# Common Knowledge and Collective Action on Directed Communication Networks: Models and Experimental Findings

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## Introduction

Social media helps protesters organize and reach a critical participation mass [1].

- In repressive regimes, a single protestor risks prosecution and violence, but can mitigate risk if many others coordinate action.


**Collective action problem:** Join only if joined by "enough" others.

**Coordination game:** Two or more people each make a participation decision with the potential to achieve shared mutual benefits only if their decisions are consistent.

Coordination requires that people know about each other and that this information is common knowledge (CK) [2].

Common knowledge refers to an infinite string of embedded levels of knowledge: If I want to participate, but I don't know whether you know it, then I don't participate. This is because I don't expect you to participate without sufficient information (that I want to participate if you do).


Social networks facilitate information sharing that generates common knowledge within groups.
We use models of Facebook and Twitter-type communication networks to understand how information can spread locally and facilitate common knowledge and collective action.

## Previous Theoretic Models

Chwe[3] and Korkmaz et al.[4] provide game-theoretic models of collective action on bidirectional communication networks. Both models have the following features:

| |
|---|
| Incomplete information coordination game with heterogeneous agents with private thresholds (willingness to participate). |
| Knowledge of what other players know about other players is crucial for coordination. Agents choose to stay home or participate. |
| Communication networks facilitate coordination through common knowledge creation. |

The models differ on the following features:

| Feature | Chwe[3] | Korkmaz et al.[4] |
|---|---|---|
| Communication Type | Directed (unreciprocated) "Communication network" with distance-1 communication | Undirected Facebook Wall posting |
| Network Knowledge | Globally Known | Locally Known |
| Minimal Substructure | Cliques | Complete Bipartite Graphs |

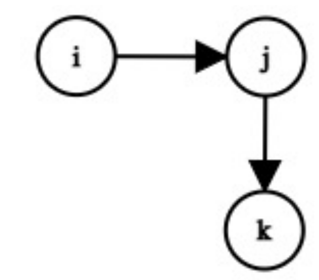
## Research Questions

1. What are the characteristics of **directed** network structures that generate CK of thresholds among a group of agents when the network structure is globally and locally known? What are the minimal substructures required for CK to occur?

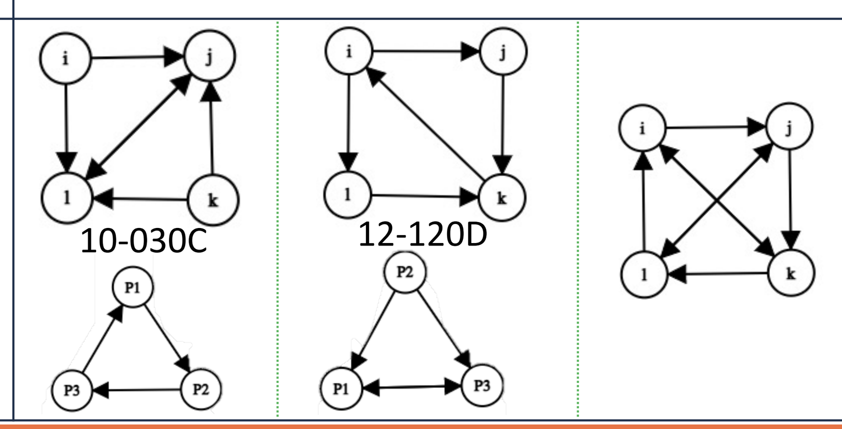
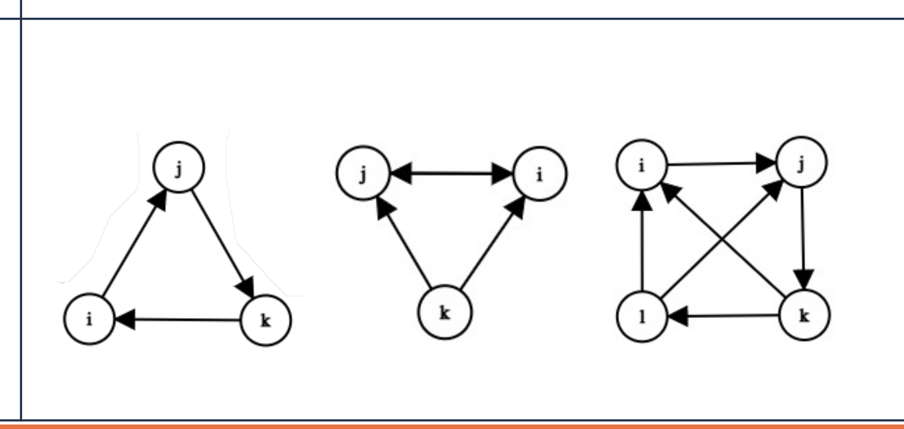
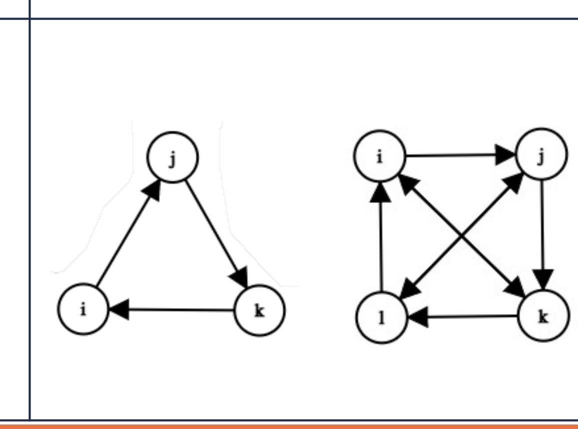
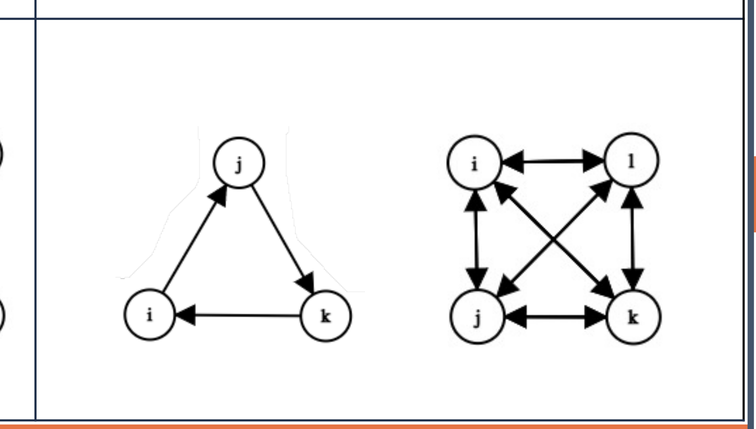
2. Do our theoretic predictions hold in experimental data?

## Network Assumptions

| Facebook | Twitter |
|---|---|
| A link from *i* to *j* indicates that *i* writes her threshold on the *j*'s wall.<br>We say that *k* is a friend of *j* if there is a link from *j* to *k* or *k* to *j*.<br>All *j*'s friends can see 1) *i*'s threshold, and 2) that *i* writes on the wall of *j*. | A link from *i* to *j* indicates that *j* follows *i*, and thus that *j* views the threshold of *i*.<br>Additionally, we assume that *j* retweets the threshold of *i*.<br>Thus, since *k* follows *j*, *k* knows the threshold of *i*, and that *j* observes the threshold of *i*. |

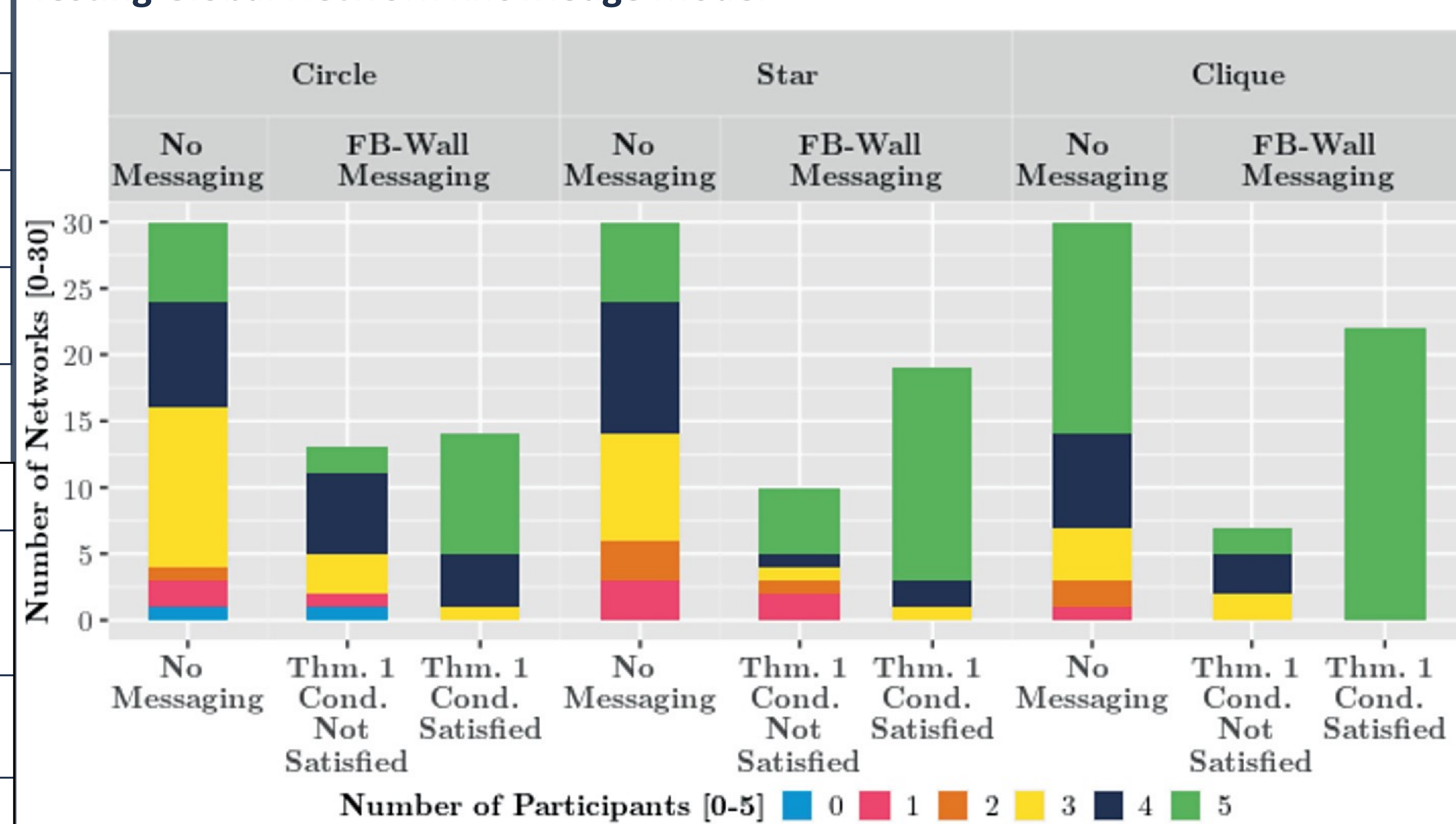



## Theoretic Findings

| | Facebook | | Twitter | |
|---|---|---|---|---|
| | Globally Known Structure | Locally Known Structure | Globally Known Structure | Locally Known Structure |
| Conditions | Agents know each others' thresholds either (1) directly or (2) through the wall of a friend. | Agents know each others' thresholds either (1) directly or (2) through the wall of a friend, and (3) all agents must observe the communication between all other agents. | Agents learn of each others' thresholds directly or through a retweet. | All subsets of three agents must form a cyclic triad, and any agent not in that subset must follow the agents in the cyclic triad. |
| Minimal Substructures | No named graph sub family, but includes (1) maximal, reciprocal distance-2 paths between agents and (2) complete tripartite graph with cyclic partitions in the form of 10-030C and 12-120D[5]. | Each agent has at least one outgoing link and all agents are neighbors. | Reciprocal, maximal paths of distance-2. | Cyclic triad or complete digraph. |
| Example Substructures |  10-030C 12-120D |  |  |  |

## Experimental Results

### Testing Global Network Knowledge Model

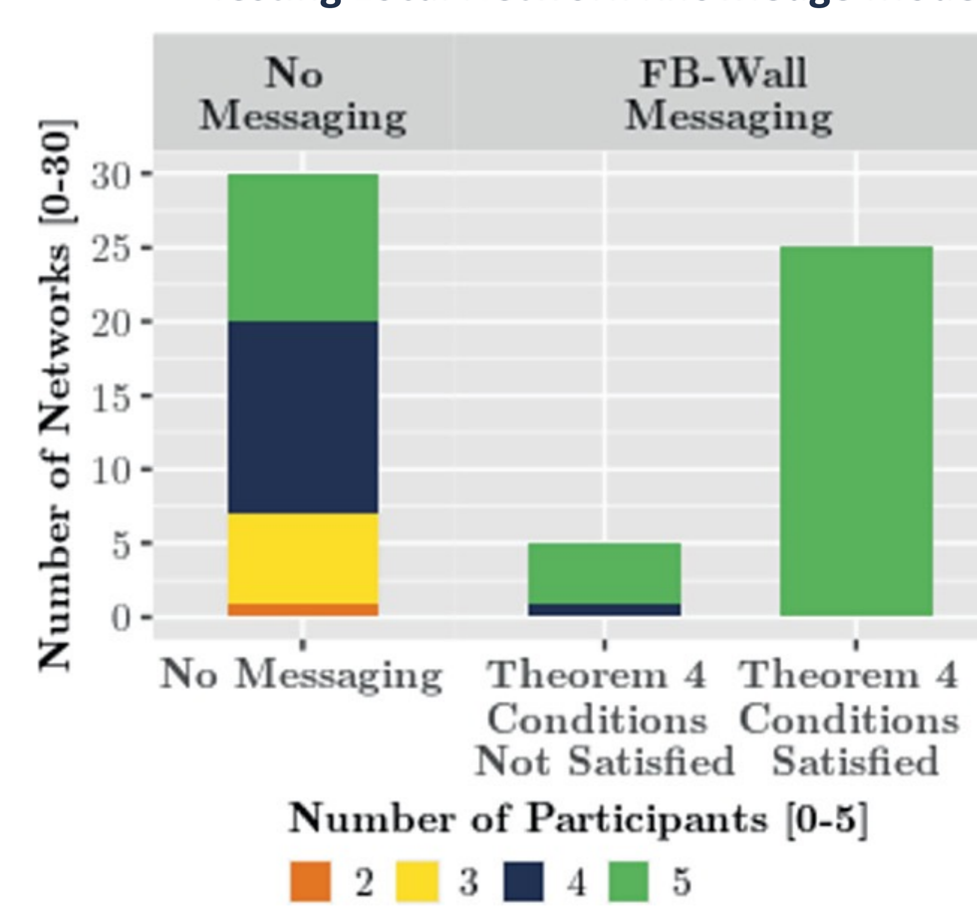



1. Cliques result in highest network participation, followed by star, and circle, in the global network knowledge cases.

2. There are more cases where all five players participate when there is Facebook-wall messaging.

3. There are more cases with full participation when our theoretic conditions are satisfied.

### Testing Local Network Knowledge Model




## Experimental Design

Completely randomized crossover design with a two-way treatment structure.

**Between-session** conditions (8 sessions):

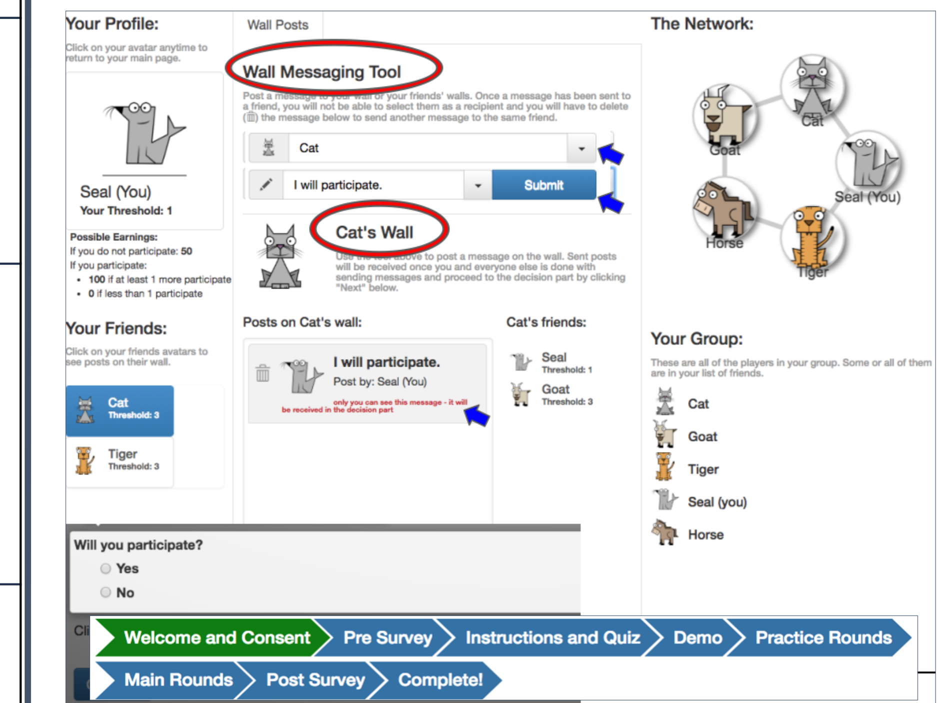
- Messaging condition: *none, wall*.
- Network information: *local, global*.

**Within-session** conditions (15 runs):

- Threshold: *low-1, high-3*.
- Network structure: *star, circle, clique*.

**Group:** 5 players in a network structure (120 subjects).

**Outcome:** Participation decision where players are rewarded only if a sufficient number of others in the group participate.




## Discussions

**Key takeaways**

1. The conditions for CK are less restrictive for Facebook wall posting communication than in Twitter-retweet communication.
2. We find higher participation when our theoretic conditions are satisfied in the experimental setting.

**Next steps**

Use real network data to understand the dynamics of our models in larger complex networks, model additional Twitter functions, conduct experiments on Twitter-type networks, open form messaging, and repeated games where individual perceptions of each player are based on previous outcome[6].

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