0d89#:~:text=Most%20edge,11%5D%20of%20the) [[73]](file://file_000000004aac61f5b9e518601d7b0d89#:~:text=movements%20,our%20results%2C%20in%20subsequent%20sections) [[74]](file://file_000000004aac61f5b9e518601d7b0d89#:~:text=results%20to%20those%20from%20node,We%20also) [[75]](file://file_000000004aac61f5b9e518601d7b0d89#:~:text=We%20show%20that%20for%20complex,can%20be%20prevented%20from%20being) [[76]](file://file_000000004aac61f5b9e518601d7b0d89#:~:text=Most%20edge,11%5D%20of%20the) [[77]](file://file_000000004aac61f5b9e518601d7b0d89#:~:text=Table%20I%20provides%20a%20perspective,This%20work%20fills%20that%20void) [[78]](file://file_000000004aac61f5b9e518601d7b0d89#:~:text=tions%20alone%2C%20edge%20removal%20is,is%20the%20degree%20of%20v) [[79]](file://file_000000004aac61f5b9e518601d7b0d89#:~:text=There%20are%20many%20situations%20in,how%20two%20opposing%20countries%2C%20C1) [[80]](file://file_000000004aac61f5b9e518601d7b0d89#:~:text=of%20edges%20to%20be%20deleted,factor%2C%20unless%20P%20%3D%20NP) [[81]](file://file_000000004aac61f5b9e518601d7b0d89#:~:text=nodes%20%28i,close%20schools%3B%20this%20deletes%20all) [[82]](file://file_000000004aac61f5b9e518601d7b0d89#:~:text=basic%20edge,of%20edges%20than%20those%20used) [[83]](file://file_000000004aac61f5b9e518601d7b0d89#:~:text=and%20compare%20its%20performance%20to,the%20limitations%20of%20our%20approach) [[84]](file://file_000000004aac61f5b9e518601d7b0d89#:~:text=contagions%20for%20directed%2C%20weighted%20and,Montgomery%20County%2C%20Virginia%20and%20two) [[85]](file://file_000000004aac61f5b9e518601d7b0d89#:~:text=Below%2C%20we%20summarize%20our%20main,complex%20contagions%2C%20the%20basic%20problem) [[86]](file://file_000000004aac61f5b9e518601d7b0d89#:~:text=graphs,call%20this%20the%20spread%20size) [[87]](file://file_000000004aac61f5b9e518601d7b0d89#:~:text=B) [[88]](file://file_000000004aac61f5b9e518601d7b0d89#:~:text=of%20such%20an%20action%20is,factor%2C%20unless%20P%20%3D%20NP) [[89]](file://file_000000004aac61f5b9e518601d7b0d89#:~:text=Heuristics,nodes%20and%20an%20order%20of) [[90]](file://file_000000004aac61f5b9e518601d7b0d89#:~:text=Controlling%20contagions%2C%20such%20as%20false,blocking%20is%20the%20focus%20of) [[94]](file://file_000000004aac61f5b9e518601d7b0d89#:~:text=Blocking%20Simple%20and%20Complex%20Contagion,By%20Edge%20Removal) [[95]](file://file_000000004aac61f5b9e518601d7b0d89#:~:text=Abstract%E2%80%94Eliminating%20interactions%20among%20individuals%20is,node%20blocking%20problems%20and%20show) [[96]](file://file_000000004aac61f5b9e518601d7b0d89#:~:text=CITATIONS) social-contagion-4.social-contagion-blocking-via-edge-removal.pdf

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[[92]](file://file_000000007a8861f588a3921282c3e608#:~:text=contagion%20dynamics%20to%20increase%20its,that%20we%20are%20unable%20to) [[97]](file://file_000000007a8861f588a3921282c3e608#:~:text=or%20opinion,two%20or%20more%20neighbors%20possessing) [[98]](file://file_000000007a8861f588a3921282c3e608#:~:text=inferior%20to%20slower,only%20informa) [[99]](file://file_000000007a8861f588a3921282c3e608#:~:text=Based%20on%20these%20findings%2C%20we,a%20hybrid%20method%20of%20spec) [[100]](file://file_000000007a8861f588a3921282c3e608#:~:text=on%20simple%20contagions%2C%20where%20a,We%20evaluate%20our%20method%20using) [[101]](file://file_000000007a8861f588a3921282c3e608#:~:text=Following%20,9%2C%2023) [[102]](file://file_000000007a8861f588a3921282c3e608#:~:text=Thus%2C%20from%20the%20practical%20perspective,greater%20execution%20times%20than%20proactive) [[103]](file://file_000000007a8861f588a3921282c3e608#:~:text=tation%20of%20a%20population,an%20approach%20for%20selecting%20critical) [[104]](file://file_000000007a8861f588a3921282c3e608#:~:text=intervention%20planning%20can%20be%20done,a%20hybrid%20method%20of%20spec) [[105]](file://file_000000007a8861f588a3921282c3e608#:~:text=Because%20of%20the%20anticipated%20larger,these%20boundary%20regions%20of%20com) [[106]](file://file_000000007a8861f588a3921282c3e608#:~:text=tagion%20process,on%20a%20particular%20dynamics%20model) [[107]](file://file_000000007a8861f588a3921282c3e608#:~:text=one%20in%20which%20%CE%B8%20%3D,9%2C%2023) [[108]](file://file_000000007a8861f588a3921282c3e608#:~:text=a%20contagion%20at%20cluster%20,Section%204) [[109]](file://file_000000007a8861f588a3921282c3e608#:~:text=the%20nodes%20within%20a%20cluster,edges%20are%20shown%20schematically%20in) [[110]](file://file_000000007a8861f588a3921282c3e608#:~:text=ifying%20critical%20nodes%20that%20has,larger%20number%20of%20internal%20edges) [[111]](file://file_000000007a8861f588a3921282c3e608#:~:text=about%20contagion%20dynamics,social%20networks%20from%20the%20literature) [[112]](file://file_000000007a8861f588a3921282c3e608#:~:text=5,characteristics%20of%20the%20giant%20compo) [[113]](file://file_000000007a8861f588a3921282c3e608#:~:text=ing%20a%20mass%20protest%20and,does%29%20possess) [[114]](file://file_000000007a8861f588a3921282c3e608#:~:text=munity%20ID%29%20pairs,we%20use%20the%20progressive%20threshold) [[115]](file://file_000000007a8861f588a3921282c3e608#:~:text=Appears%20in%3A%20Proceedings%20of%20the,All%20rights%20reserved) [[116]](file://file_000000007a8861f588a3921282c3e608#:~:text=tion%20,to%20analyze%20the%20entire%20graph) [[117]](file://file_000000007a8861f588a3921282c3e608#:~:text=overviewed,and%20conclusions%20comprise%20Section%206) [[118]](file://file_000000007a8861f588a3921282c3e608#:~:text=and%20Experimental%20Results,and%20Knowledge%20Discovery%2C%20sumbitted%2C%202013) social-contagion-5.social-contagion-blocking-via-community-structure.pdf

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