AI for Social Good:
Key Techniques, Applications, and Results

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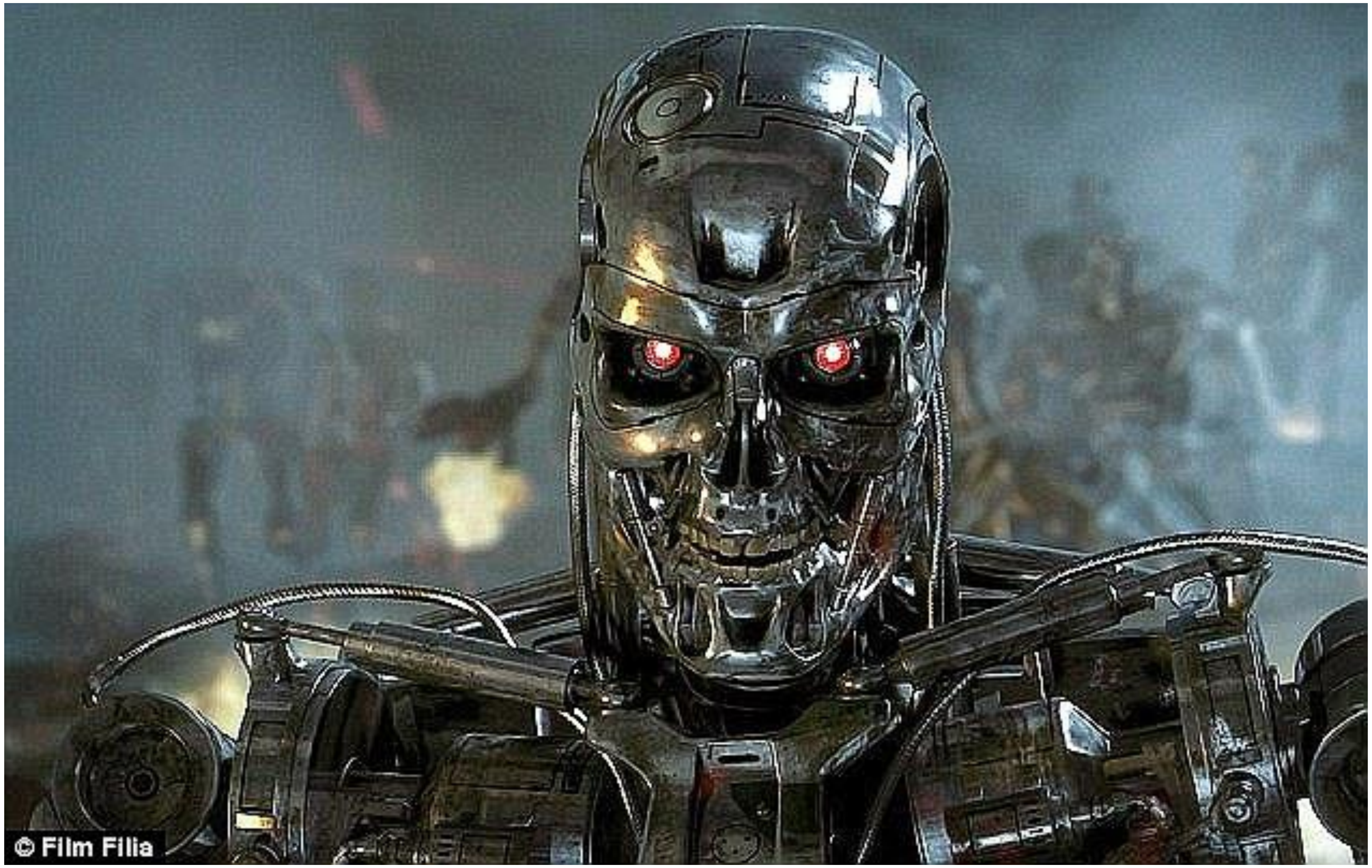
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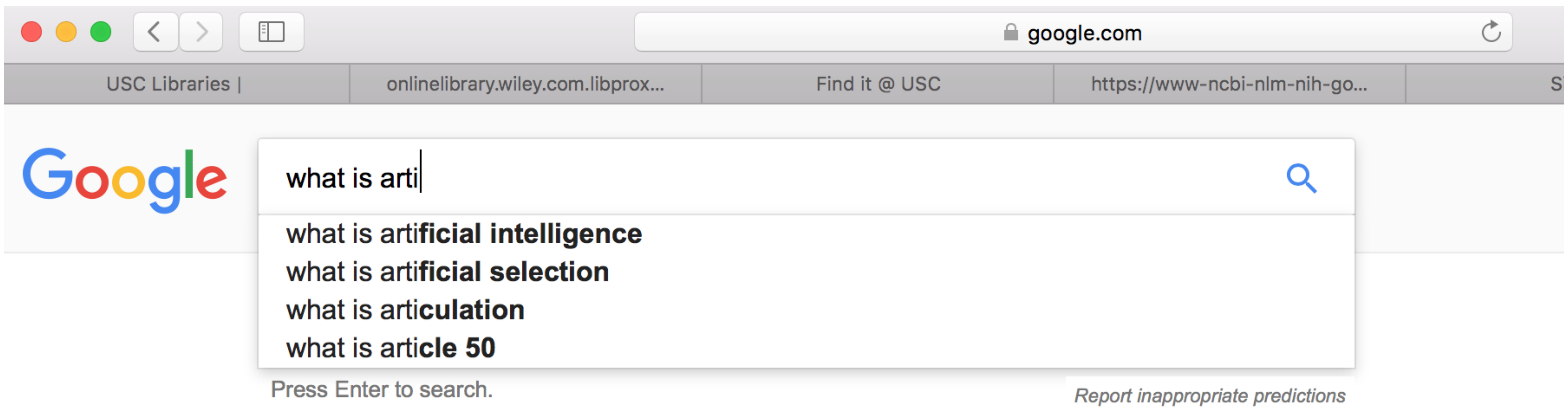
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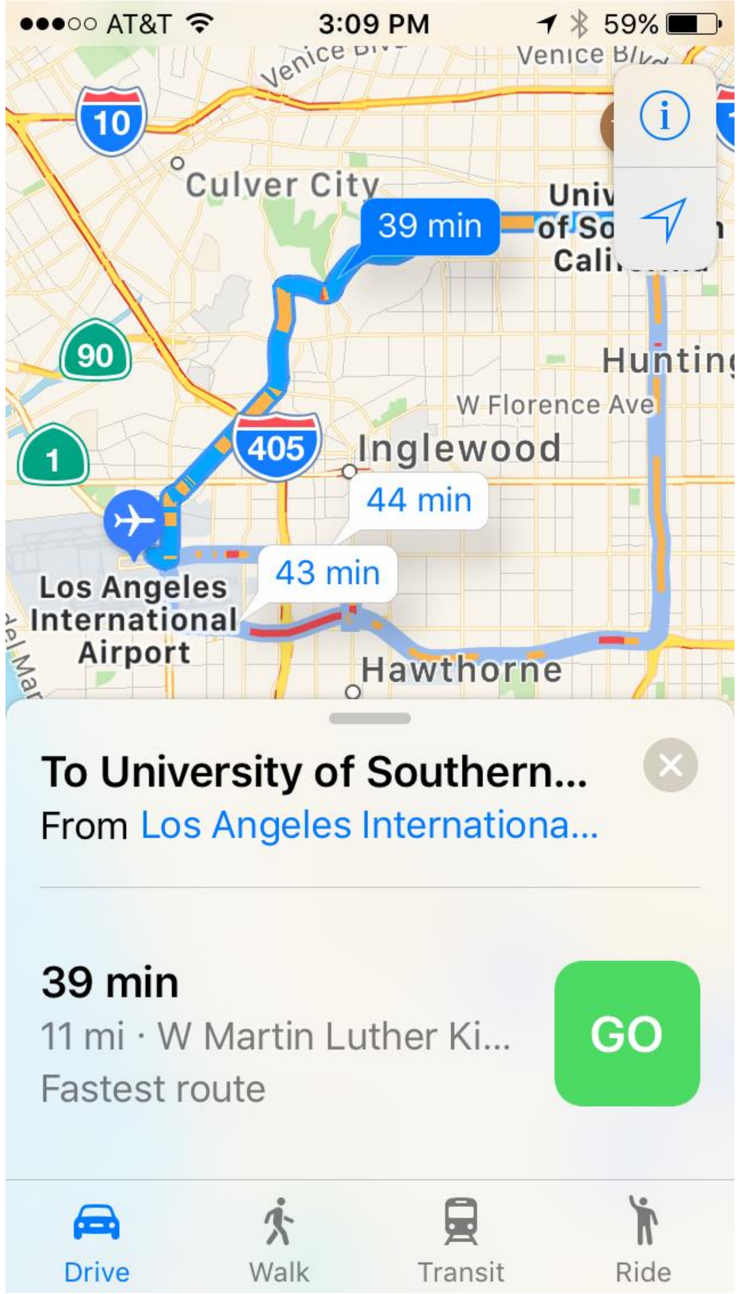

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USC Center for Artificial Intelligence in Society (CAIS.USC.EDU)

Mission Statement: Advancing AI research driven by…

American Academy of Social Work & Social Welfare

SUSTAINABLE DEVELOPMENT GOALS
17 GOALS TO TRANSFORM OUR WORLD

Grand Challenges of Social Work

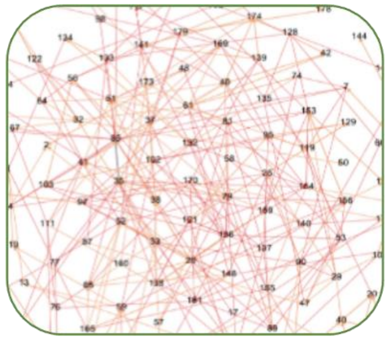
- Ensure healthy development for all youth
- Close the health gap
- Stop family violence
- Advance long and productive lives
- End homelessness
- Achieve equal opportunity and justice

…

Overview of CAIS Project Areas

AI for Assisting Low Resource Communities





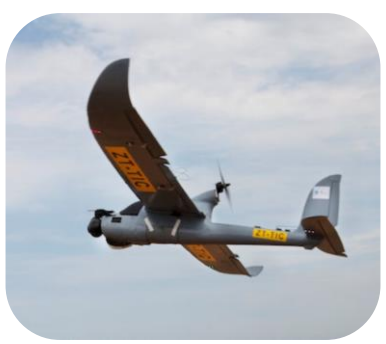
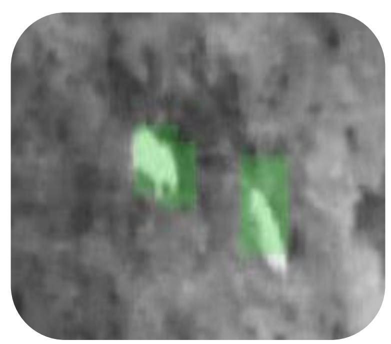

- Social networks: Spread HIV information, influence maximization
- <u>Real-world pilot tests: Big improvements</u>

Overview of CAIS Project Areas

AI for Earth






- Machine learning/planning: Predicting poaching spots, patrols
- <u>Real-world: Uganda, South Asia…</u>

Overview of CAIS Project Areas

AI for Public Safety and Security



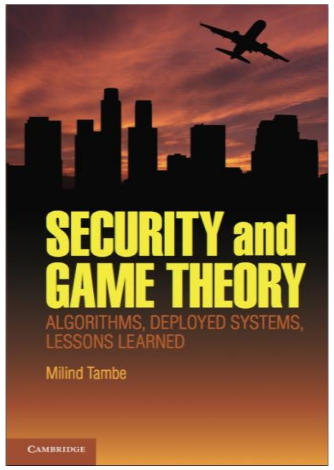


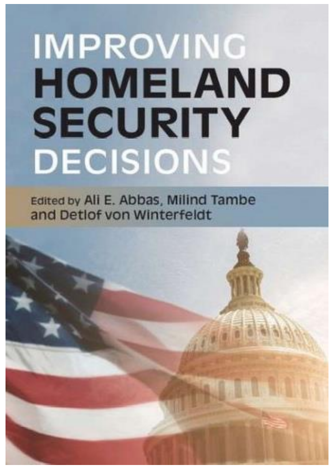

- Game theory: security resource optimization
- Real-world: US Coast Guard, US Federal Air Marshals Service…

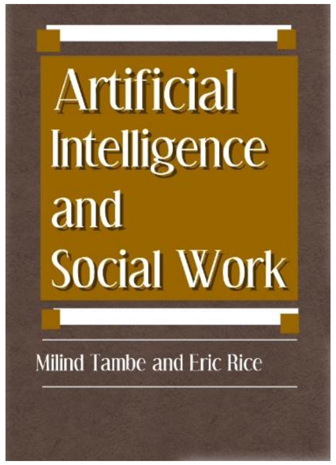
Partnerships

- Low Resource Communities
- Public Safety and Security
- Wildlife Conservation

- *AAMAS, AAAI, IJCAI*







Key Takeaways

- Significant potential: AI for low resource communities, emerging markets
- Not just applications; novel research challenges:
  - Fundamental computational challenges from use-inspired research
  - Designing AI systems in society:
    - Interpretability
    - Complementing human autonomy
- Methodological challenges:
  - Encourage interdisciplinary research: measures impact in society

Partnerships

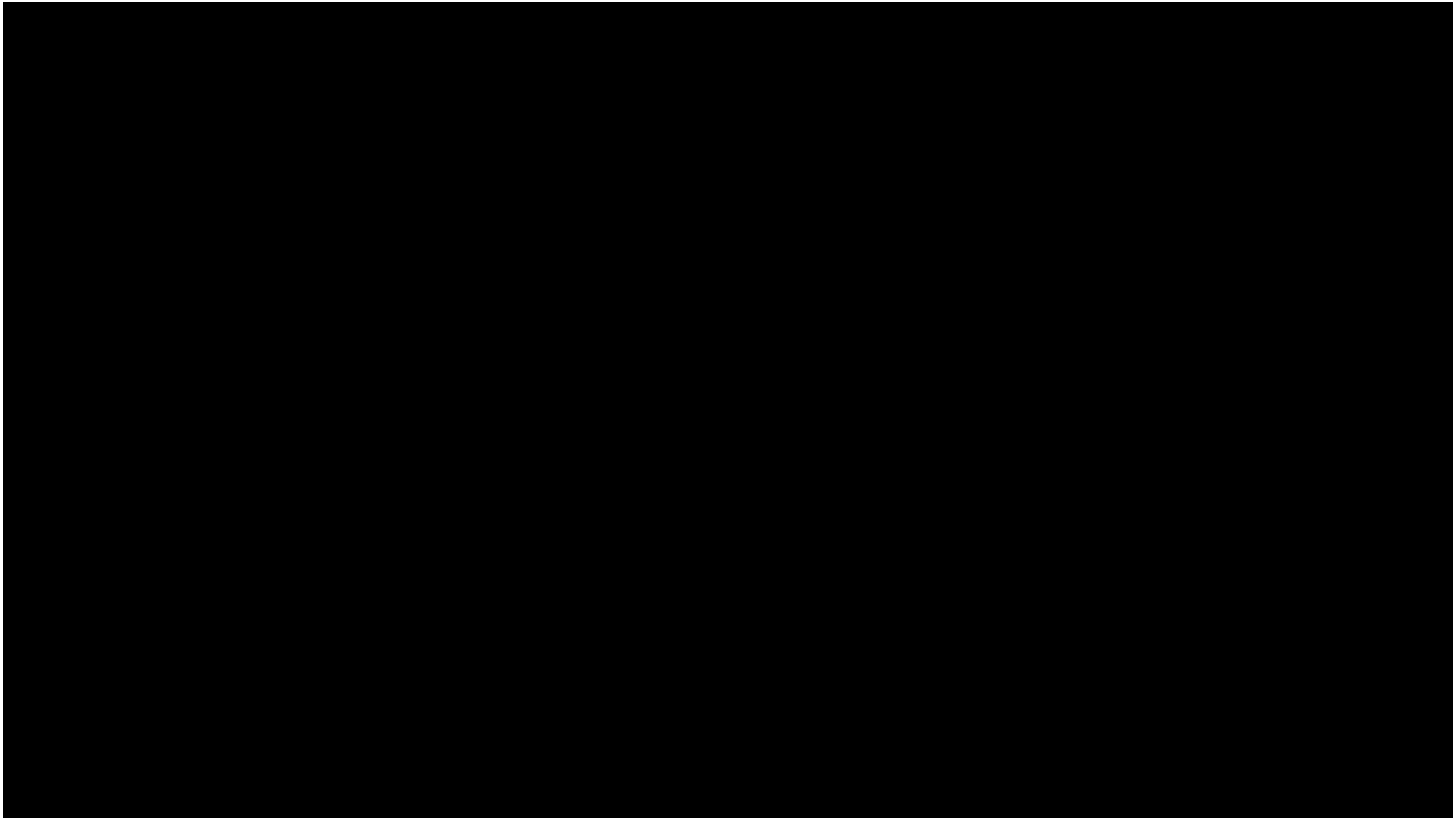
- Low Resource Communities
- Public Safety and Security
- Wildlife Conservation

PhD students/postdocs

Outline

- Introduction
- Low resource communities (homeless youth)
- Public Safety and Security
- Wildlife Conservation

AI Program: HEALER



Outline: HIV Information & Homeless Youth

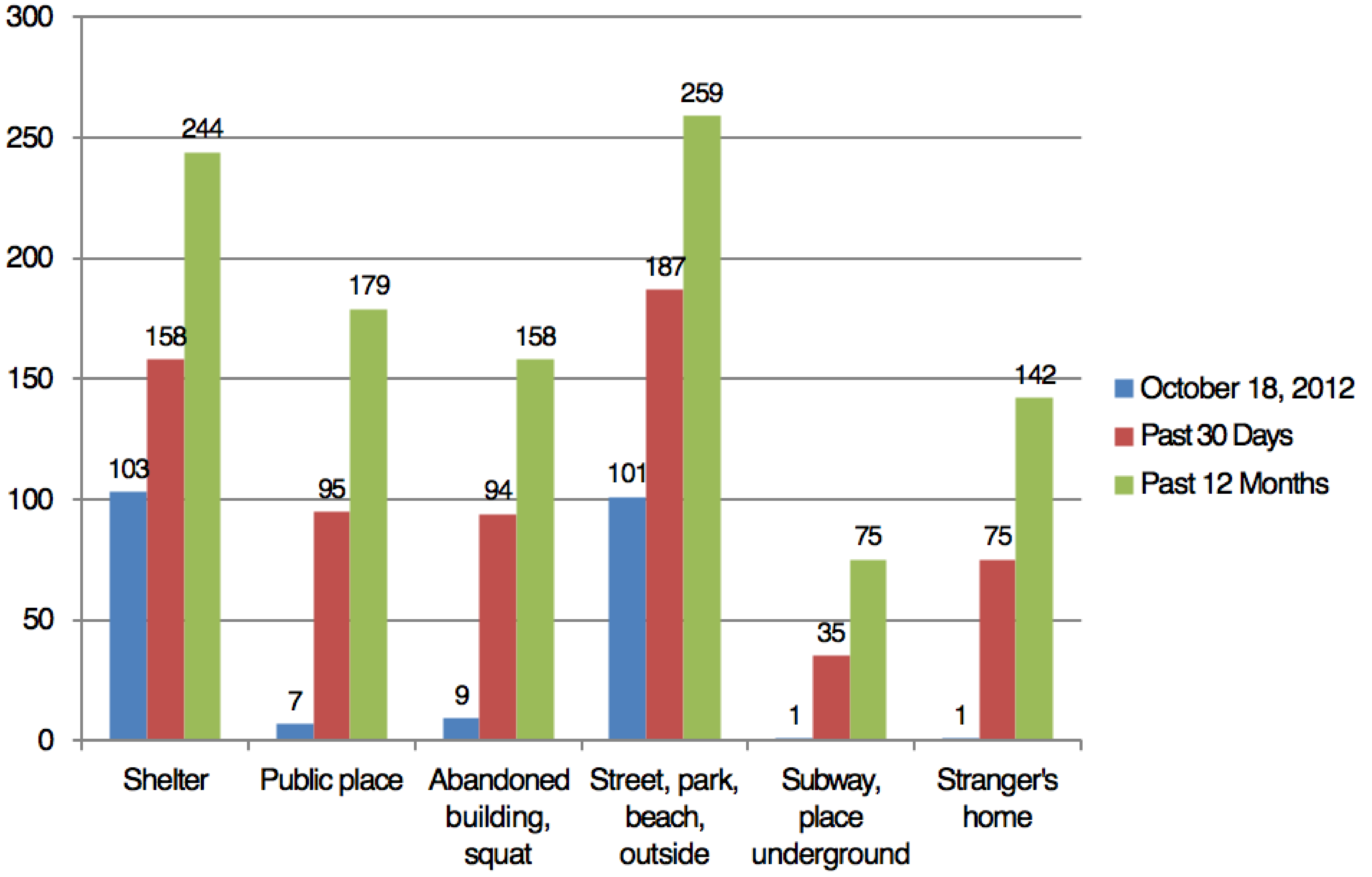
- Domain of homeless youth and HIV information dissemination
- Real World Challenges in Influence Maximization
- Sequential Decision Making under Uncertainty
- Pilot Study

Adolescent homelessness in the USA

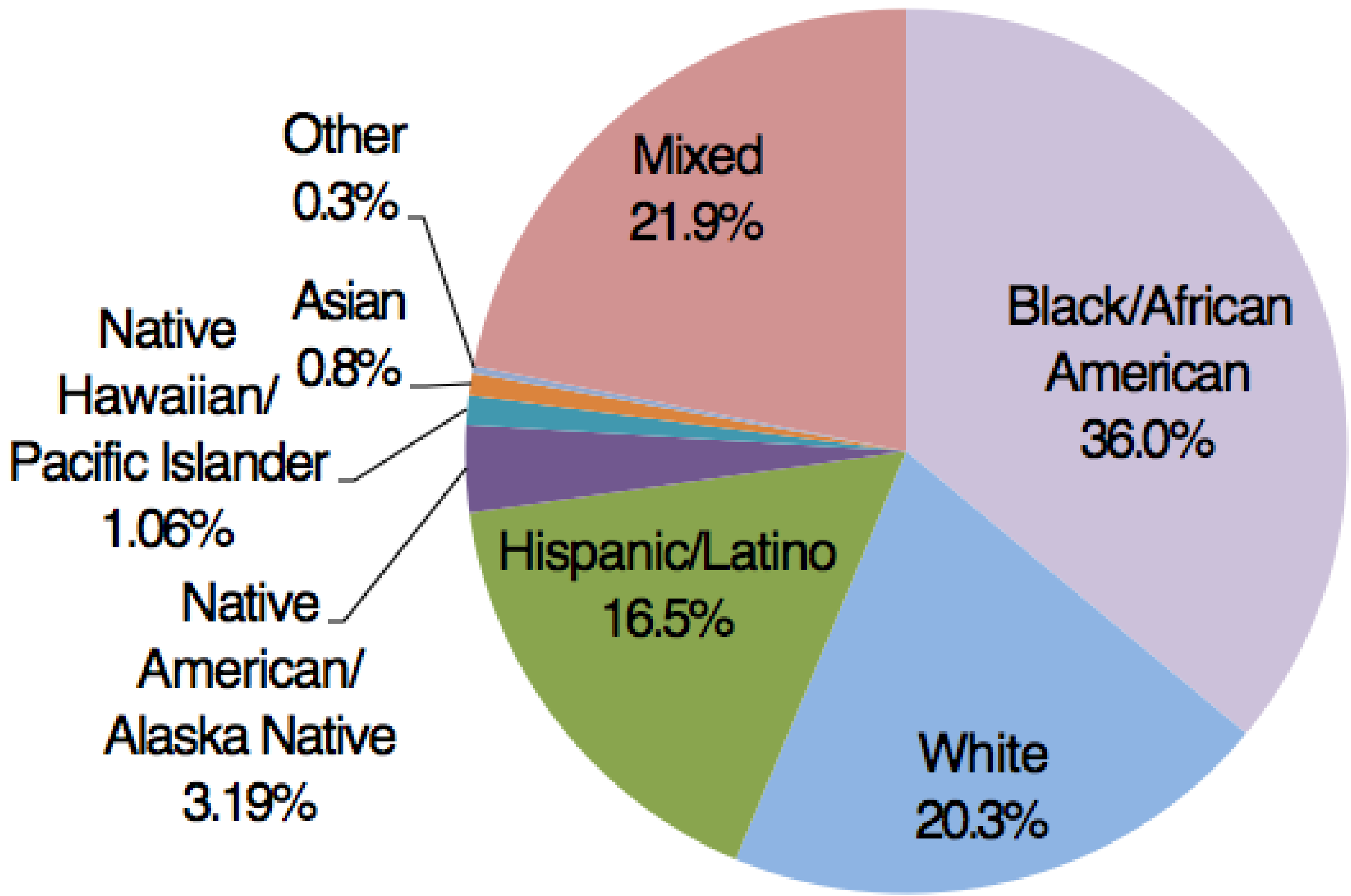
- Random Samples: 1.7 million at least one night homelessness
- From Ringwalt's 1998 work – National sample
  - 7% of 12 to 17 years olds

- Street Counts: In LAHSA Point in Time 2017
  - 57,794 homeless persons
  - 5979 youth age 13-24 unaccompanied

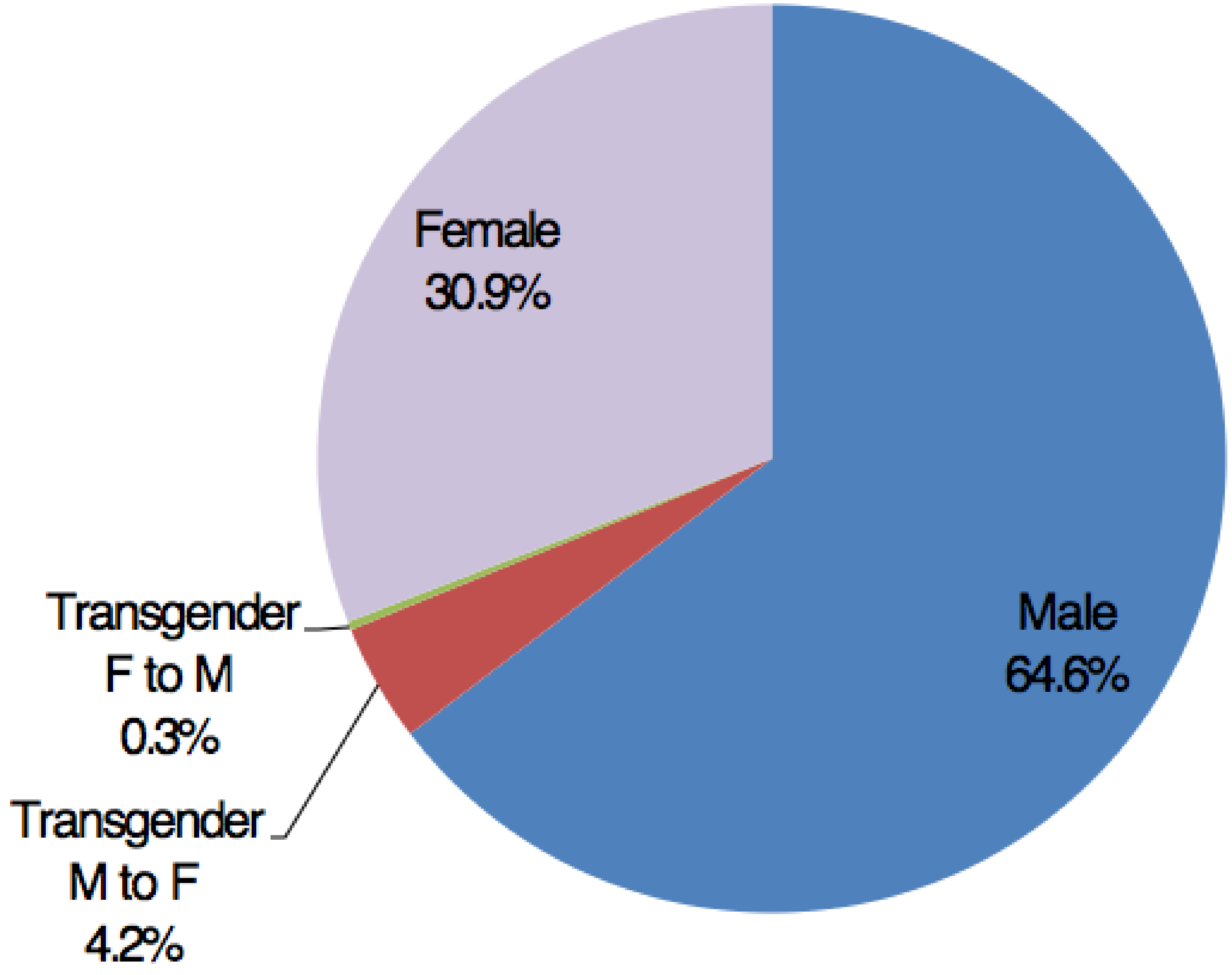
Literal Homelessness Experiences among Those with Past Year Literal Homelessness



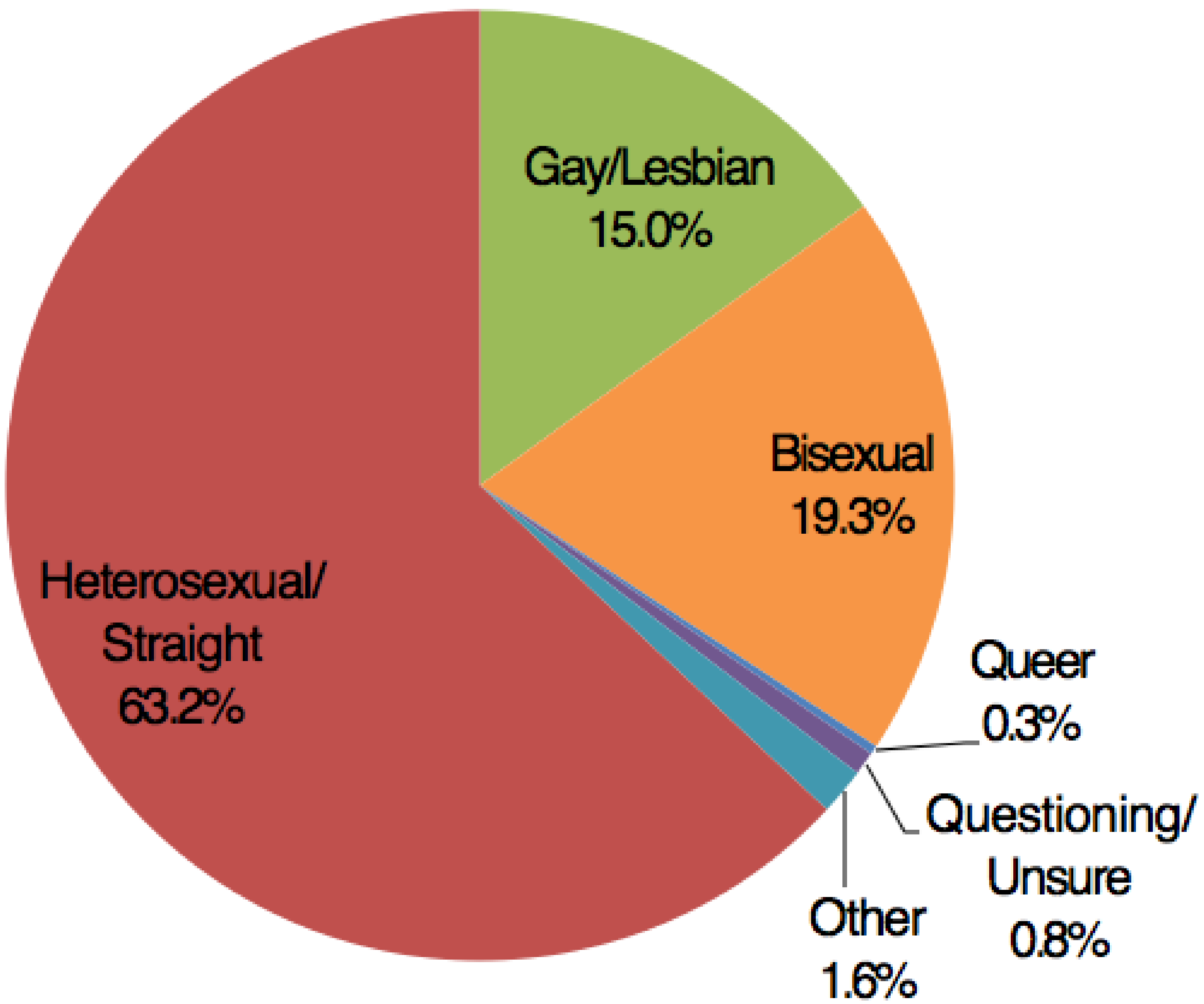
Race among Those with Past Year Literal Homelessness



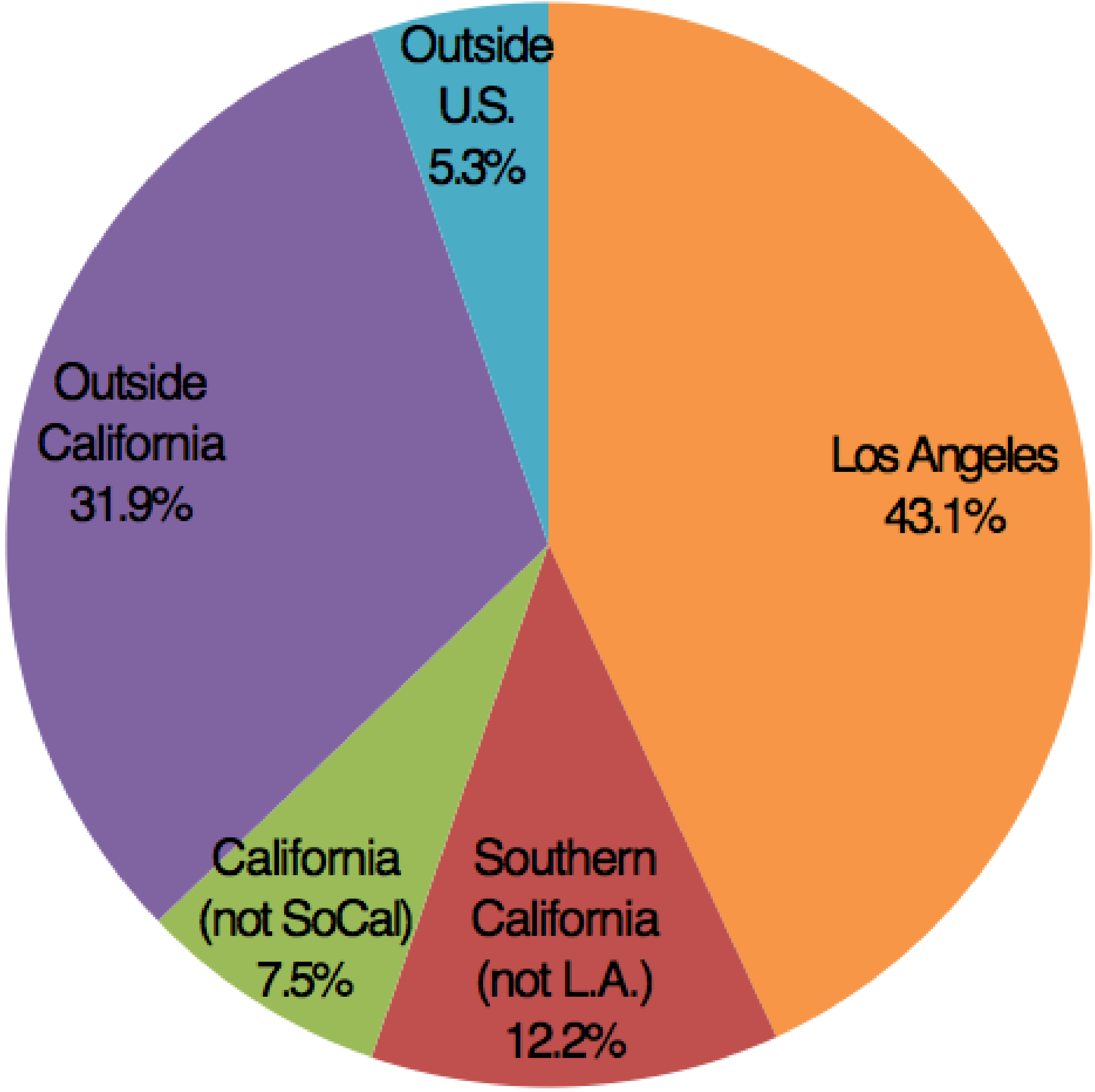
Gender among Those with Past Year Literal Homelessness

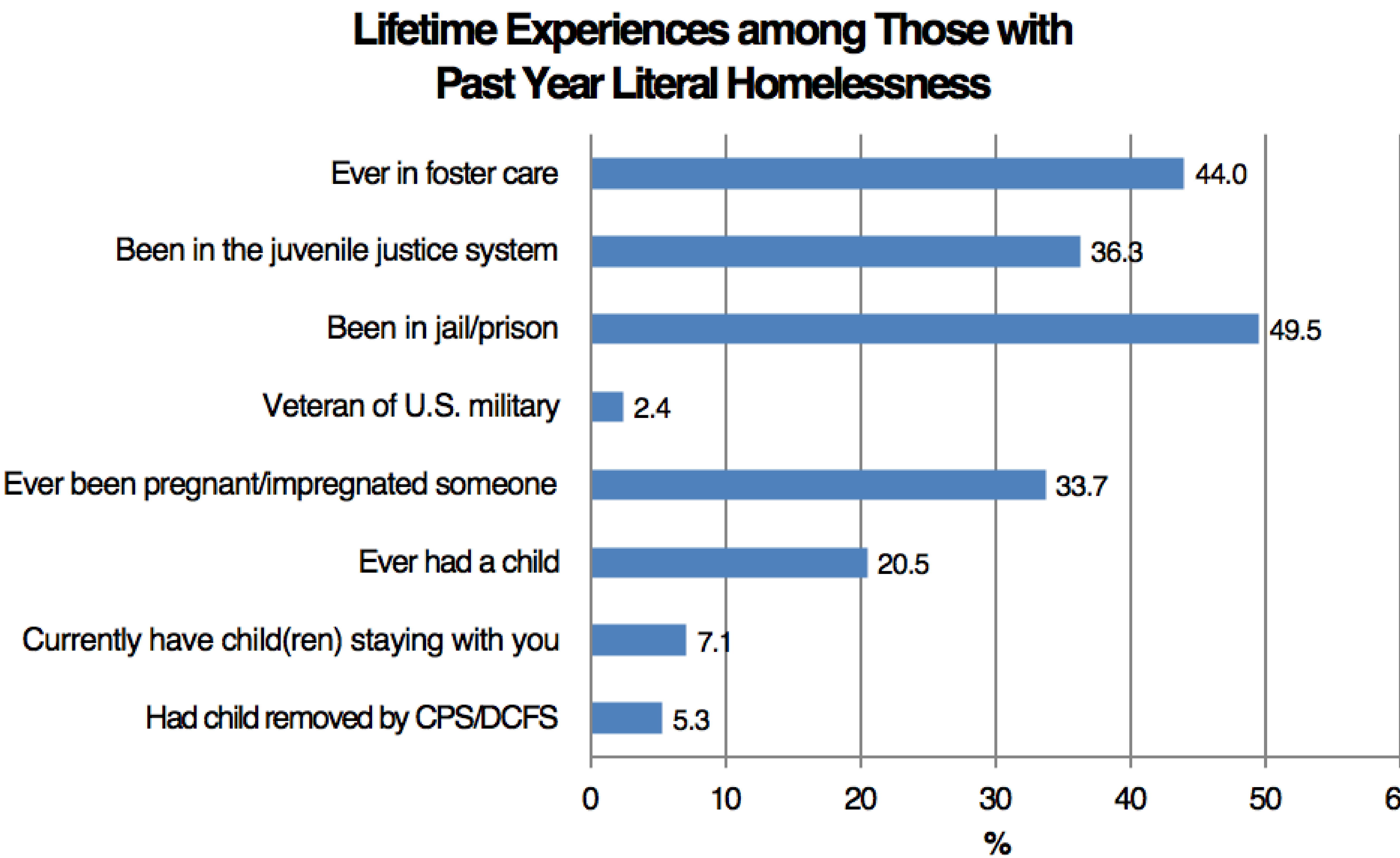


Sexual Identity among Those with Past Year Literal Homelessness



Place of Origin among Those with Past Year Literal Homelessness





Lifetime Experiences among Those with Past Year Literal Homelessness
Ever in foster care
44.0
Been in the juvenile justice system
36.3
Been in jail/prison
49.5
Veteran of U.S. military
2.4
Ever been pregnant/impregnated someone
33.7
Ever had a child
20.5
Currently have child(ren) staying with you
7.1
Had child removed by CPS/DCFS
5.3
0
10
20
30
40
50
60
%

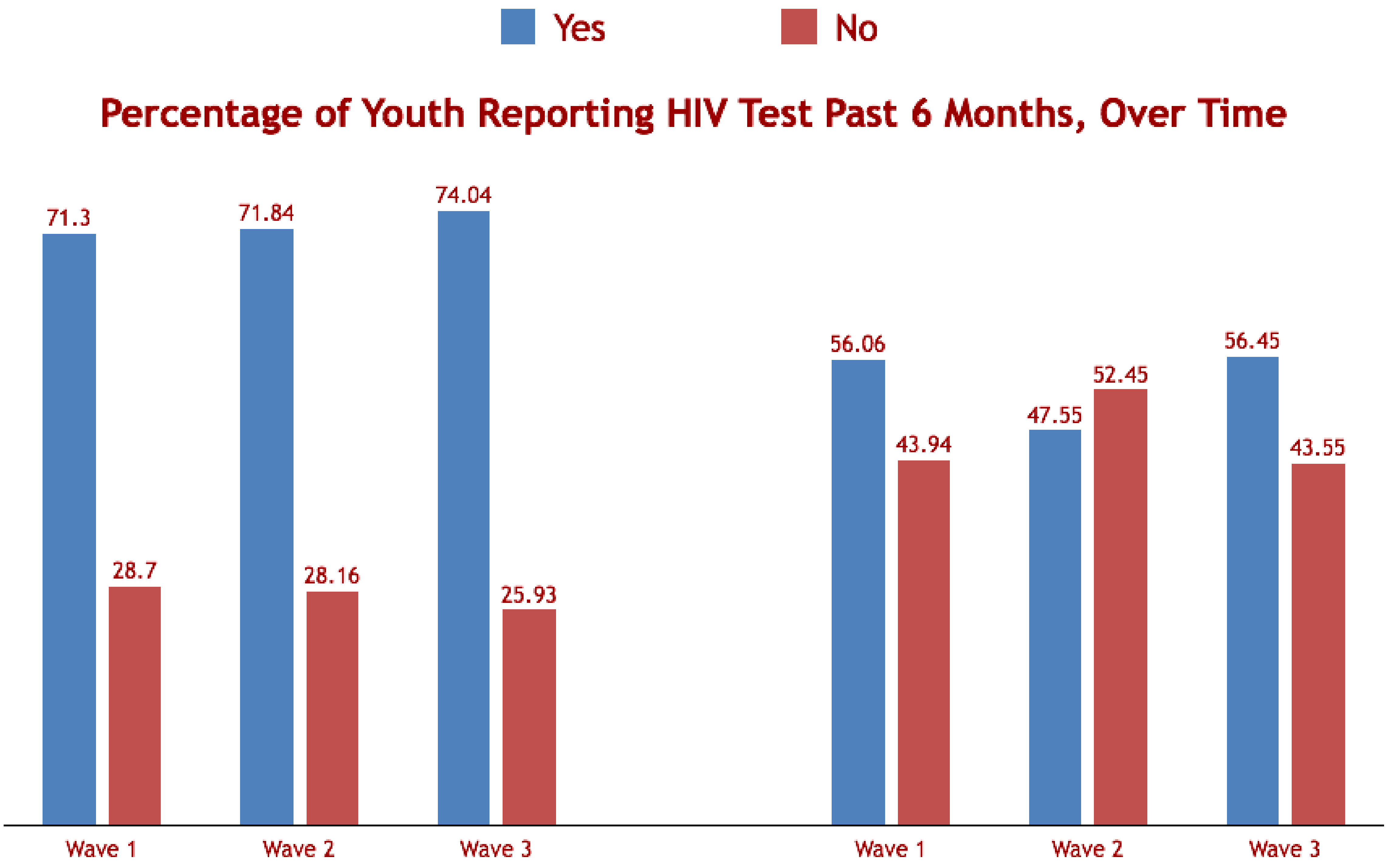
HIV and Homeless Youth

- HIV prevalence has been reported as high as 11.5%

- 2016 data suggests 7% of youth in LA drop-in centers are HIV+

- Nationally 0.3% of 15-24 year olds are HIV+

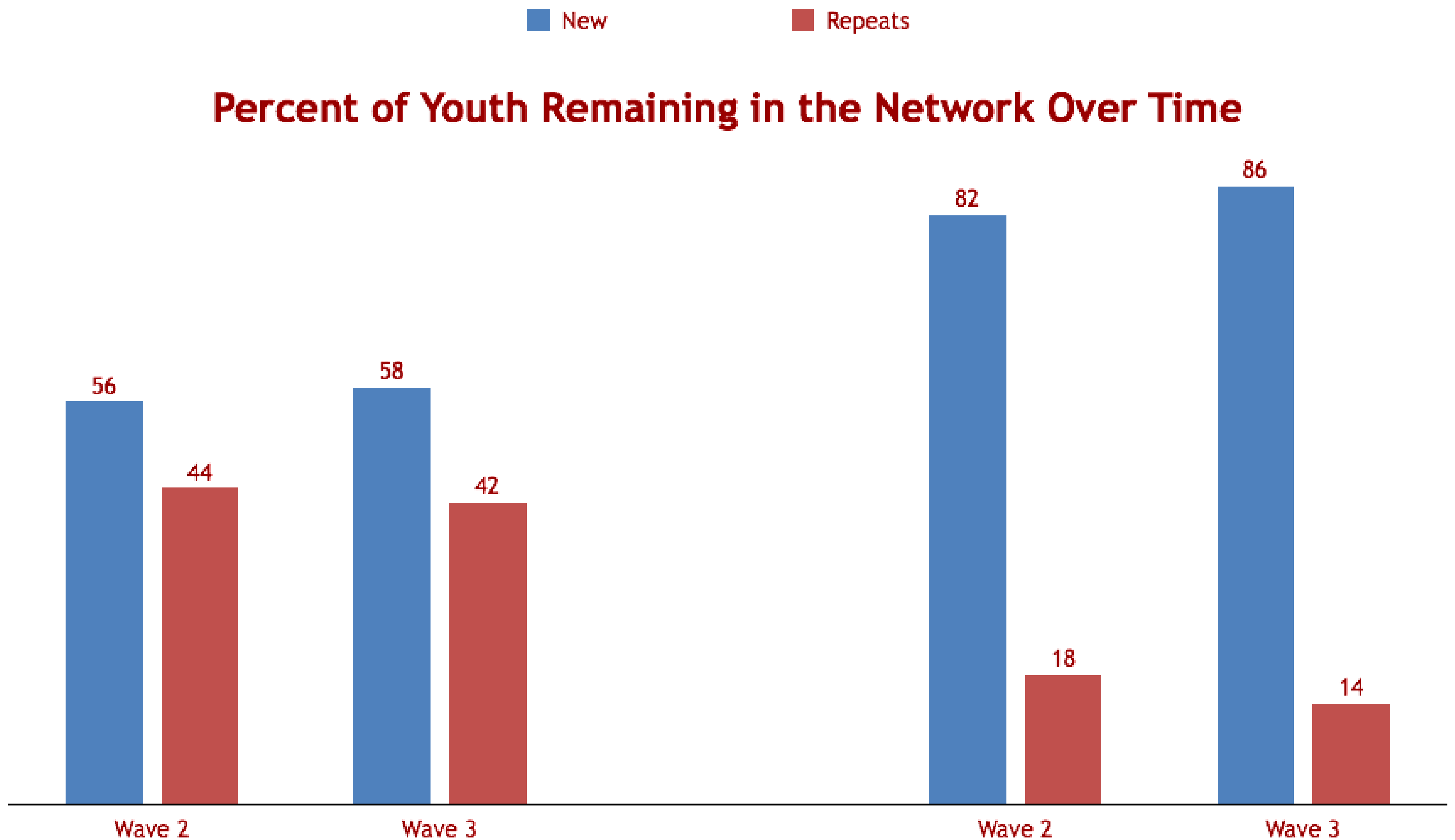
HIV and Homeless Youth



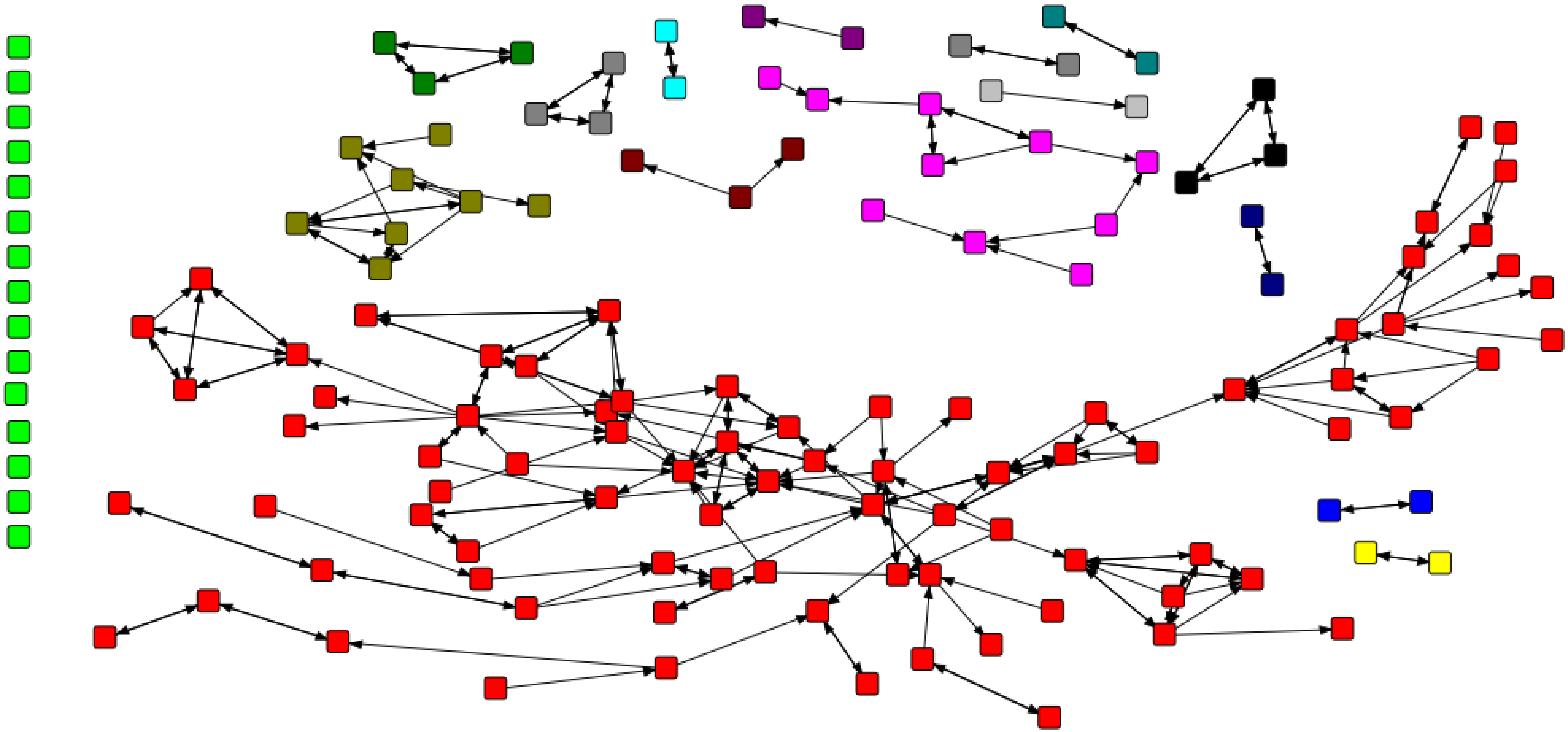

PEER LEADER?

HIV and Homeless Youth

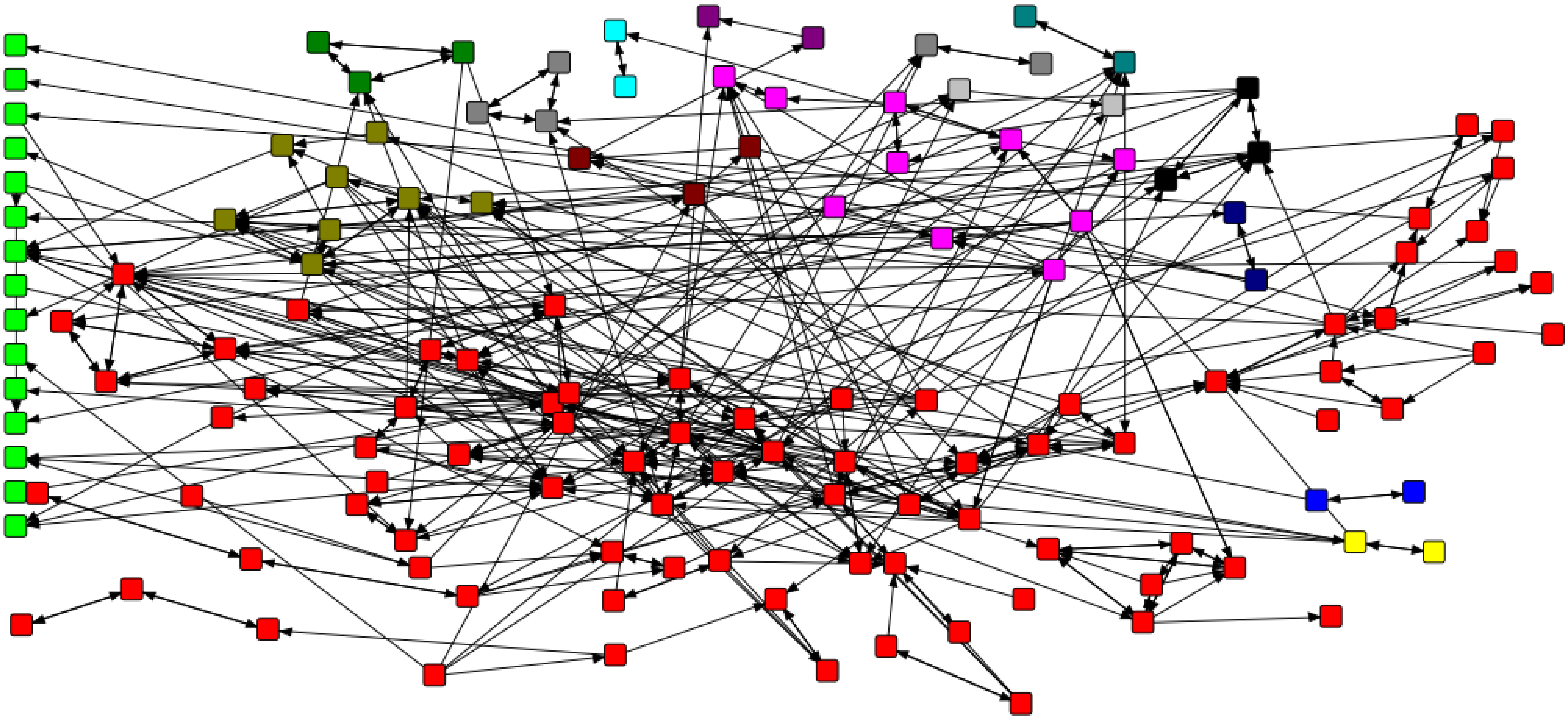
How stable are these networks over time?



But how certain are we about these networks? These ties we are certain are real



But all these other ties could be real too!



So what do we need now?

Some way to deal with the uncertainty and instability of these networks

A way to pick the “right” peer leaders – meaning what set of 15-20% of youth can diffuse messages to the rest of the population of youth?

Public health work says “pick the 10-15% most popular” – which means degree centrality (the most ties to others)

Enter Milind Tambe and Amulya Yadav

Outline: HIV Information & Homeless Youth

- Domain of homeless youth and HIV information dissemination
- Real World Challenges in Influence Maximization
- Sequential Decision Making under Uncertainty
- Pilot Study

Influence Maximization Background

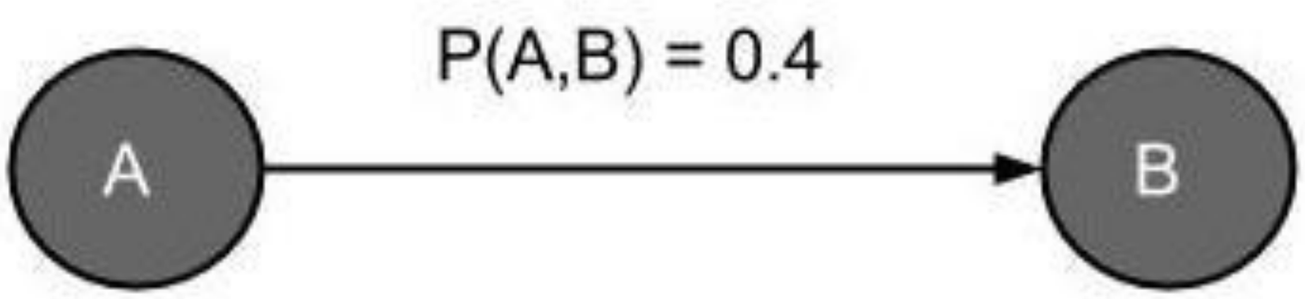
- Input:
  - Graph G
  - Influence Model I
  - Choose K nodes per time step
  - Number of time steps for influence spread T

- Output:
  - K nodes per time step maximizing expected # influenced nodes

Independent Cascade Model

$$G = (V, E)$$

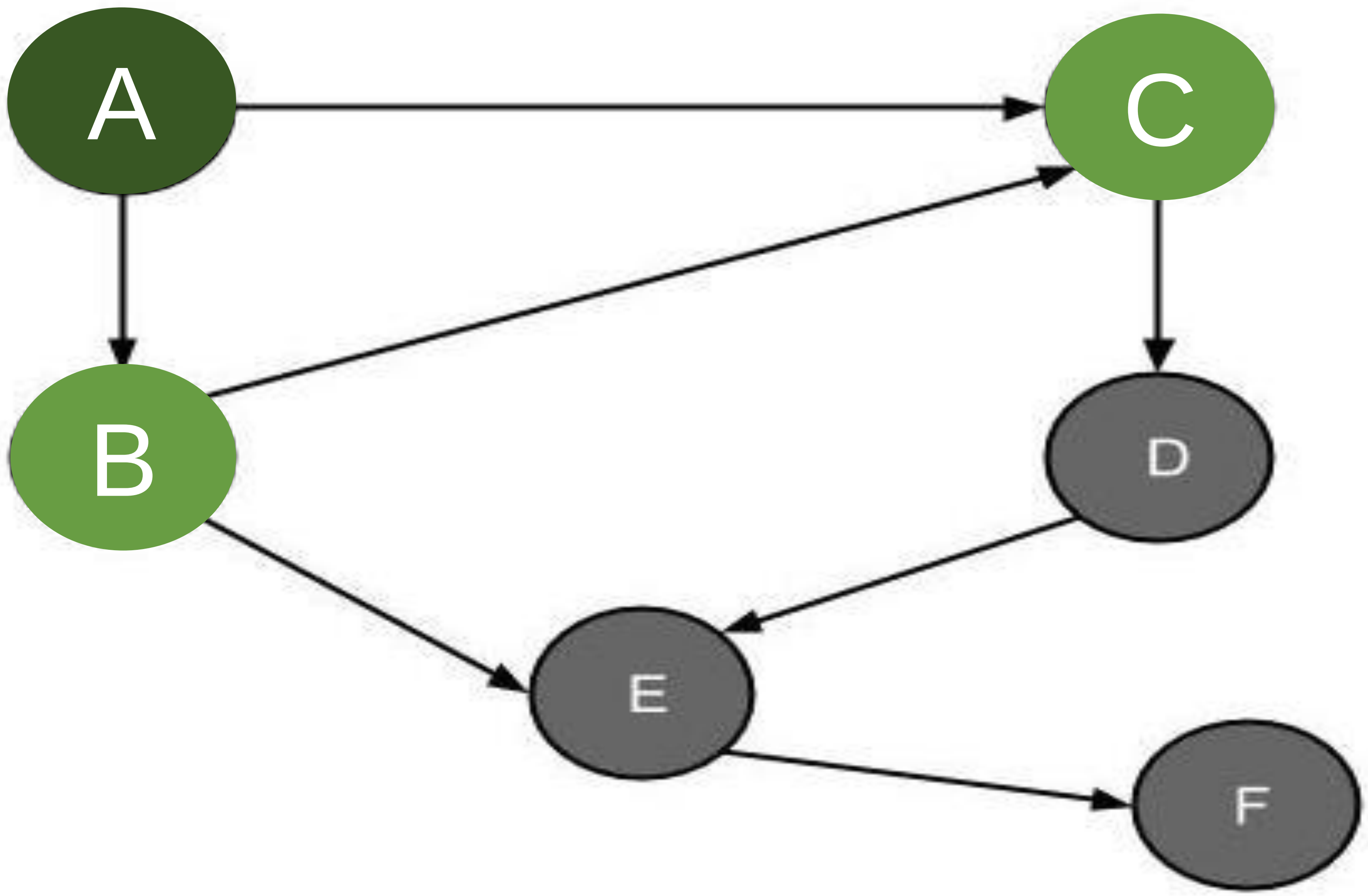
- Propagation Probability (for each edge)



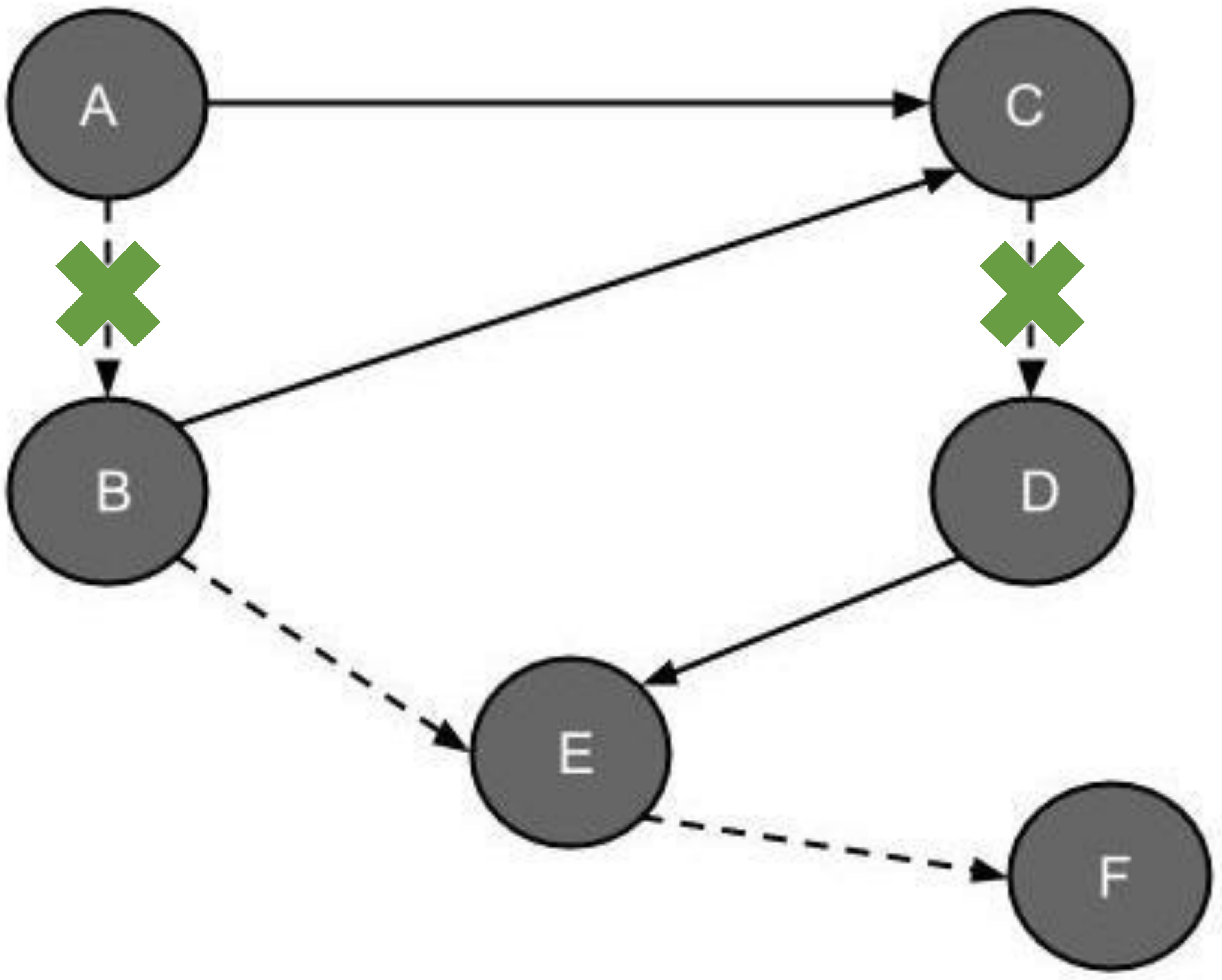
Real World Challenges

- Uncertain network state
- Uncertainty in network structure
- Adaptive selection

Challenge 1: Uncertain Network State



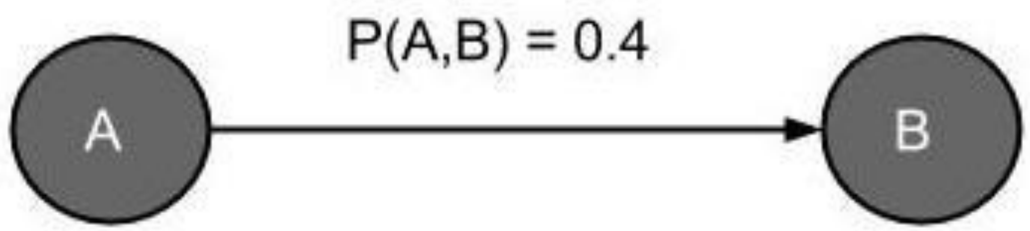
Challenge 2: Uncertain Network Structure



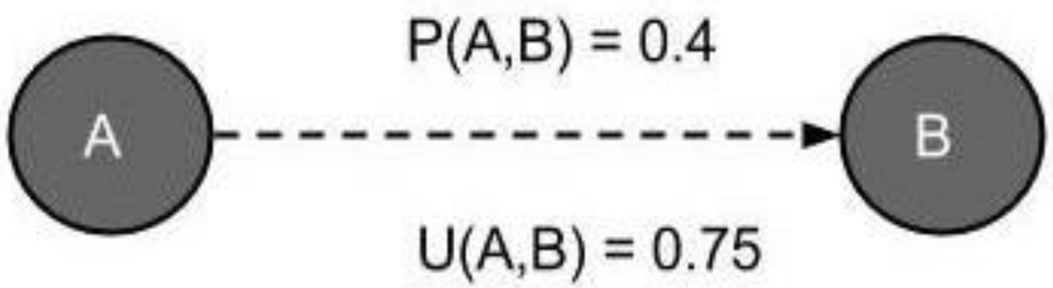
Independent Cascade Model

$$G = (V, E) \qquad\qquad E = E_{cert} \cup E_{uncert}$$

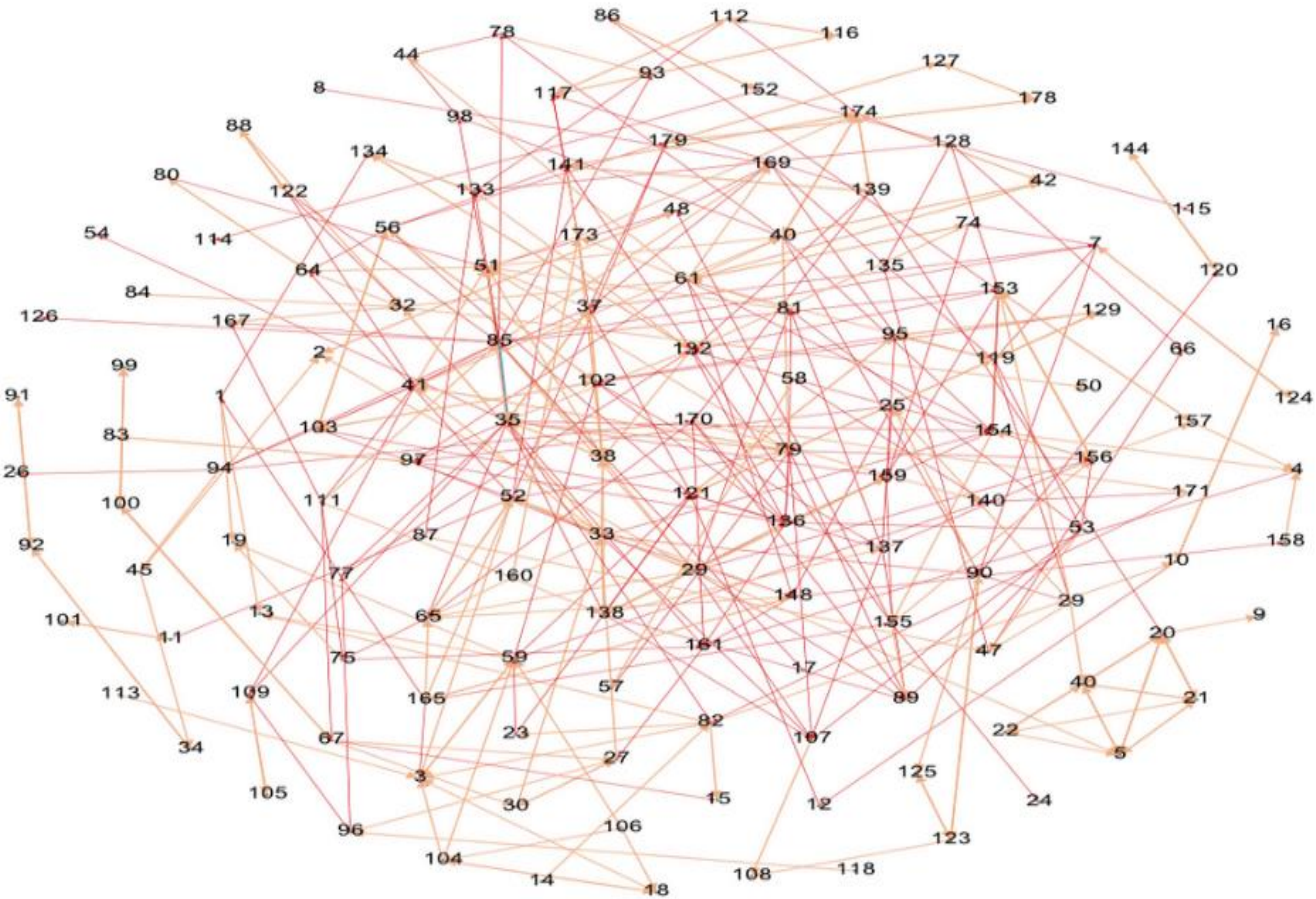
- Propagation Probability (for each edge)



- Existence Probability (for uncertain edges only)

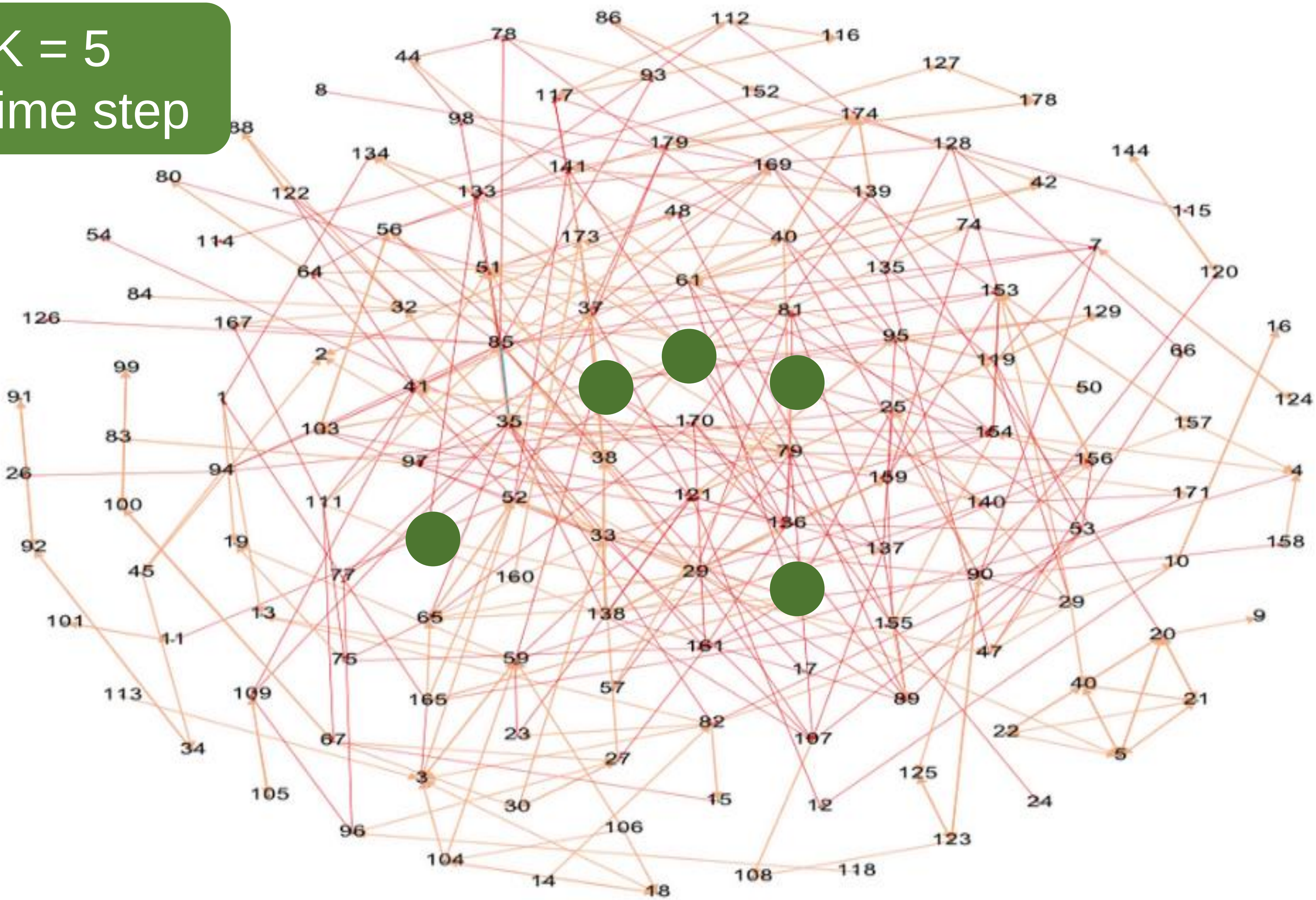


HIV Prevention Programs:
Using Social Networks to Spread HIV Information



Challenge: Adaptive selection in Uncertain Network

K = 5
1st time step

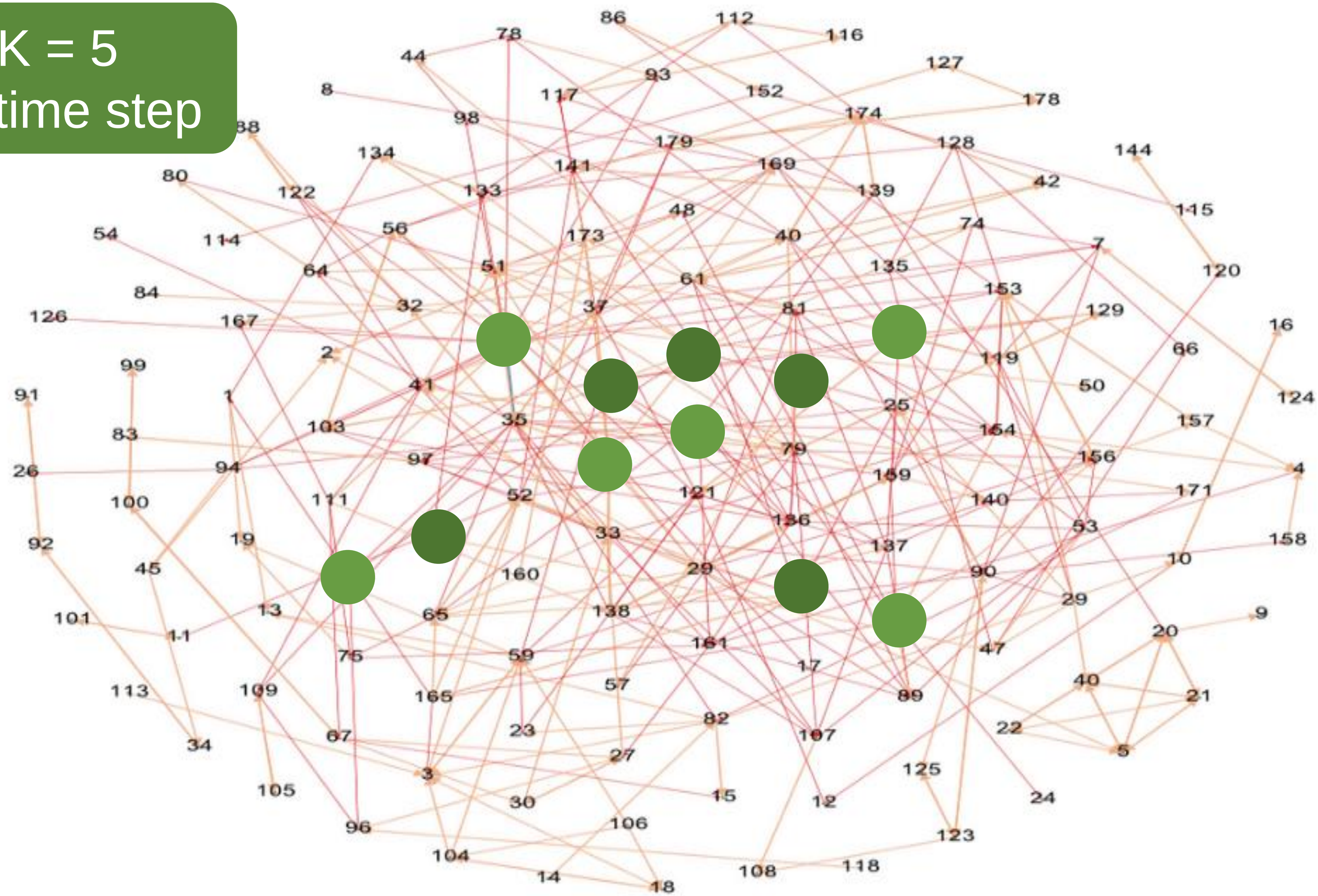



PEER LEADERS
OUR MISSION
SEXUAL HEALTH
HIV 101
COMMUNICATION
LEADERSHIP
SELF-CARE
Facts
HIV is a virus
Getting HIV from
EMPIRE
STATE
718

Challenge: Adaptive selection in Uncertain Network

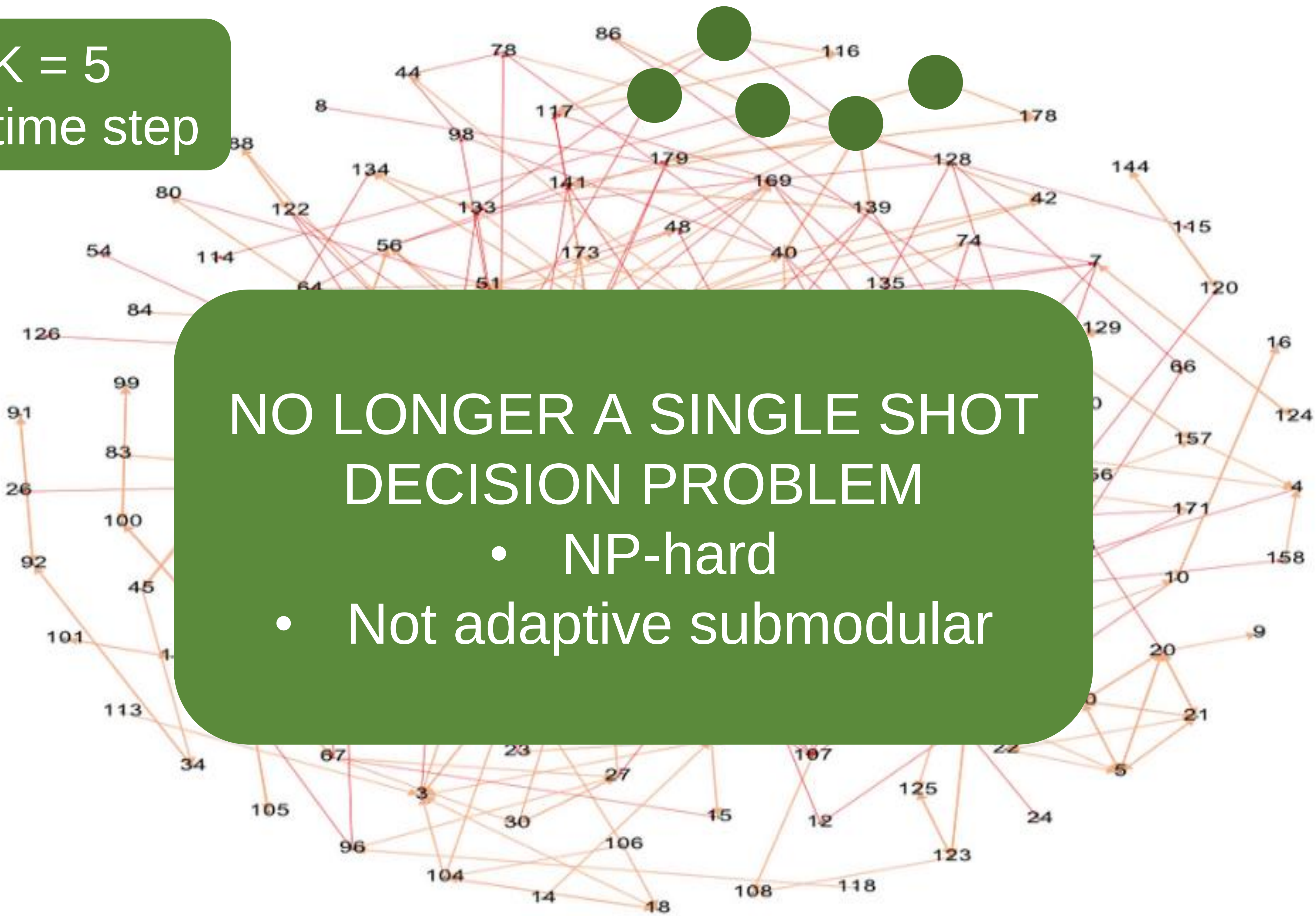
K = 5

2nd time step



Challenge 3 : Adaptive selection

K = 5
3rd time step



NO LONGER A SINGLE SHOT DECISION PROBLEM

- NP-hard
- Not adaptive submodular

Outline: HIV Information & Homeless Youth

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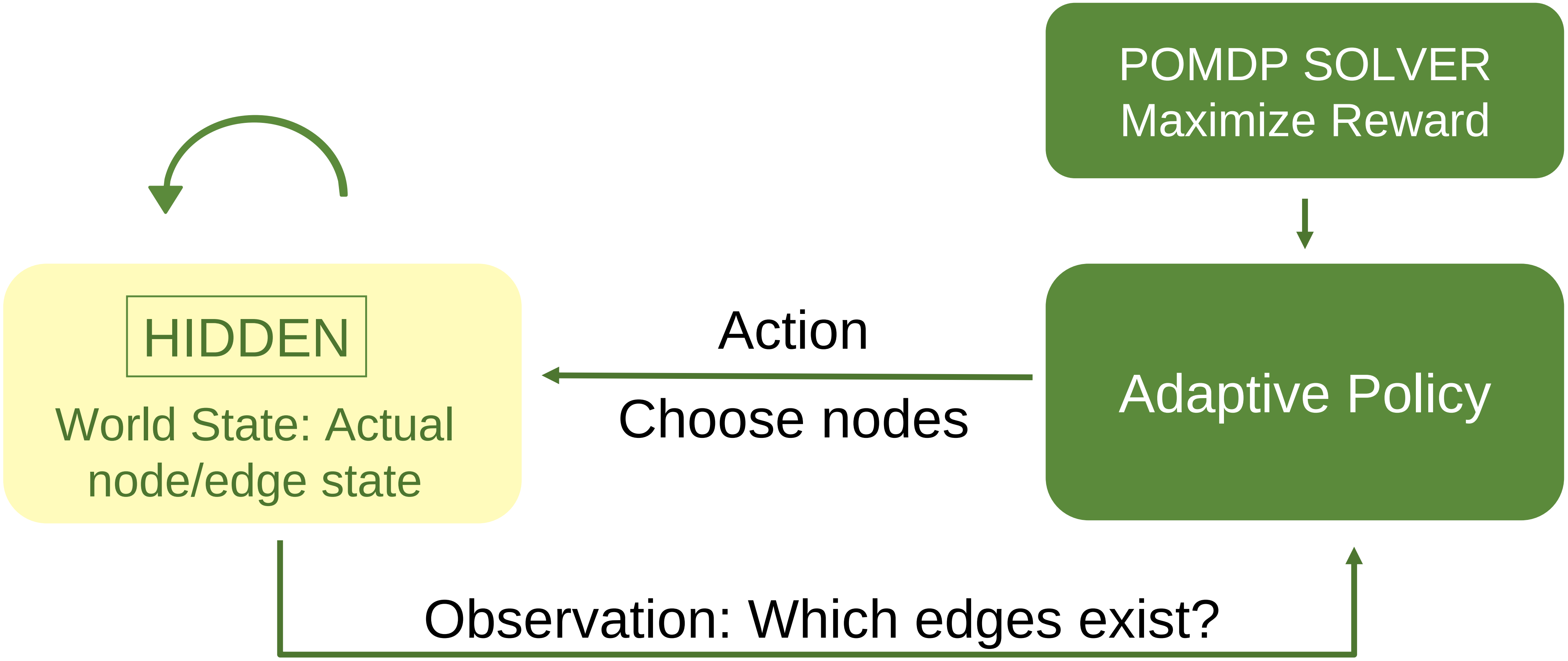
POMDP Model: Create a Policy [2015]

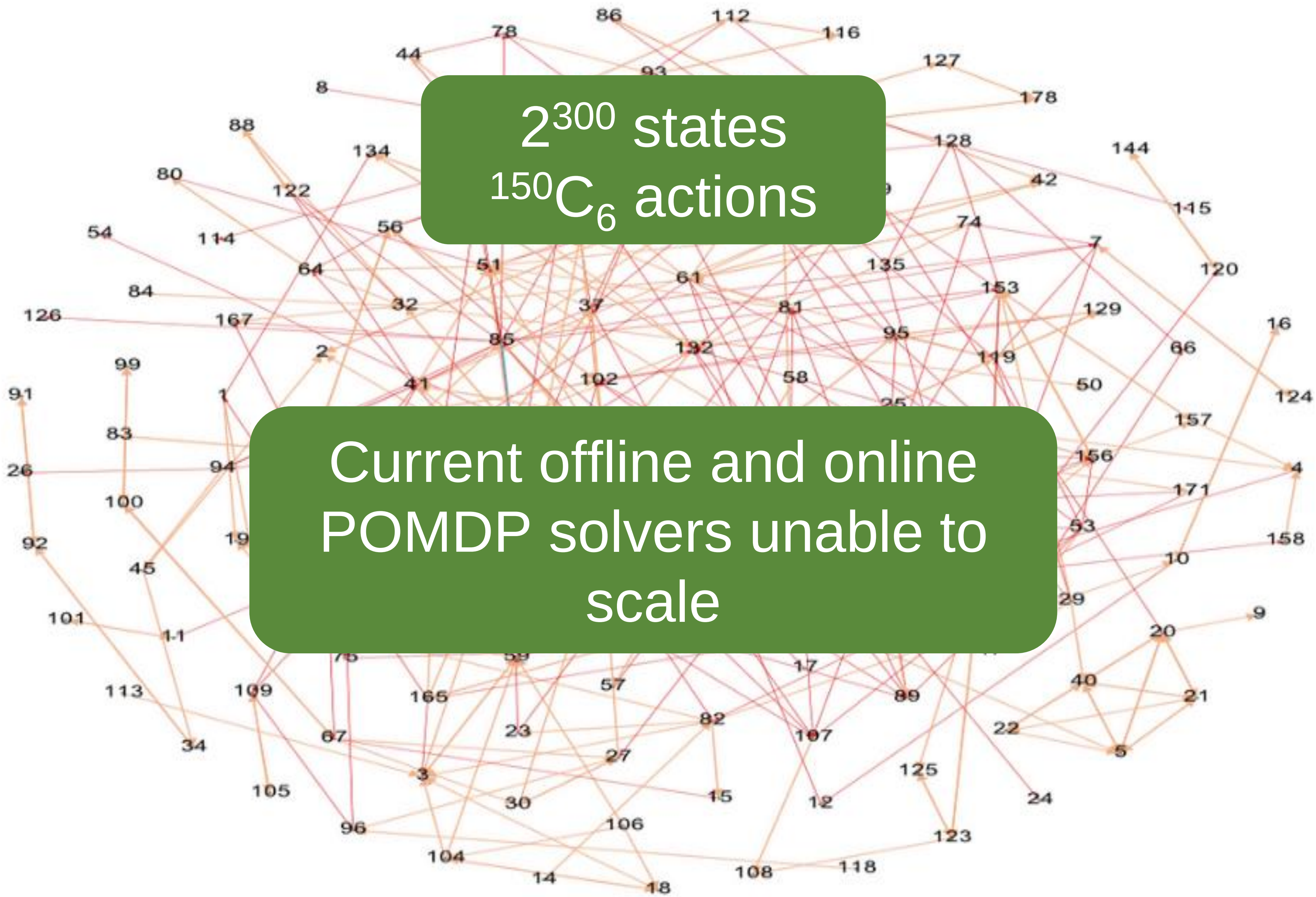

Yadav

- Homeless shelters – sequentially select nodes under uncertainty
  - Policy driven by observations about edges



Optimal Policy at Real world scale: Why is it hard to solve?

Yadav

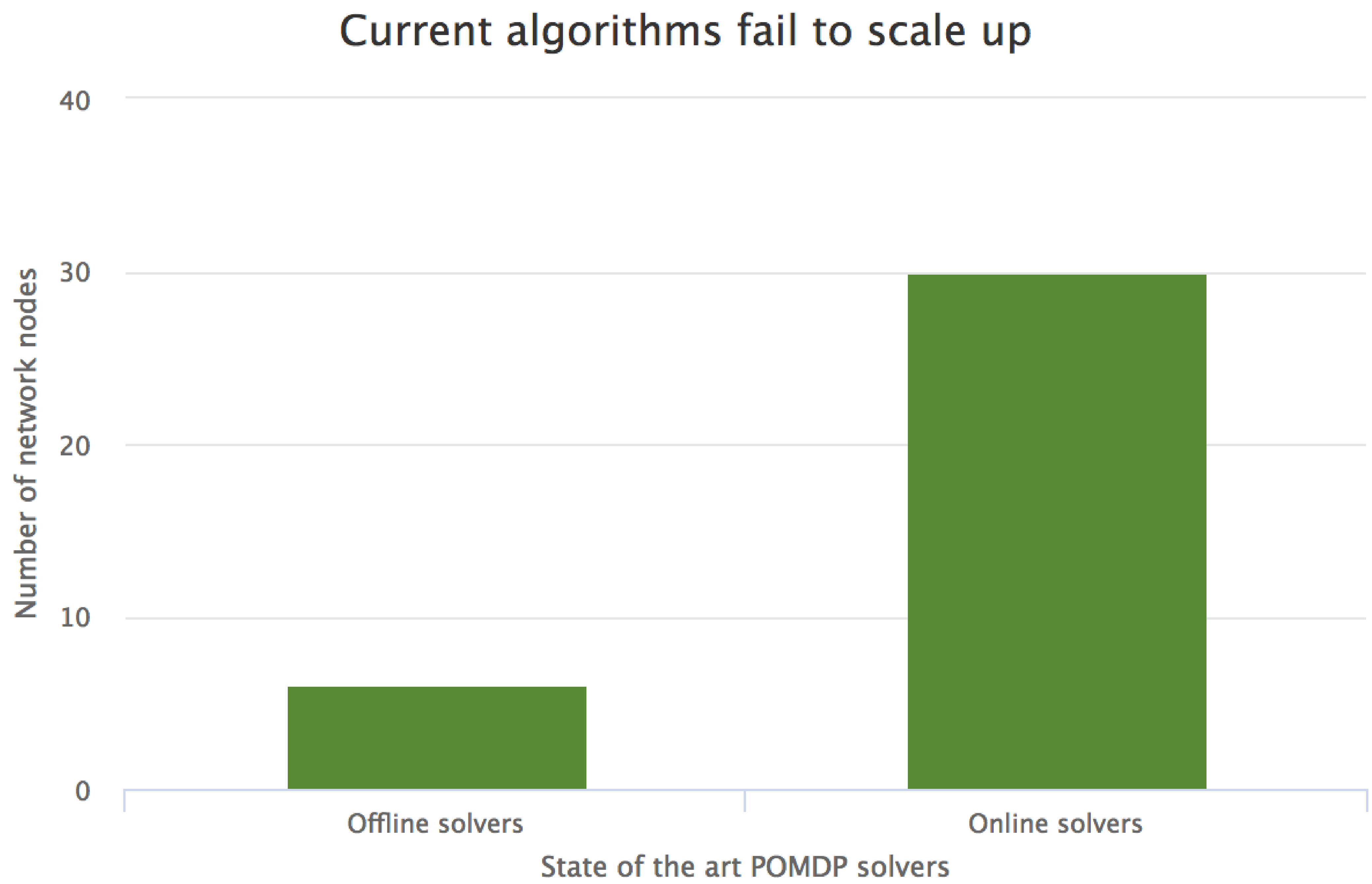


2^{300} states

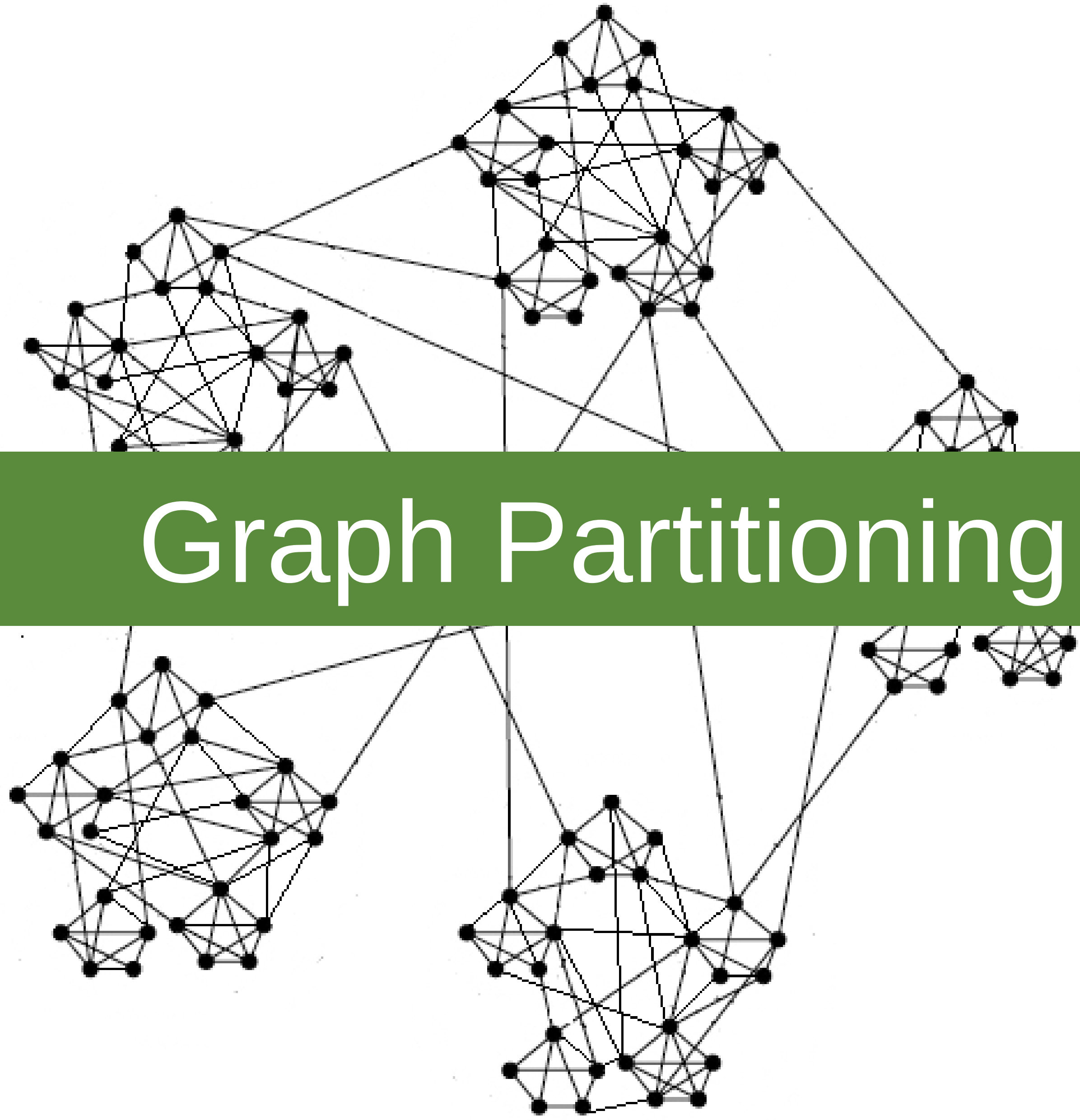
${}^{150}C_6$ actions

Current offline and online POMDP solvers unable to scale

Real world scale: Why is it hard to solve?



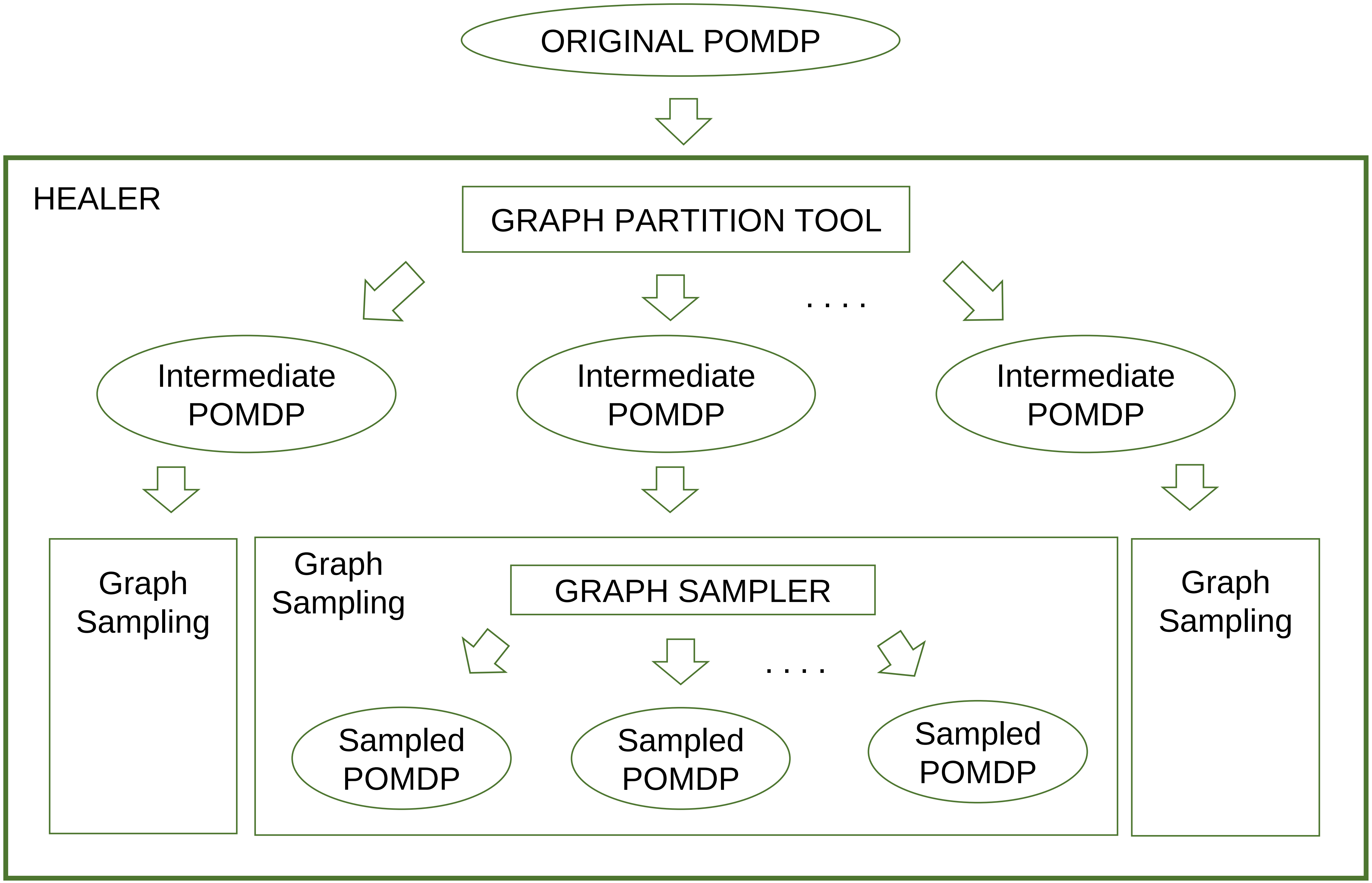
POMDP Heuristics
Real world networks have community structure



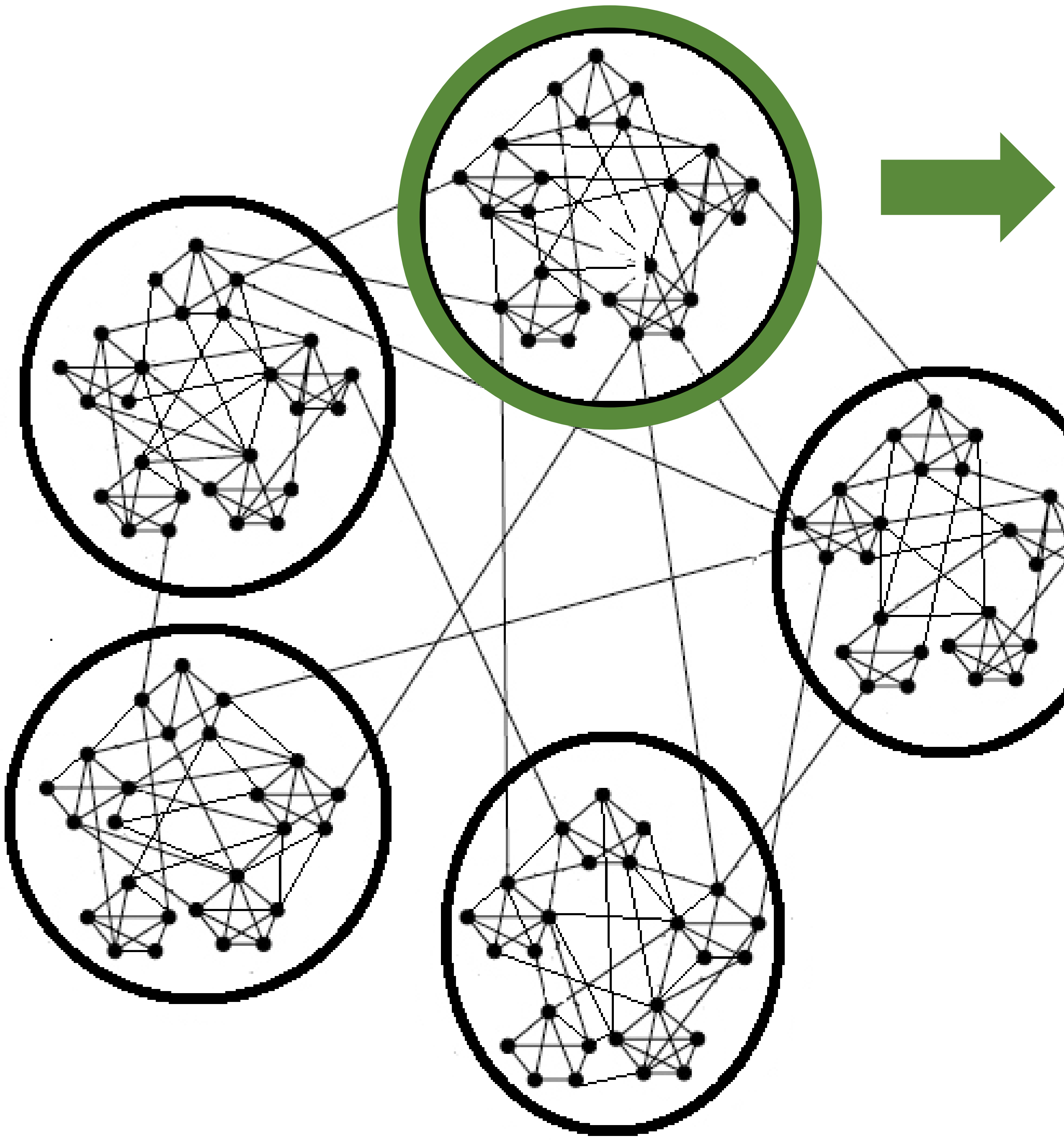
Graph Partitioning

HEALER v1: Hierarchical Ensembling [2016]


Yadav



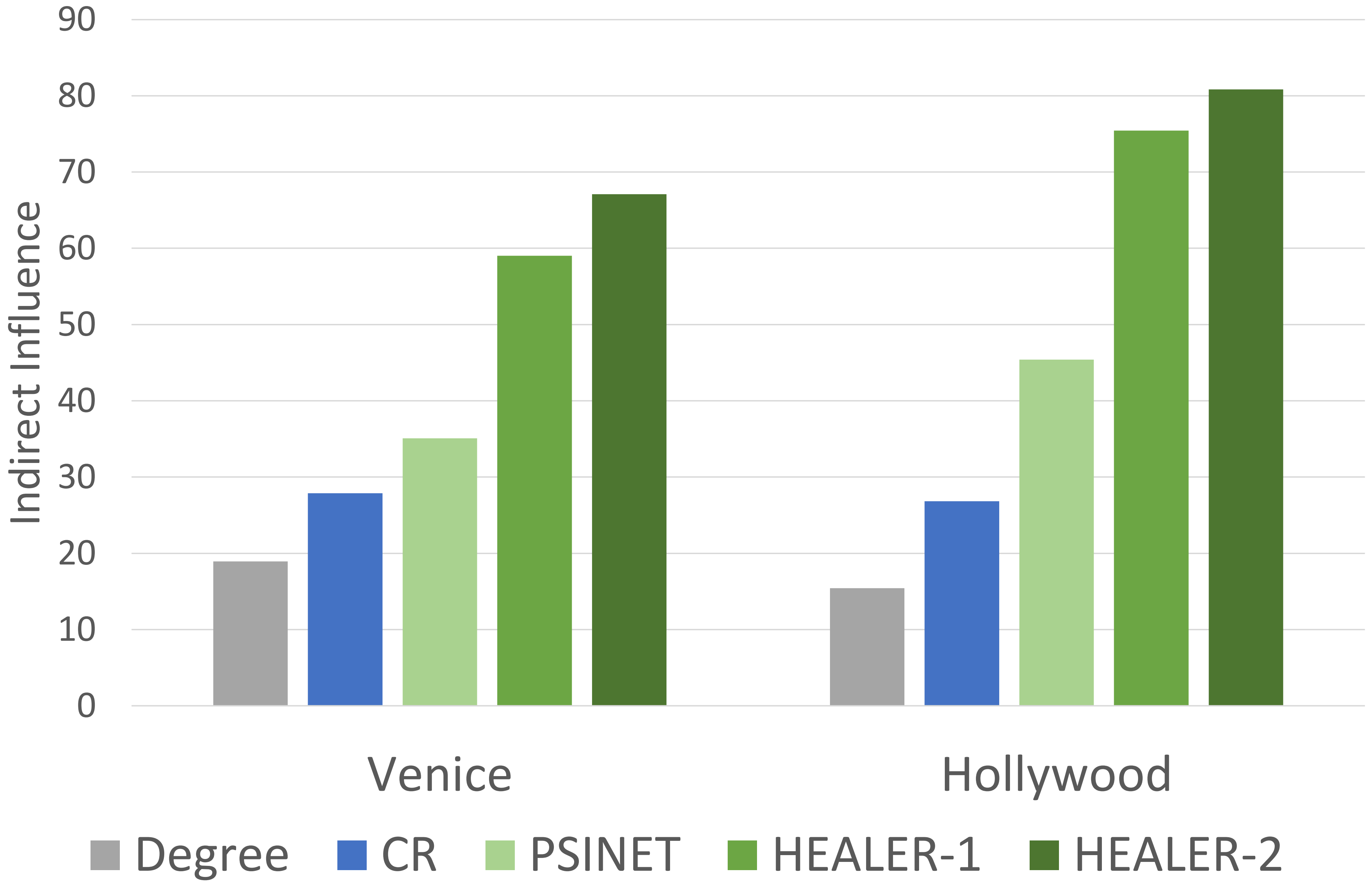
HEALER v1: Partitioned Policies Combined for Final Result



INTERMEDIATE POMDP POLICY

Cross Community Edges Ignored

Real Networks – Simulation Results [2016-2017]



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Pilot Tests with 170 Homeless Youth [2017]

Petering

Craddock

Yoshioka-Maxwell

Recruited youths:

HEALER	HEALER++	DEGREE CENTRALITY
62	56	55

Preliminary network —> HEALER

Bring 4 youth for training, get edge data —> HEALER

Bring 4 youth for training, get edge data —> HEALER

Bring 4 youth for training

Safe Place for Youth

Petering

Craddock

Yoshioka-Maxwell

- Collaborating with Safe Place for Youth (SPY)

Safe Place for Youth

Petering

Craddock

Yoshioka-Maxwell

- Collaborating with Safe Place for Youth (SPY)

Results: Pilot Studies

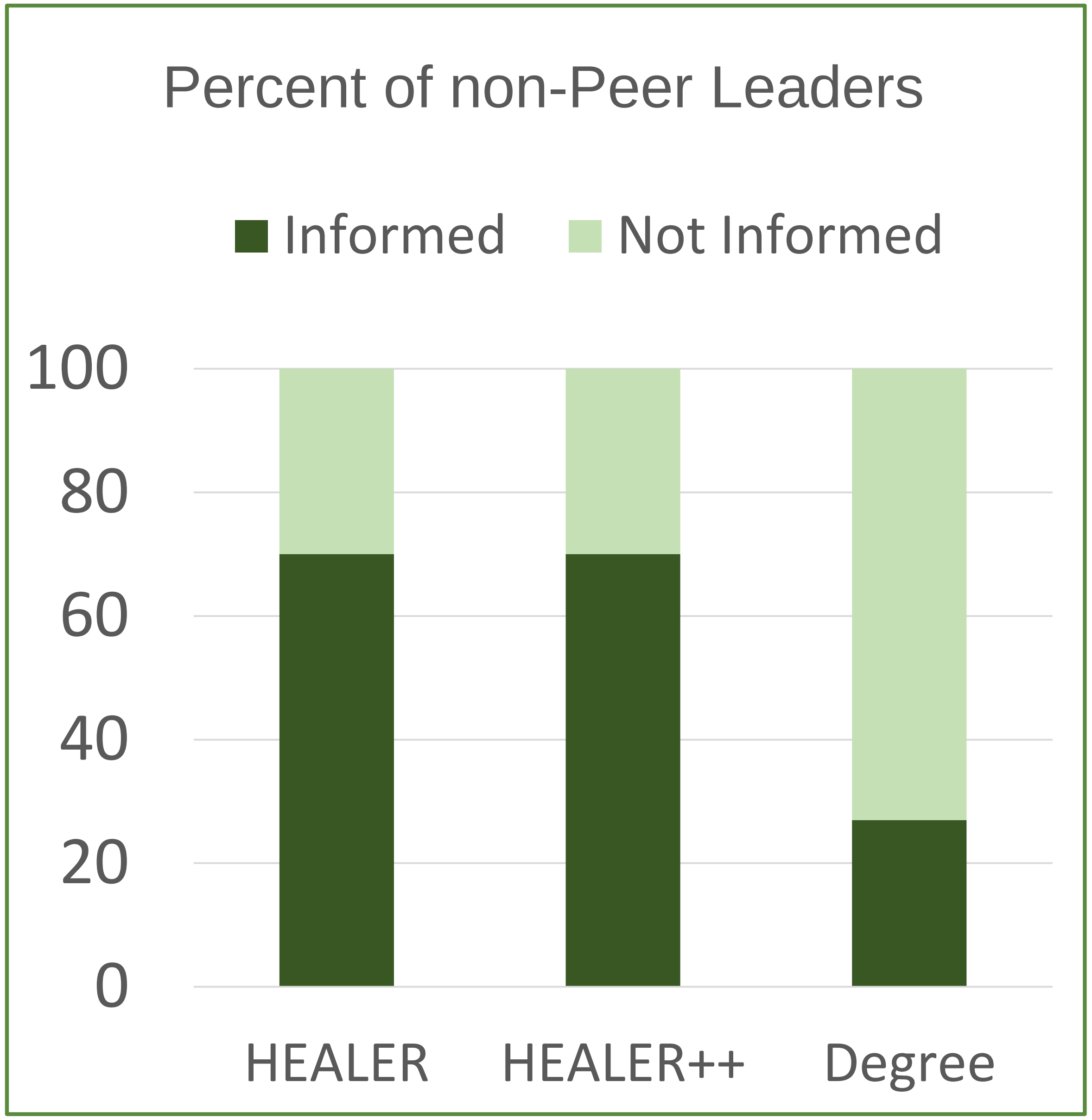

Yadav

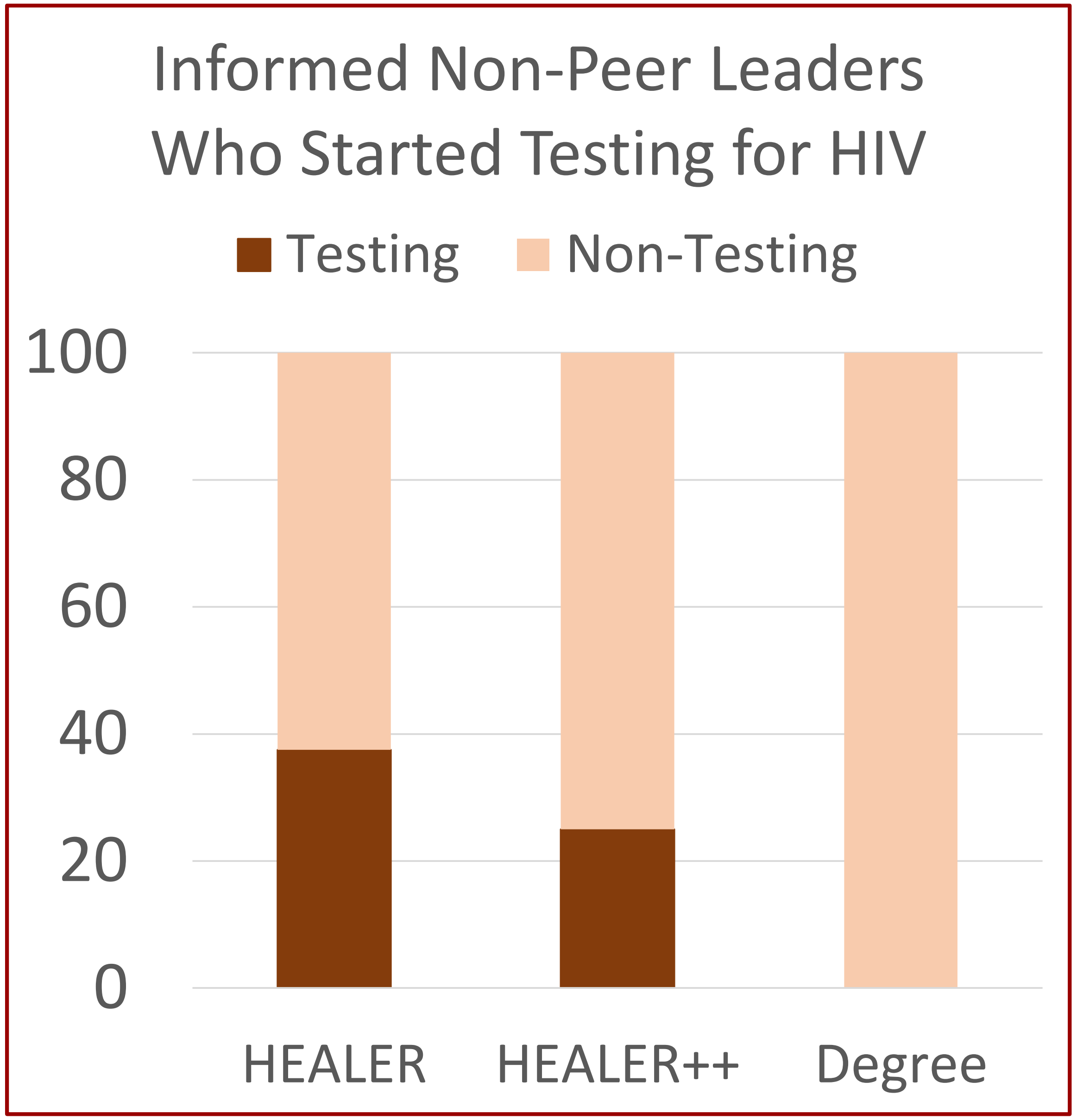

Wilder


Petering

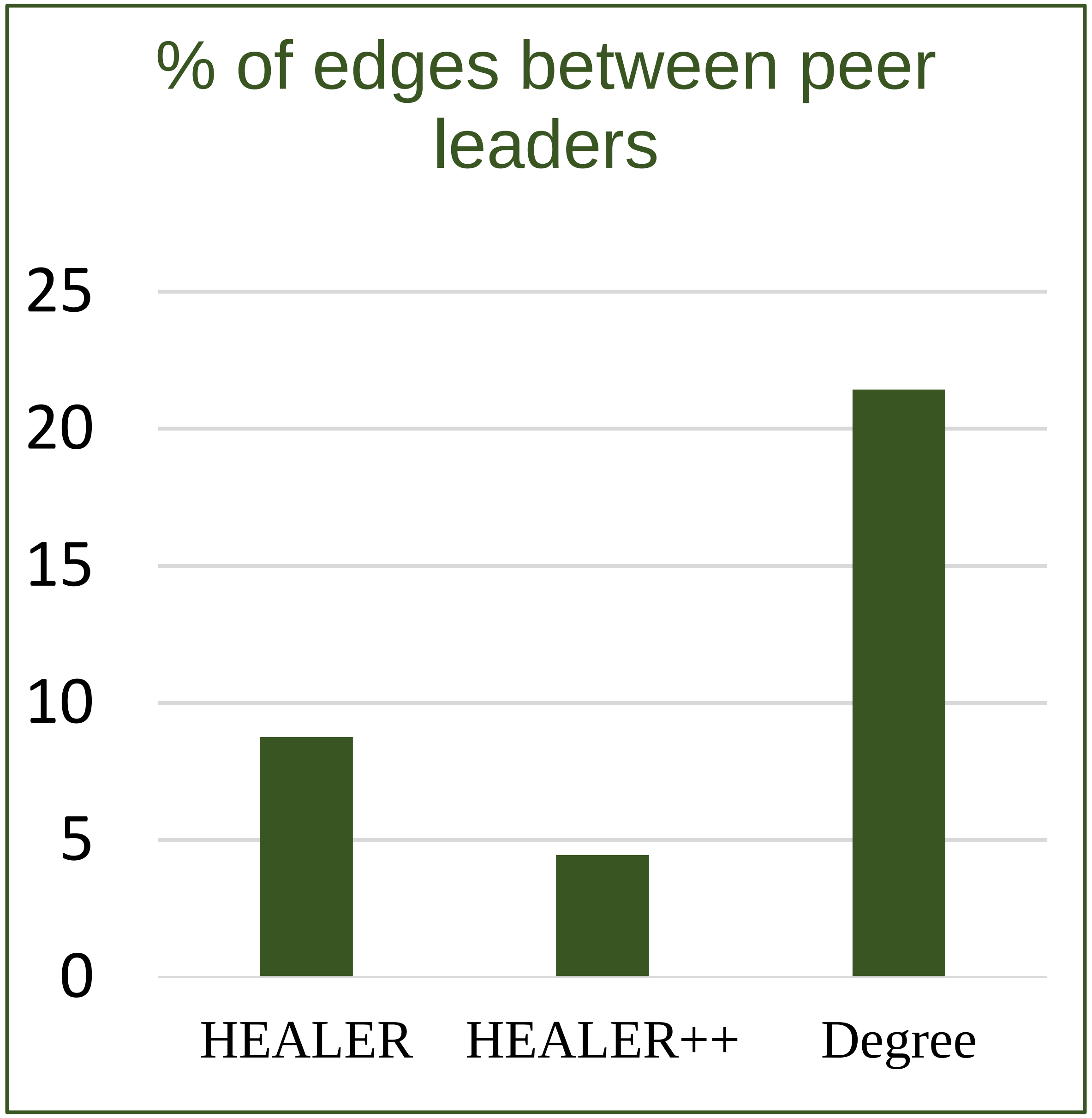

Craddock

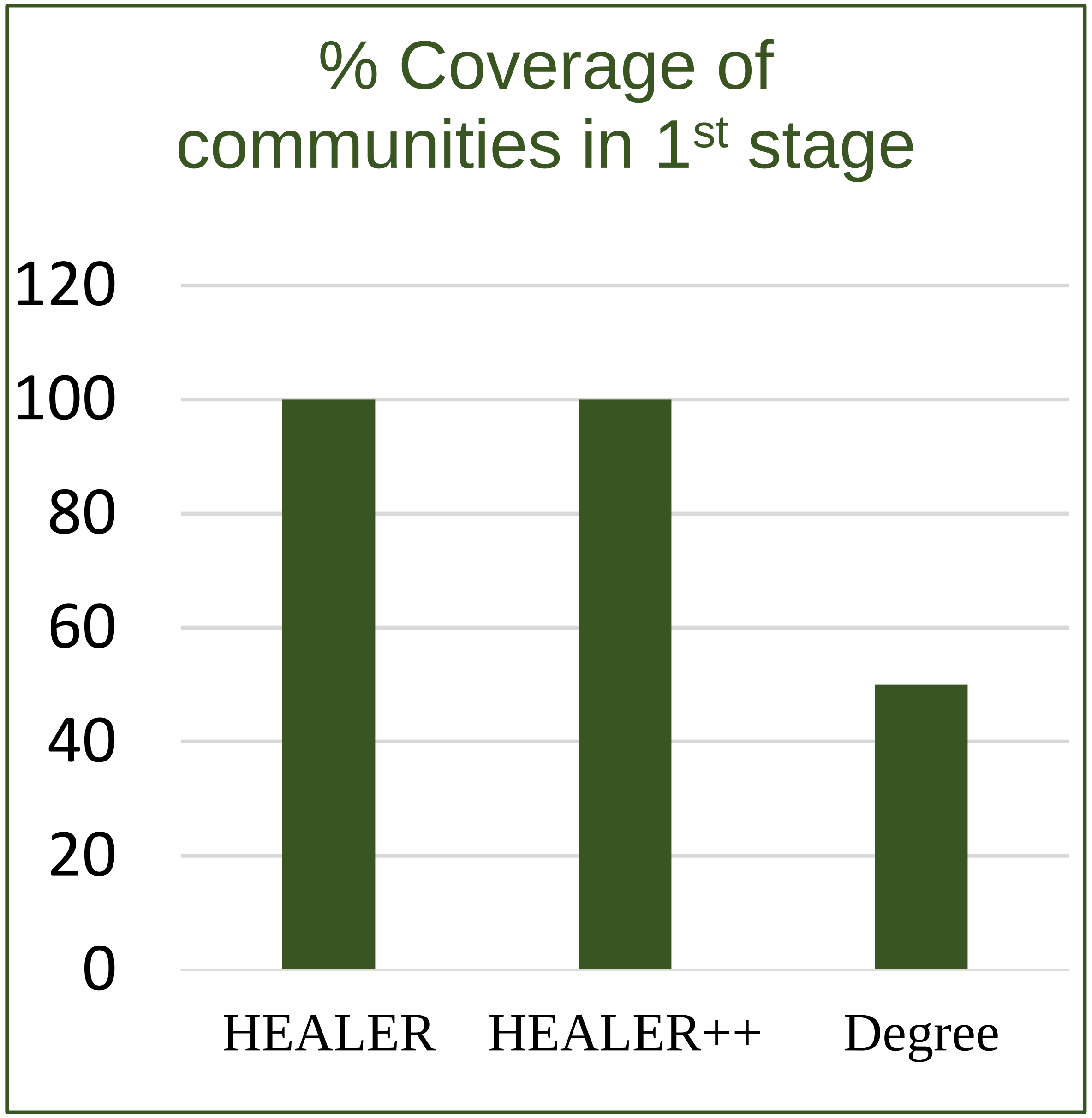

Yoshioka-Maxwell





Analysis: Pilot Studies





AI Program: HEALER

Next Steps

- 900 youth study begun at three locations in Los Angeles
  - 300 enrolled in HEALER/HEALER++
  - 300 enrolled in no condition
  - 300 in Degree centrality

Phebe’s Section

Outline

- Introduction
- Low resource communities (homeless youth)
- Public Safety and Security
- Wildlife Conservation

Optimizing Security Resource Allocation [2007]

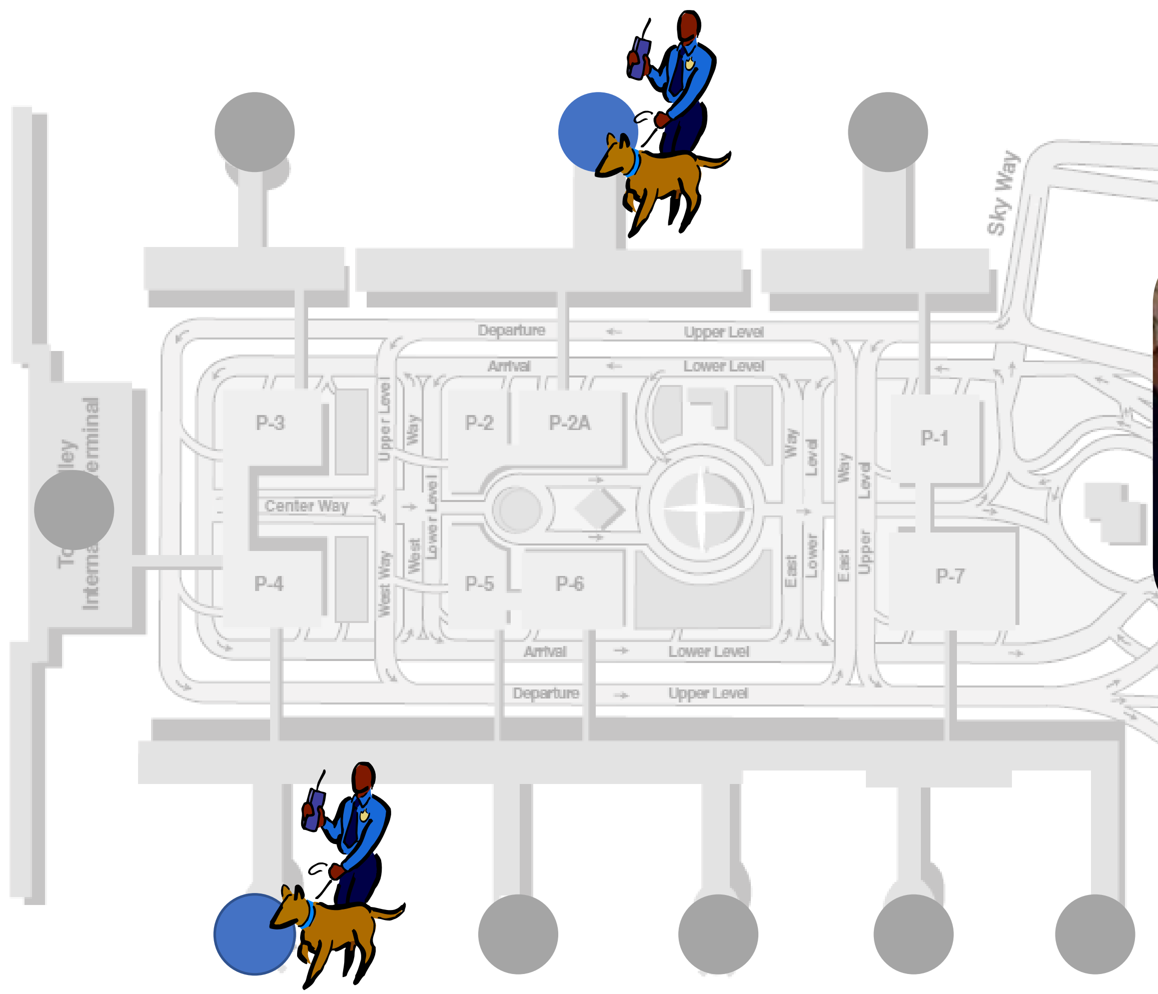
Jain

Pita

ARMOR: Assigning Limited Security Resources

Airports

2007



Canine patrol at LAX (ARMOR)

AI-based DECISION AIDS TO ASSIST IN SECURITY

AI-based DECISION AIDS TO ASSIST IN SECURITY

Game Theory

Airports

2007

Player B

Player A	Paper	Rock	Scissors
Paper	0, 0	1,-1	-1,1
Rock	-1, 1	0, 0	1, -1
Scissors	1, -1	-1, 1	0, 0

Model: Stackelberg Security Games

Kiekintveld

Set of targets, payoffs based on targets covered or not…

Stackelberg: Defender commits to randomized strategy, adversary responds

Security optimization: Not 100% security; increase cost/uncertainty to attackers

Challenges faced: Massive scale games; difficult for a human planner

Adversary

Defender

	Terminal #1	Terminal #2
Terminal #1	4, -3	-1, 1
Terminal #2	-5, 5	2, -1

IRIS: FEDERAL AIR MARSHALS SERVICE [2009]

Visiting TSA Freedom Center

Security Game Deployments [2009]

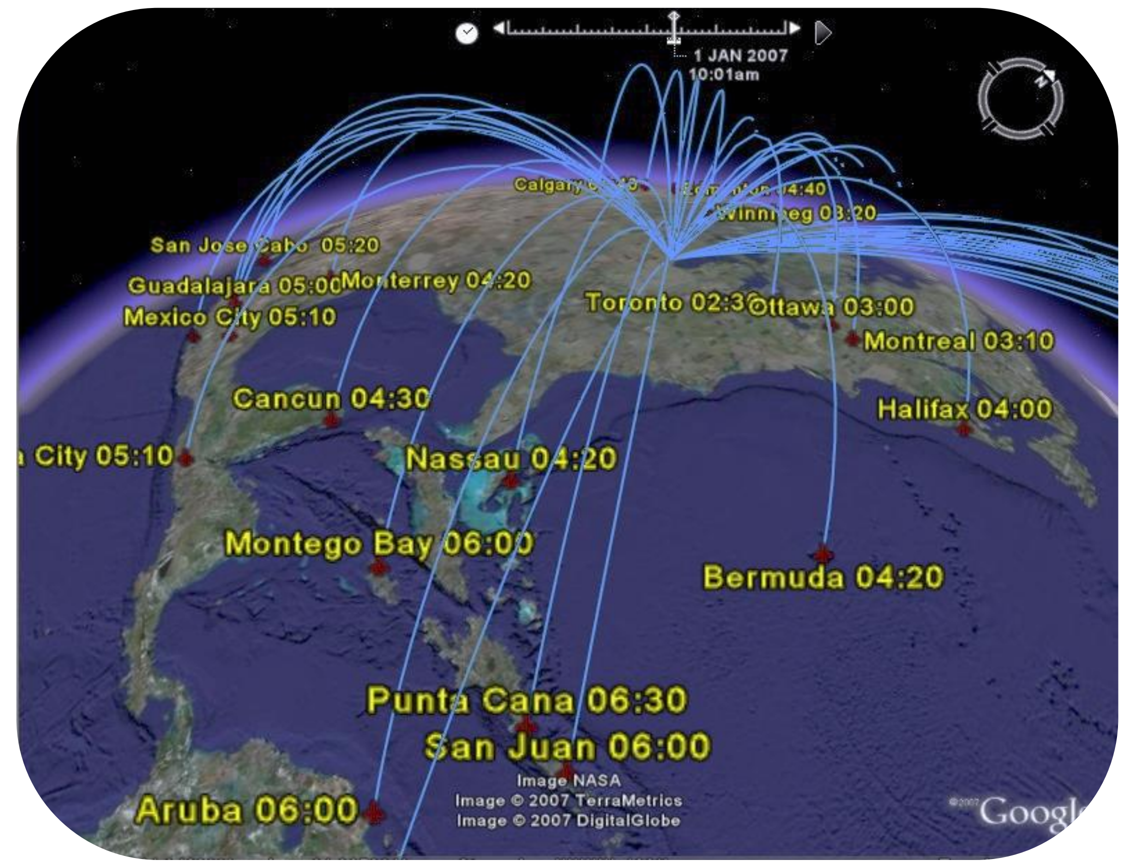
Jain

Airports

Air Marshals

2007

2009



Security Game Deployments

Fang

Security Games

Airports

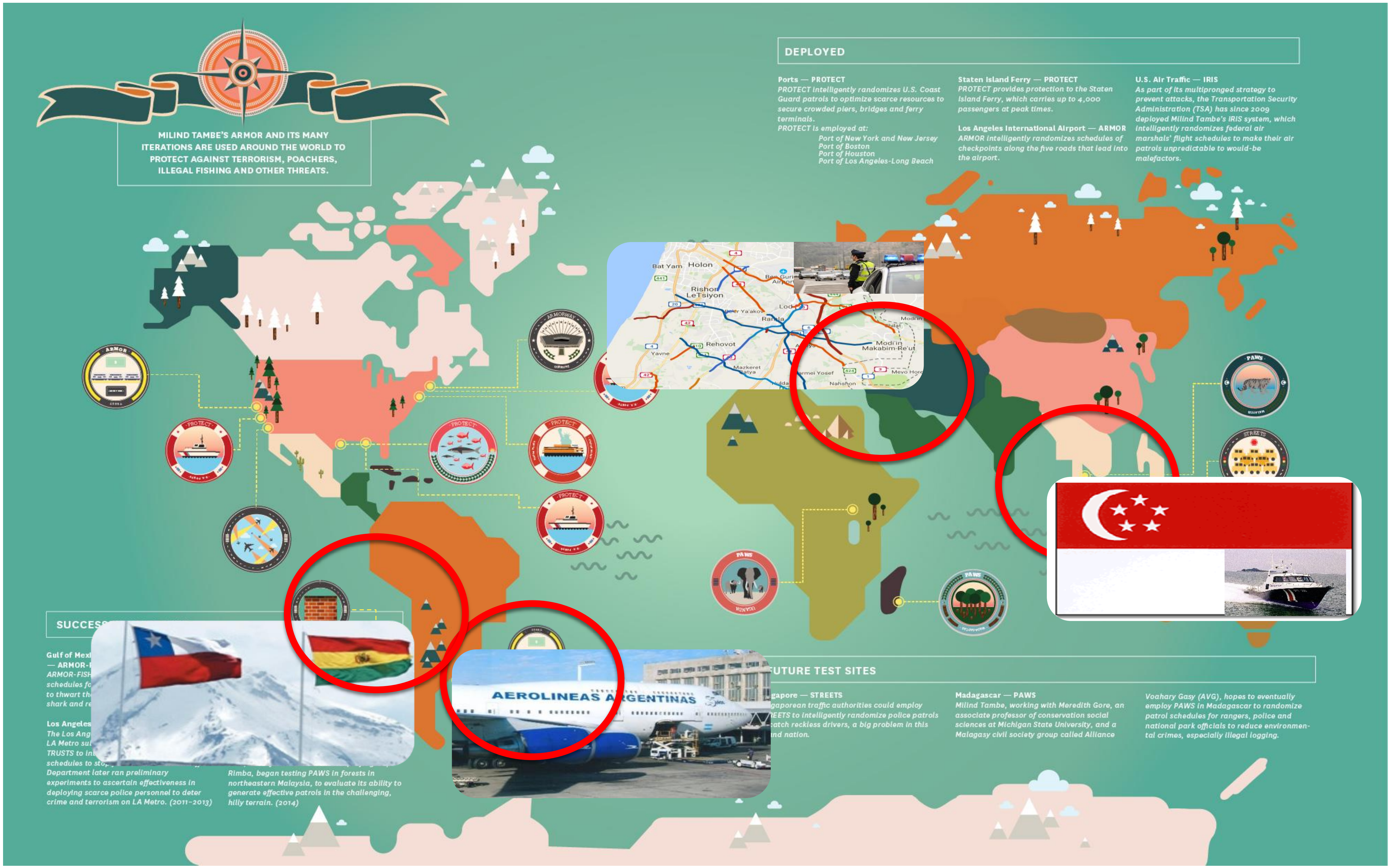
Air Marshals

Ports

2007 2009 2011

PROTECT: Ferry Protection Deployed [2013-]

Global presence of Security using Game Theory [2015-2017]

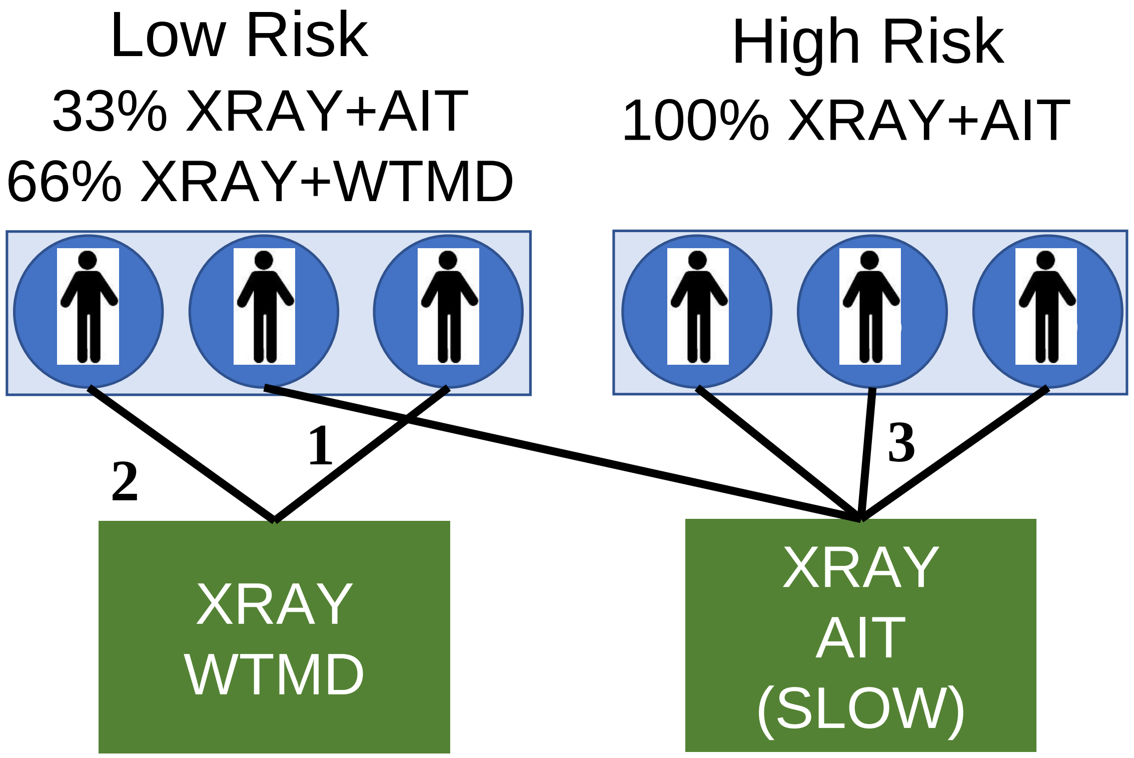


Threat Screening Games (TSG) [2016-2017]


Sinha


Schlenker

- TSA: ~640 million passengers per year; "TSA Pre"
- New concept: More passenger categories using **<u>flight</u>** & **<u>risk level</u>**
- TSG: Tailor screening to categories, balance efficiency & effectiveness



Security Games in Cyberdefense: New MURI Project [2017-]

Realizing Cyber Inception:

Towards a Science of Personalized Deception for Cyber Defense

University of Southern California

Carnegie Mellon University

University of Texas El Paso

Arizona State University

North Carolina State University

University of North Carolina Chapel Hill

Avata Intelligence

Jain

Pita

Avata
INTELLIGENCE

Operational Efficiency Through AI

Los Angeles Unified School District Police

Glendale PD

Los Angeles Sheriff's Department

University of Southern California

US Coast Guard

RAND Corporation

Outline

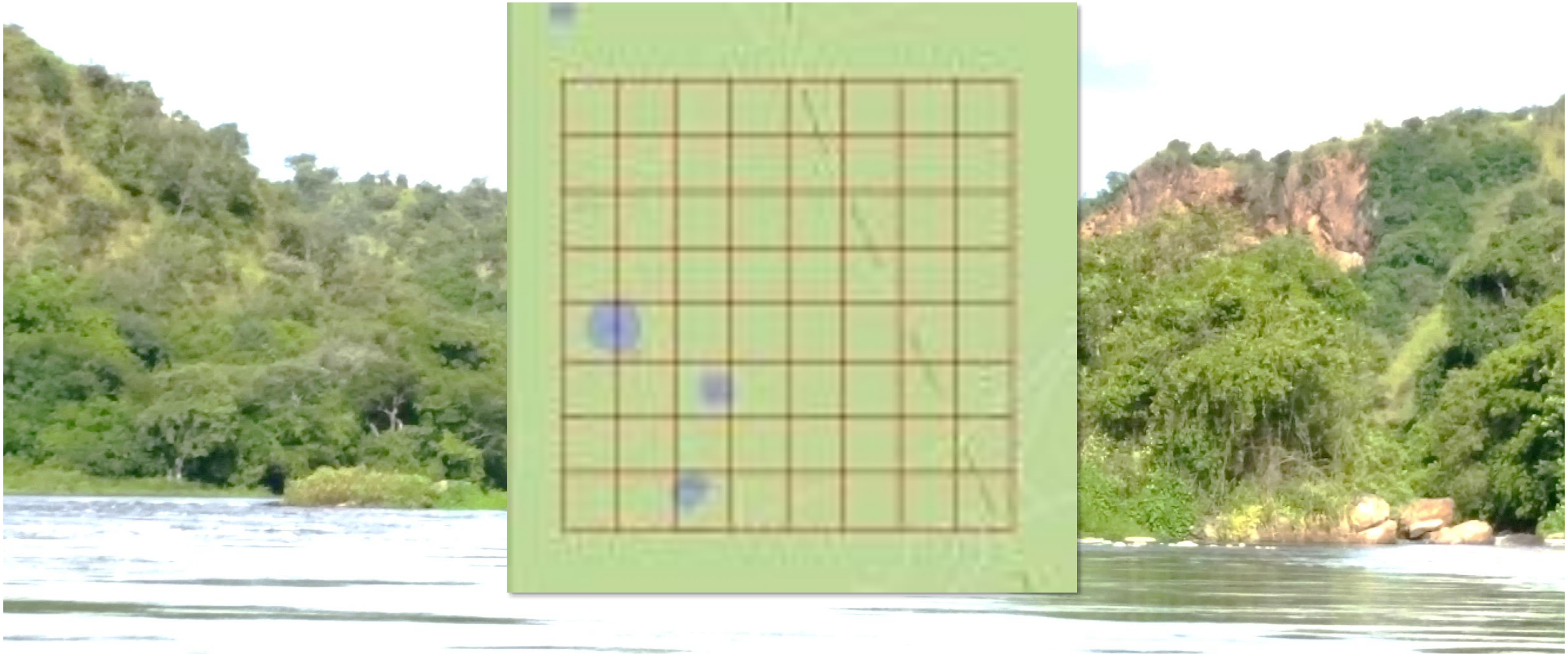
- Introduction
- Low resource communities (homeless youth)
- Public Safety and Security
- Wildlife Conservation

Protecting Wildlife in Uganda

PAWS: Applying AI for protecting wildlife

Poacher Behavior Prediction

Predicting Poaching from Past Crime Data

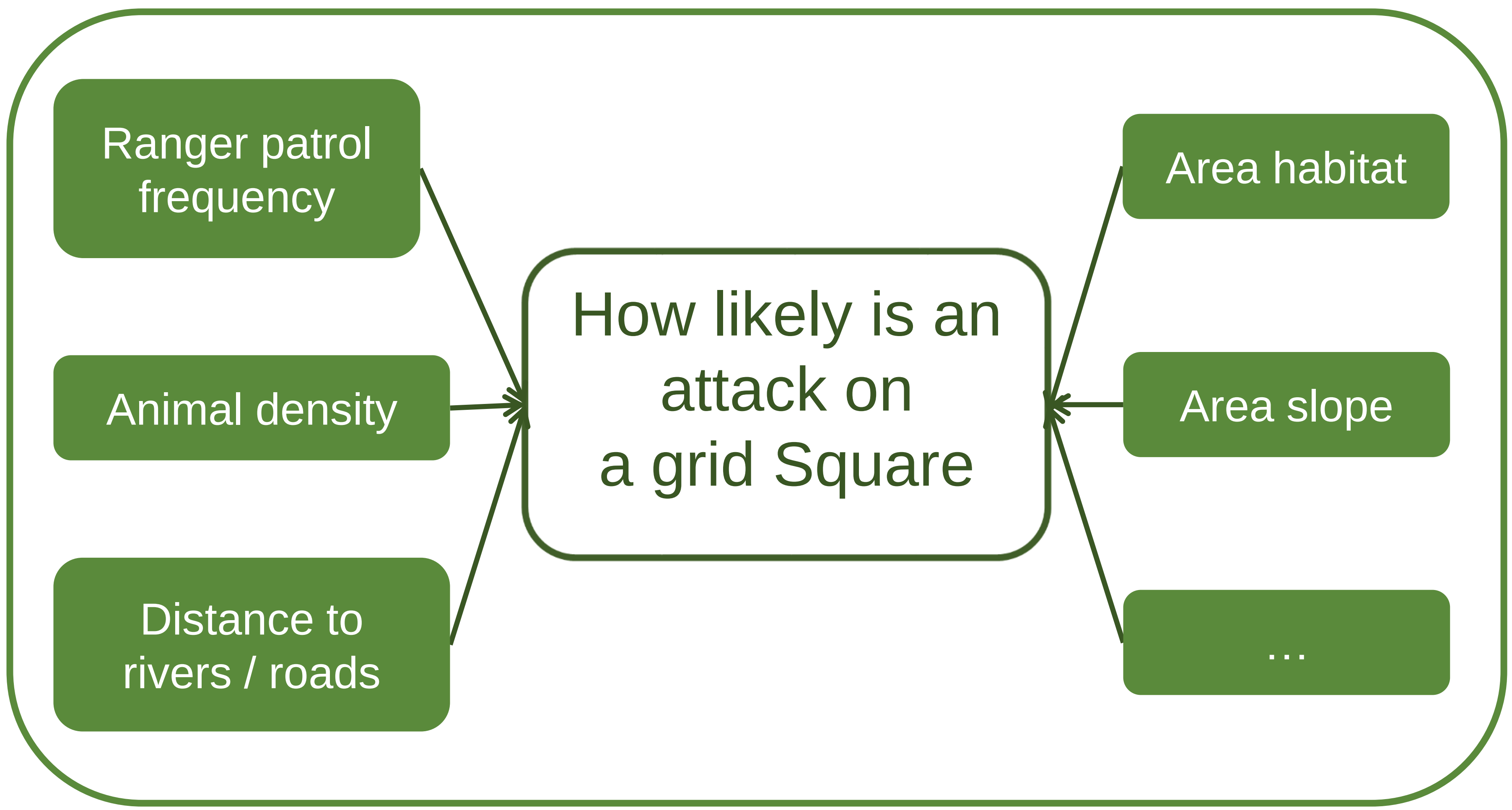


Poacher behavior prediction [2016]

Nguyen

Data from Queen Elizabeth National Park, Uganda

Number of poaching attacks over 12 years: ~1000



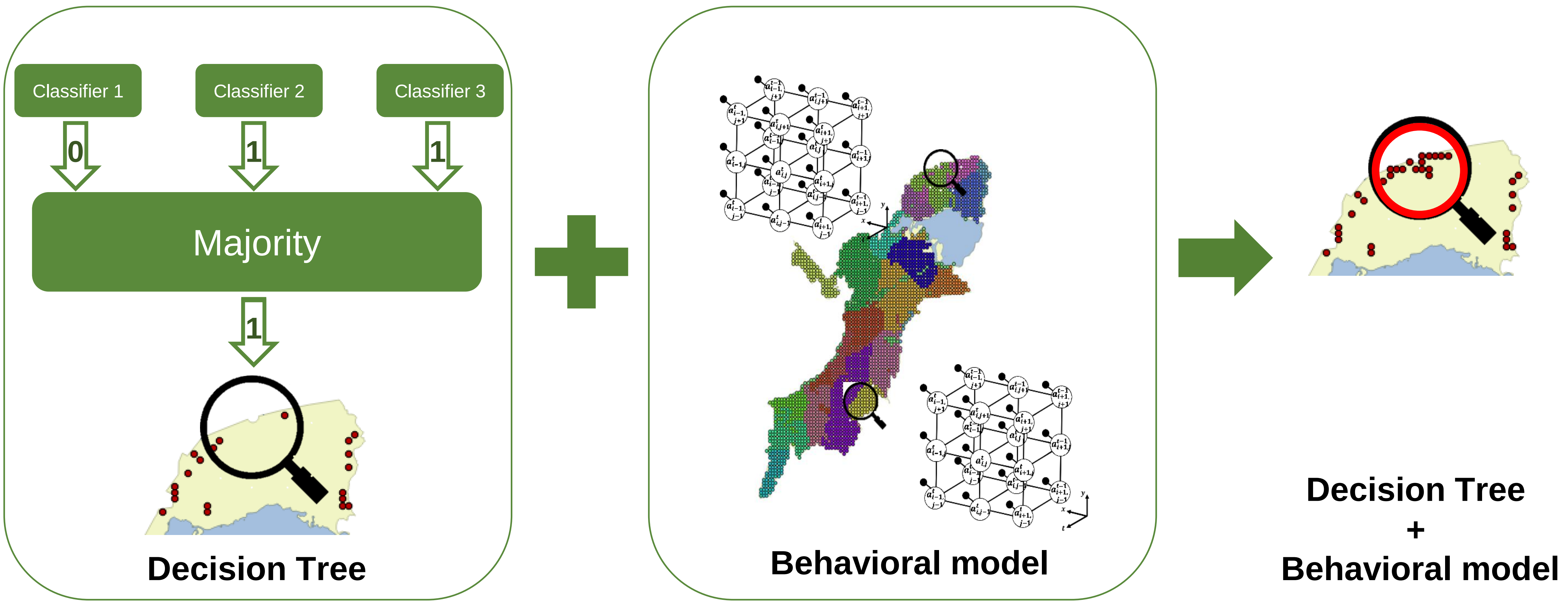
Boost Decision Tree Ensembles with with Behavioral Game Theory Models


Gholami


Kar


Ford

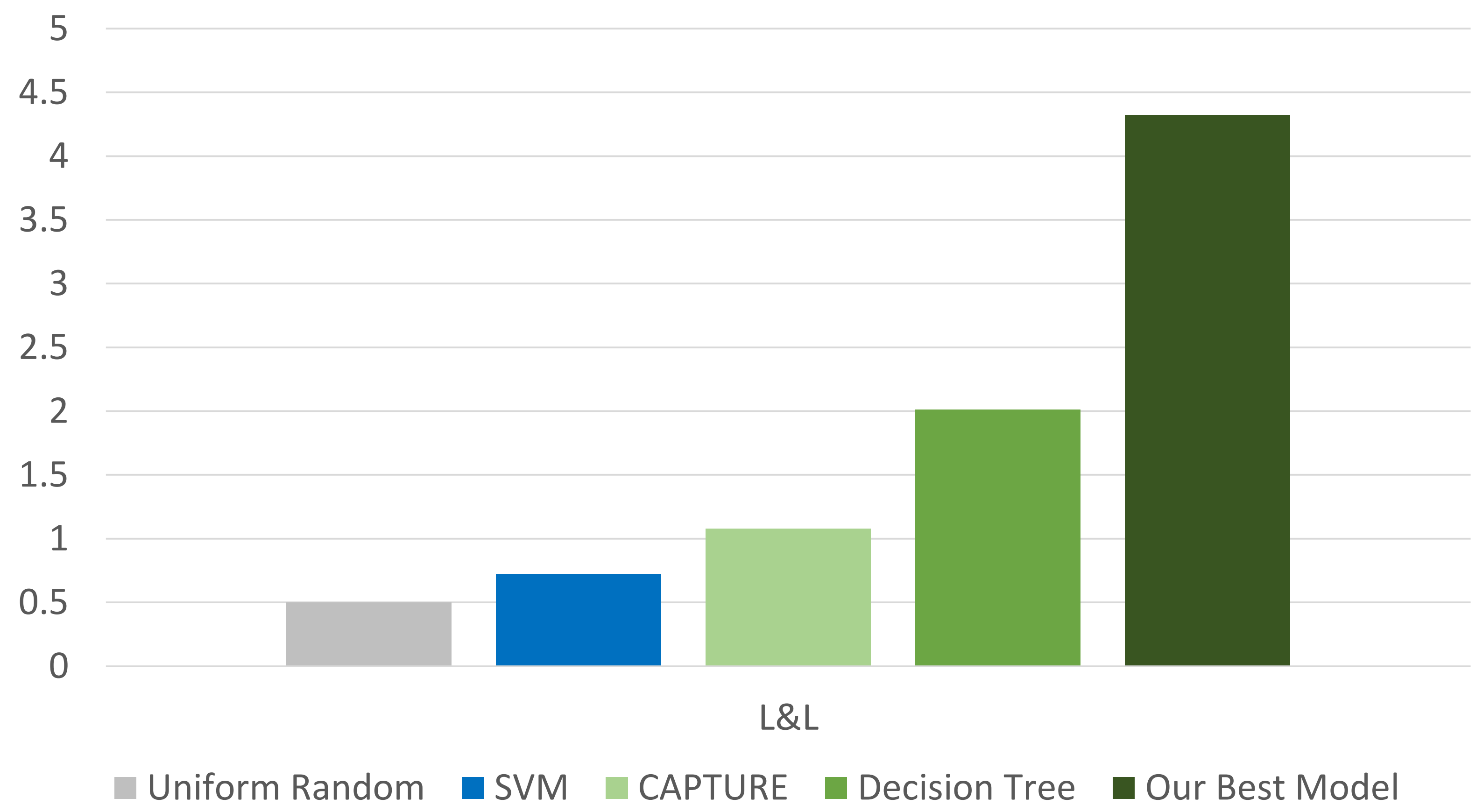
- Boost in “heavily monitored” regions of the park:
  - Improve accuracy
  - Learn local poachers’ behavior; distinct parameters



Poacher Attack Prediction [2017]

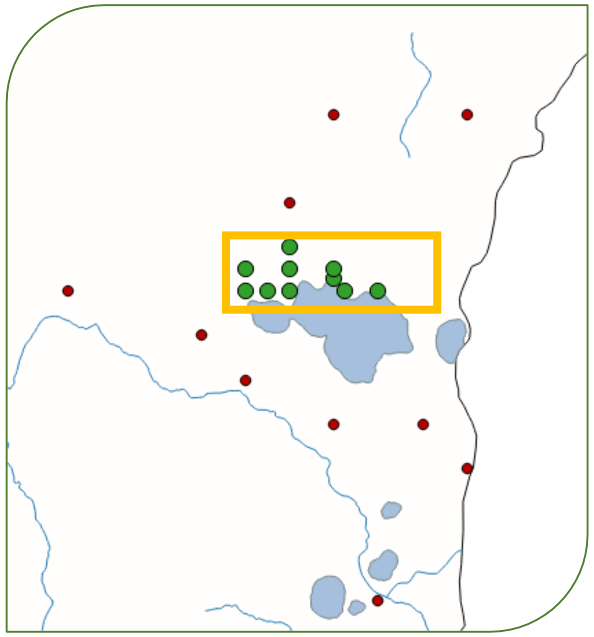
Poacher Behavior Prediction

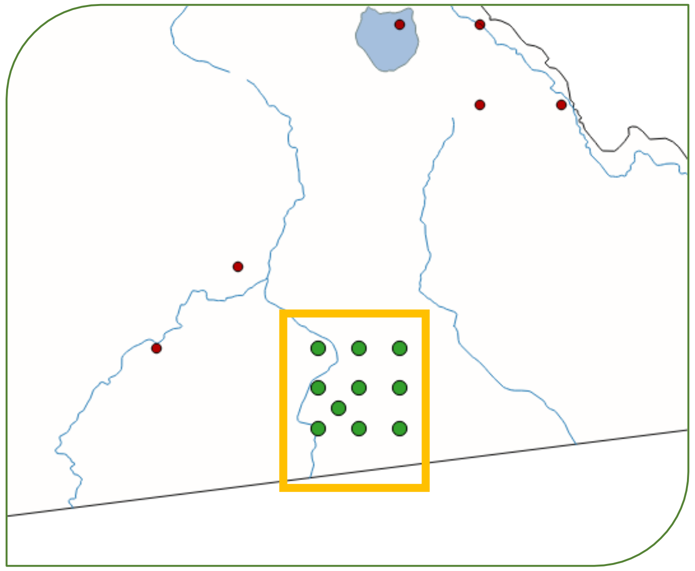
Results from 2015

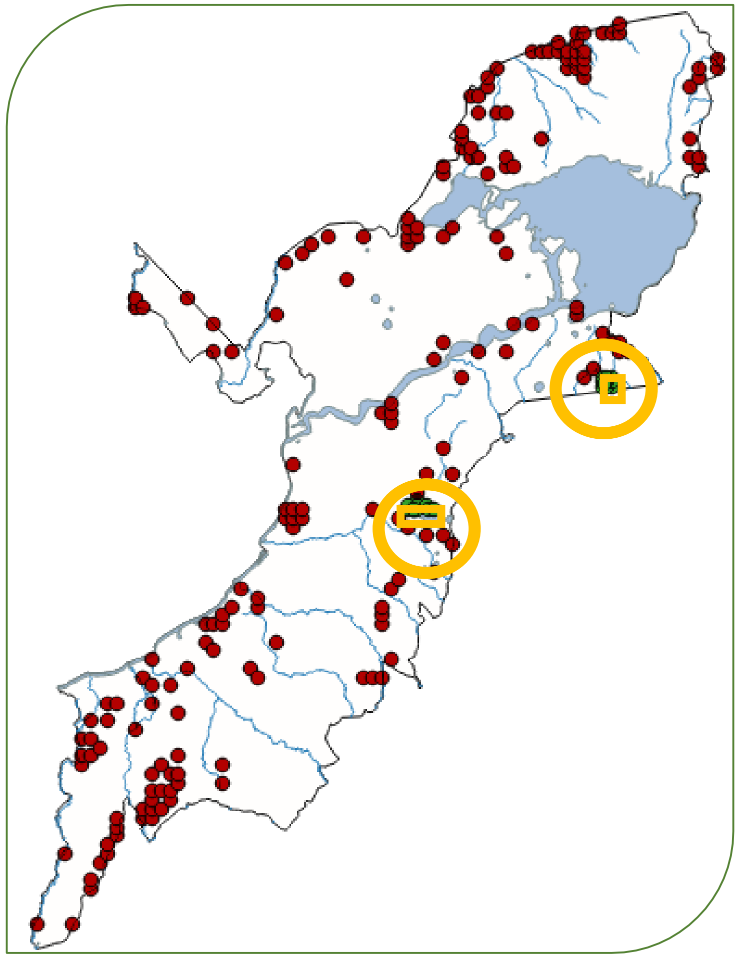


Real-world Deployment (1 month)

- Two 9-sq. km patrol areas
  - Where there were infrequent patrols
  - Where no previous hot spots







Real-world Deployment: (1 month)

Real-world Deployment: Results

- Two 9 sq KM patrol areas: Predicted hot spots with infrequent patrols

- Trespassing: 19 signs of litter etc.
- Snaring: 1 active snare
- Poached Animals: Poached elephant
- Snaring: 1 elephant snare roll
- Snaring: 10 Antelope snares

- Hit rates (per month)
  - Ours outperforms 91% of months

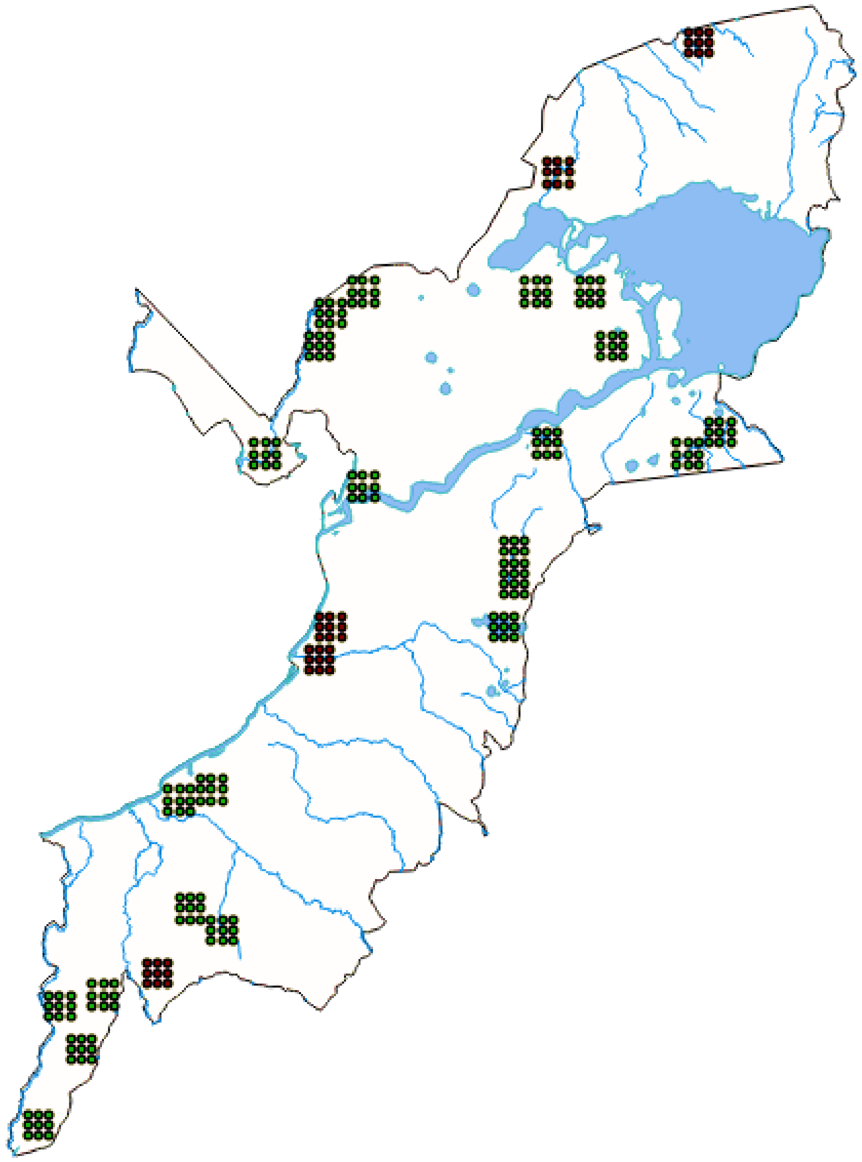
Historical Base Hit Rate	Our Hit Rate
Average: 0.73	3

Real-world Deployment:
Field Test 2 (6 months) [2017]


Gholami


Ford

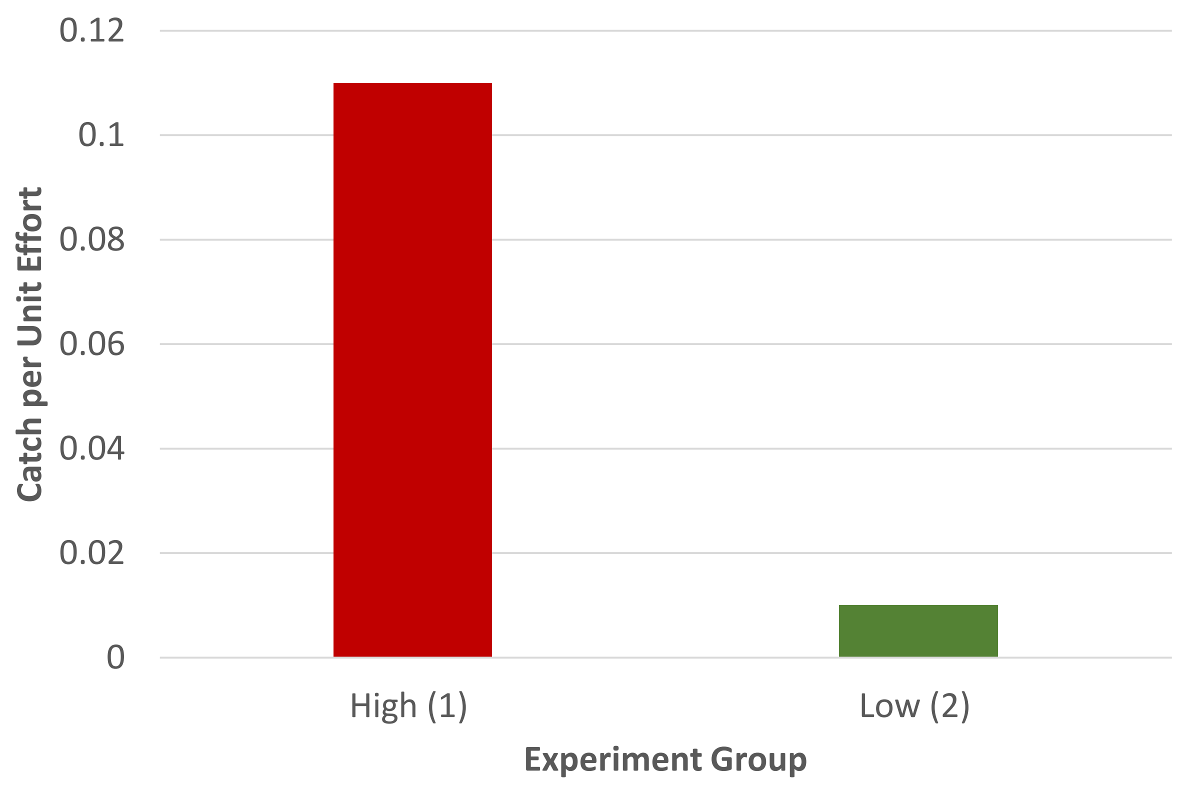
- 2 experiment groups (27 areas of 9 sq KM each)
  - **1:HIGH** >= 50% attack prediction rate
    - 5 areas
  - **2: LOW** < 50% attack prediction rate
    - 22 areas

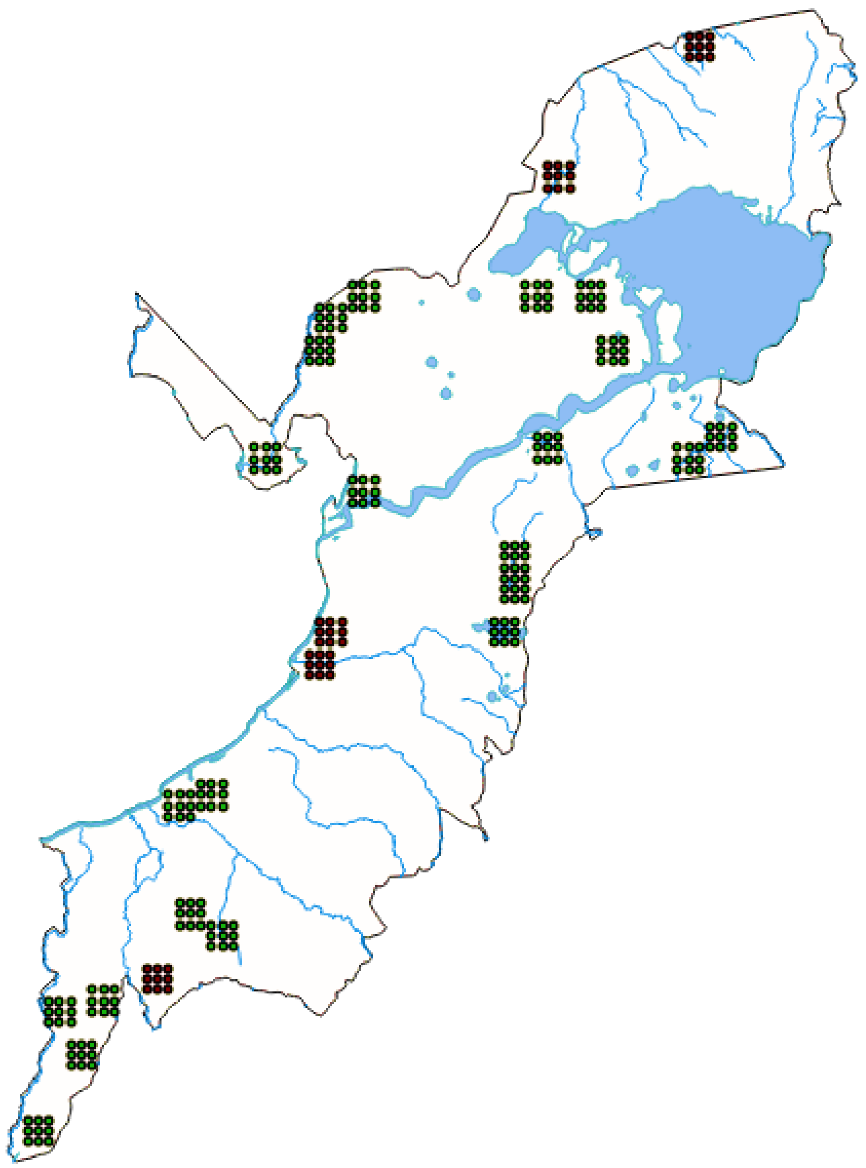


Real-world Deployment: Field Test 2 (6 months)

- Catch Per Unit Effort (CPUE)
  - Unit Effort = km walked
  - Our high CPUE: **0.11**
  - Our low CPUE: **0.01**

Historical CPUE: **0.04**



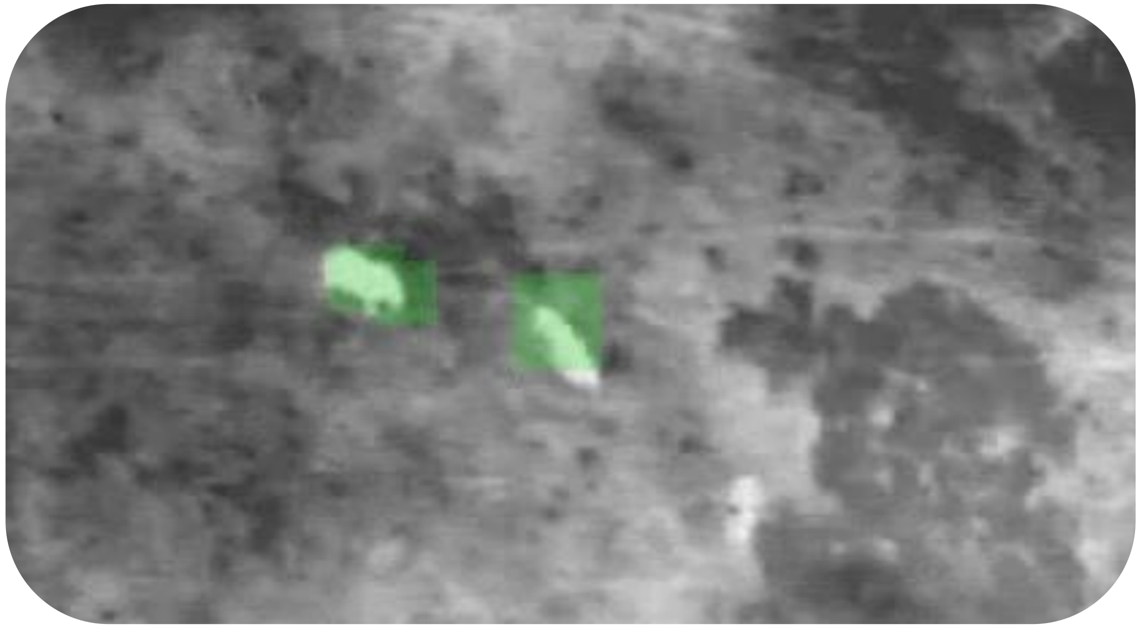


Green Security Games: Patrolling From the Sky [2017 ongoing]

Bondi

UAV Patrolling: cheaper and more flexible

Credit: Arvind Iyer, AirShepherd



Credit: Liz Bondi

AI for Social Good

THANK YOU

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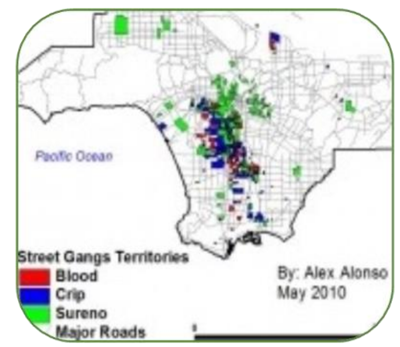
Overview of CAIS Project Areas

AI for Assisting Low Resource Communities



- Substance abuse, suicide prevention…
- Modeling gang violence, matching homeless and homes…

AI for Social Good: Essential Nature of Human Machine Partnership

- Build decision aids/assistants ("wrapping humans"):
  - *Humans focus on their expertise, e.g., social workers interact with youth*
  - *AI systems focus on complementary tasks, e.g., select influential youth*

- Lessons in Building Assistants:
  - *Right level of autonomy for humans vs machines*
  - *Explanation of output*

- Individual and organization level partnership:
  - *Immersion opens up our eyes; builds up trust over time*