**Simulating the Bystander Effect Using Agent Based Modeling**

Megan Church

Data Science, William & Mary

DATA 444: Agent Based Modeling

Dr. Melanie Swartz

May 16, 2022

**Abstract**

The bystander effect is a theory that states individuals are less likely to help a victim when there are other people present. This paper summarizes the use of an agent-based model to simulate the bystander effect as observed in real situations in Copenhagen, Denmark. The model is a visual representation of how the individual reactions of bystanders influence the magnitude of the bystander effect. A few key patterns emerged from the model: (1) a decrease in interveners as the number of bystanders increase, (2) an increased likelihood of intervention if the bystander has a social relationship with a conflict party member, (3) an increased likelihood of intervention if the bystander is a man, (4) an increased likelihood of escalatory intervention if the bystander is a man, and (5) an increased likelihood of intervention if the bystander is within close spatial proximity of the event.
**Keywords:** bystander effect, agent-based modeling, Denmark

## Introduction

The bystander effect is a theory that states individuals are less likely to help a victim when other people are present (Fischer et al., 2011). This behavior stems from a diffusion of responsibility — when a person's sense of responsibility decreases as the number of people around them increases. In the case of the bystander effect, help is defined as bystander intervention and occurs when a bystander offers support to the victim. Situations where no help is offered are considered bystander apathy (Heuvel & Treur, 2020). This paper documents the agent-based model, allowing the reader to gain a deeper understanding of the key factors that predict bystander intervention. This research aims to create a visualization of the bystander effect to gain perspective on how different factors lead to a bystander's decision to intervene.

## Background

### The Topic

Research on bystander intervention has produced a considerable number of studies showing that the presence of other people in a critical situation reduces the likelihood that an individual will help (Fischer et al., 2011). A study conducted by Liebst et al. (2019) in Copenhagen, Denmark, examines the generalization of the bystander effect to violent emergencies. They hypothesized that a reverse bystander effect would occur when the bystanders perceived that the danger to the victim was high. In short, more people would intervene if they believed the victim was in greater danger. Additionally, research suggests that pre-existing social relations between bystanders and conflict party members are a key factor in predicting if bystanders will provide help. This paper documents an agent-based model developed to simulate the bystander effect as found in real situations in Copenhagen, Denmark.

### Related Research

A meta-analysis of current research on the bystander effect found that the bystander effect was diminished in situations perceived as dangerous, where perpetrators were present, and when the intervention costs were physical. A reduction in the bystander effect was also found when the bystanders were exclusively male and when the bystanders were not strangers (Fischer et al., 2011). These findings align with the Denmark study in that bystanders were more likely to intervene if they had a social relationship with the involved party. Additionally, the Denmark study hypnotized a reverse bystander effect in the case of violent incidents, when the effect was significantly smaller (Liebst et al., 2019). This finding is also supported by current research where the bystander effect was diminished in situations that were perceived as dangerous (Fischer et al., 2011).

Models attempting to simulate the bystander effect have been created by data scientists in the past. Heuvel and Treur's (2020) model utilizes temporal-causal networks to simulate the bystander effect in different and new scenarios. However, their research focused on bystander apathy and perceived danger, and did not include the quantity of bystanders as a factor in predicting intervention.

### Why Utilize Agent-Based Modeling

An agent-based model describes a system using a collection of autonomous decision-making entities (agents) that individually make decisions based on a set of rules and their current situation. Agent-based models are favorited for their ability to capture agents' behavior from a series of individual decisions (Bonabeau, 2002). The bystander effect model consists of agents whose unique decisions reflect those of real people. Each agent's decisions ultimately affect the outcome of the incident, making an agent-based model the ideal choice.

## Data

The data was obtained from Liebst's et al. (2019) study on social relationships and the bystander effect and consists of surveillance camera recordings of police reported public violent assaults in central Copenhagen between 2010 and 2012. For each incident, the conflicting parties were determined along with bystander intervention behavior and environmental properties. In addition to the visual information obtained from the video recordings, each clip was also paired with a police case file that provided descriptive accounts of the event.

For the purpose of the model, the data was split into two CSV files: event data and individual data. The event data provides environmental context for each incident (density, location, etc.). The individual data provides the traits (gender, action type, etc.) for each intervener, for each incident. Both datasets were loaded into Netlogo using the CSV extension and were used to initialize a proportional display and population during the model setup.

## Model Design

This section summarizes key model components. Appendix A includes a detailed description of the bystander effect model following the Overview, Design concepts, and Details (ODD) protocol (Grimm et al., 2006). The ODD enables transparency of the model components and allows for both reproducibility and reuse of the model (Grimm et al, 2020).

### Model Development

The modeling framework Netlogo, version 6.2.2, was used to develop the agent-based model (Wilensky, 1999). Netlogo is a multi-agent programmable modeling environment that utilizes its own coding language to support agent-based model development. For this data-driven model, the CSV extension for Netlogo was used to support the use of tabular data, which informed inform agent and environment attributes as well as model parameterization. All required data preprocessing was performed using Python version 3.8.3 and Numbers version 12.0.

### Model Components

#### *Model Initialization and Parameters*

The model allows users to select the number of bystanders present. Since each scenario is a real event that occurred in Copenhagen, Denmark, the event variables and number of bystanders who intervene are predetermined.

#### *Agents*

There are two breeds of agents: bystanders and interveners. Bystanders are people present for the event who decide not to intervene. They move about randomly for the entirety of the model run. Interveners have a few key attributes that help them navigate throughout the event: proximity, location, and the event patch. An intervener's proximity to the event determines where they are initialized. The location of the event determines the speed and rotation of random movement. Lastly, when the event patch turns on, all interveners display their traits and head towards the event. The key attributes and behaviors are noted in Table 1, more detailed information can be found in Table A2.

Table 1: Agent Attributes and Behaviors

| Agent | Select attributes | Key behaviors |
|---|---|---|
| Bystanders | Location | |
| Interveners | Proximity, Location, Event Patch | Heading |

***Environment***

This model simulates the bystander effect as observed in real situations in Copenhagen, Denmark. The model includes spatial data describing the proximity of interveners and the density of the environment, which is loaded in during the model setup. An intervener in close proximity to the event is initialized within a 2-meter radius of the event patch. This area is gray. A high-density environment is defined as an area in which a bystander could not walk in a straight line without running into anyone else (Liebst et al., 2019). In the model a high-density environment is created by decreasing the number of patches in the display while keeping the total area of the display identical. This has a magnifying effect on the display, causing the agents to appear larger. For more detailed information on the environment see Table A4.

***Submodels***

The key sub-models incorporated in this agent-based model are the agent-event interactions creating the bystander effect in the model, agent-environment interactions, and the movement logic agents follow when evacuating. These are briefly summarized.

- **Setup:** During model setup, this function loads in the data and sets up the environment. It also generates and distributes the agent population with the appropriate traits.
- **Set-event-variables:** During model setup, this function loads in the data and sets up the environment based on the specific details for that event.
- **Set-interveners:** After the model has run for ten ticks, this function changes the color, shape, and fill of the interveners according to their individual traits.
- **Move-(location):** Interveners move to the next patch, getting them closer to the event patch. Bystanders move about randomly with the speed and rotation of the movement depending on the location of the event.

## Model Logic and Flow

The processes that take place during each model iteration are summarized as a flow diagram in Figure 1. There is no temporal element in the model.

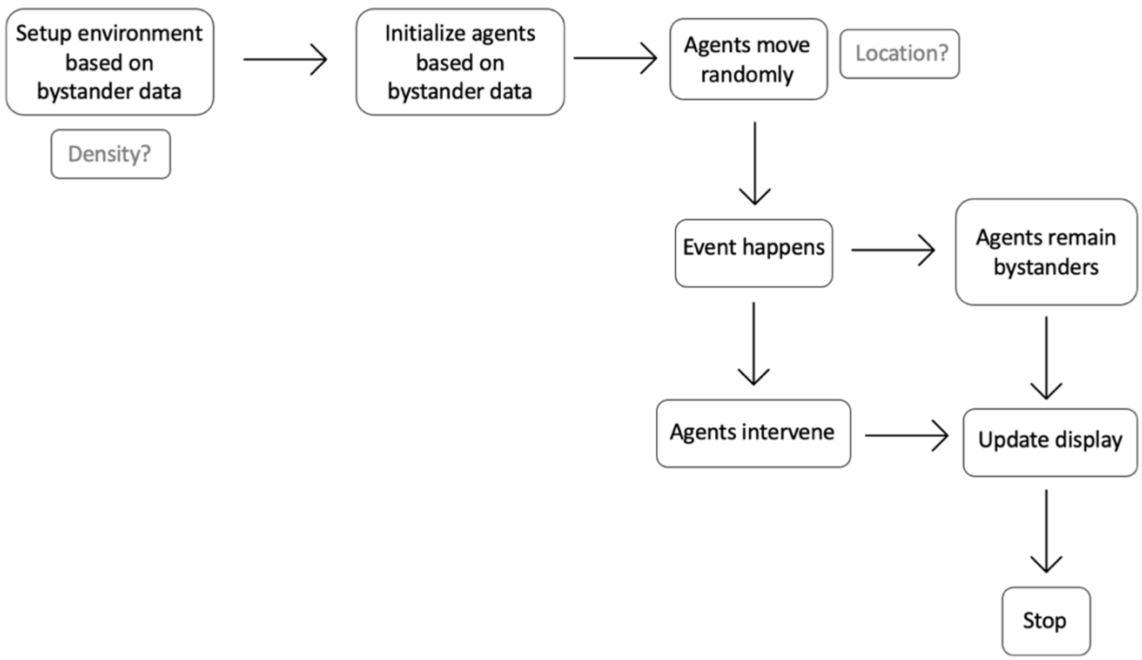


Figure 1: Model Flow Diagram

## Model Interface

A screenshot of the model interface and results during a sample snapshot are shown in Figure 3.

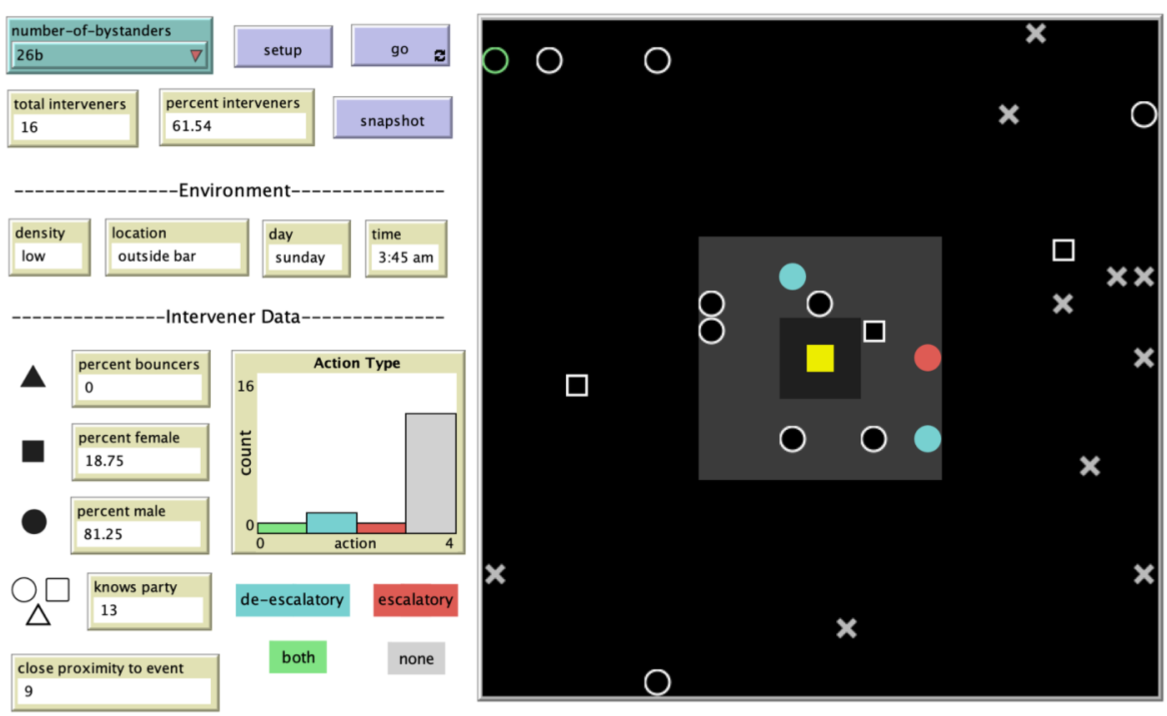


Figure 2: Graphical User Interface

## Experiments and Results

Due to the nature of the model, traditional experiments are not necessary. However, there are identifiable patterns in the data. These patterns provide deeper insight into what causes the bystander effect. These are briefly summarized below.

**Pattern 1**

As the number of bystanders increases the number of interveners decreases. This pattern is the defining characteristic of the bystander effect and reflects the diffusion of responsibility it stems from.

**Pattern 2**

Having a social relationship with a conflict party member is positively correlated with intervention. Compared to a stranger, the odds of intervening are more than 20 times larger for a bystander with a social relation to a conflict party.

**Pattern 3**

Men are more likely to intervene than women. Of the 528 interveners, 43 (8%) were bouncers, 164 (31%) were female, and 321 (61%) were male.

**Pattern 4**

When comparing the different types of actions interveners took (Figure 2), there are interesting relationships between action and gender and action and spatial proximity. Proportionally, men took more actions than women with more than three times the number of escalatory actions. Unsurprisingly, bouncers took the most actions, and the majority were de-escalatory. Among interveners, those in close proximity to the event were more likely to take action than those not in proximity to the event.


Figure 3: Distribution of Action Type

## Discussion

The bystander effect states that individuals are less likely to offer help to a victim when there are other people present. This is due to a diffusion of responsibility and collective apathy generated by people being together with others. Therefore, the main purpose of testing for these patterns was to see if the number of bystanders had an effect on the number of interveners.

The data and model results support the bystander effect, in that the number of interveners decreased as the number of bystanders increased. Additionally, the study the data was gathered from presented an alternative explanation for bystander involvement. They hypothesized that bystanders with social relationships with the conflict party are more likely to intervene. This hypothesis was also supported by the model results. With the support of these two widely accepted theories, the model appears to be an accurate representation of the bystander effect.

Due to the model utilizing data from real incidents, the user is only able to select the number of bystanders. With more data, future versions of this model might allow for more user input and customization. For example, a predictive model could allow the user to specify the number of bystanders, the gender composition of the crowd, how many bystanders are in close proximity to the event, and how many bystanders have a social relationship with a conflict party member. Then, based on these variables, the model would create a unique situation, where the number of interveners and type of actions taken become the dependent variables.

## References


Bonabeau, E. (2002). Agent-based modeling: Methods and techniques for simulating human systems. Proceedings of the National Academy of Sciences of the United States of America, 99, 7280–7287. https://doi.org/10.1073/pnas.082080899

Fischer, P., Krueger, J. I., Greitemeyer, T., Vogrincic, C., Kastenmüller, A., Frey, D., Heene, M., Wicher, M., & Kainbacher, M. (2011). The bystander-effect: A meta-analytic review on bystander intervention in dangerous and non-dangerous emergencies. Psychological Bulletin, 137(4), 517–537. https://doi.org/10.1037/a0023304Heuvel

Grimm, V., et al. (2006). A standard protocol for describing individual-based and agent-based models. Ecological Modelling, 198(1-2), 115–126.

Grimm, V., Railsback, S., et al. (2020). The ODD Protocol for Describing Agent-Based and Other Simulation Models: A Second Update to Improve Clarity, Replication, and Structural Realism. Journal of Artificial Societies and Social Simulation 23 (2) 7. http://jasss.soc.surrey.ac.uk/23/2/7.html

Joey & Treur, Jan. (2020). To Help or Not to Help: A Network Modelling Approach to the Bystander Effect. 10.1007/978-3-030-65596-9_64.

Liebst, L. S., Philpot, R., Bernasco, W., Dausel, K. L., Ejbye-Ernst, P., Nicolaisen, M. H., & Lindegaard, M. R (2019). intervention_data.dta (Version: 1). Center for Open Science (OSF). https://osf.io/8wk4d/

Liebst, L. S., Philpot, R., Bernasco, W., Dausel, K. L., Ejbye-Ernst, P., Nicolaisen, M. H., & Lindegaard, M. R. (2019). Social relations and presence of others predict bystander intervention: Evidence from violent incidents captured on CCTV. Aggressive behavior, 45(6), 598–609. https://doi.org/10.1002/ab.21853

**Appendix A**

## ODD: Bystander Effect ABM

This document provides the detailed overview, design concepts, and details (ODD) of the agent-based model on the bystander effect, following the framework by Grimm *et al.* (2020).

### 1 Overview

#### 1.1 Purpose and Patterns

The overall purpose of this model is to illustrate the bystander effect. The model also accounts for the gender composition and density of the crowd, relation to the individuals involved, location, proximity to the incident, and if it is a bystander's job to intervene (i.e., a bouncer). The model will also depict any actions (escalatory and de-escalatory) that interveners took. Due to the variability of the data, there are only two major patterns identified from the model. The first is the movement of bystanders who are identified as interveners towards the incident. The second is a decrease in the percent of interveners as the number of bystanders increases.

#### 1.2 Entities, State Variables, and Scales

This model includes the following entities: bystanders, interveners, the event, and the environment. The state variables used to describe the agents can be found in Table A1 and Table A2, the state variables describing the event can be found in Table A3, and the state variables describing the environment can be found in Table A4.

Table A1: State variables describing the bystanders

| State Variable | Description | Data Type |
|---|---|---|
| n/a | there is no data for bystanders | n/a |

Table A2: State variables describing the interveners

| State Variable | Description | Data Type |
|---|---|---|
| id | unique identifier | static, text |
| gender | bouncer, male, or female | static, text |
| action | de-escalatory, escalatory, both, none | static, text |
| proximity | is the intervener within two meters of the event when the event occurs? | static, text |
| social relationship | does the intervener have a social relationship with an involved party member? | static, text |

Table A3: State variables describing the event

| **State Variable** | **Description** | **Data Type** |
|---|---|---|
| pcolor | the status of the incident | dynamic, text |

Table A4: State variables describing the environment

| **State Variable** | **Description** | **Data Type** |
|---|---|---|
| density | high or low | static, text |
| day | day of the week | static, text |
| time | time of day | static, text |
| location | inside bar, outside bar, public street, station, shop or restaurant | static, text |

The spatial resolution of the model varies depending on the density of the event. Specific dimensions can be found in Table A5 and Table A6. Each cell represents an area of 1.5m$^2$.

Table A5: Dimensions for High Density Display

| Total Bystanders | Patch Size | Total Patches |
|---|---|---|
| 1-11 | 48 | 121 |
| 12-21 | 40 | 169 |
| 22-27 | 35 | 225 |
| 28-35 | 31 | 289 |
| 44 | 25 | 441 |

Table A6: Dimensions for Low Density Display

| Total Bystanders | Patch Size | Total Patches |
|---|---|---|
| 1-11 | 25 | 441 |
| 12-21 | 23 | 529 |
| 22-27 | 21 | 625 |
| 28-35 | 18 | 841 |
| 35+ | 17 | 961 |

**1.3 Process Overview and Scheduling**

The user selects the number of bystanders in the model run. The model will then depict an incident, showing how many bystanders intervened for that event in the dataset along with the gender composition of the interveners and any actions the interveners performed.

**Scheduling**:

1. Model executes the setup sub model, loads the data, and sets the event patch.
    a The model sets the event variables according to the event data.

    b. The model creates agents according to the intervener data and initializes starting locations for all agents.
2. The go sub model is executed allowing all agents to move randomly for 10 ticks, depending on the event's location.
    a. After 10 ticks, the event patch turns on, and agents either intervene or remain bystanders.
    b. Intervener agents move towards the event patch, exhibiting their individual traits.
3. The model stops after all interveners are within 1.5 meters of the event patch.

Below is the model flow diagram highlighting the model overview and scheduling process.

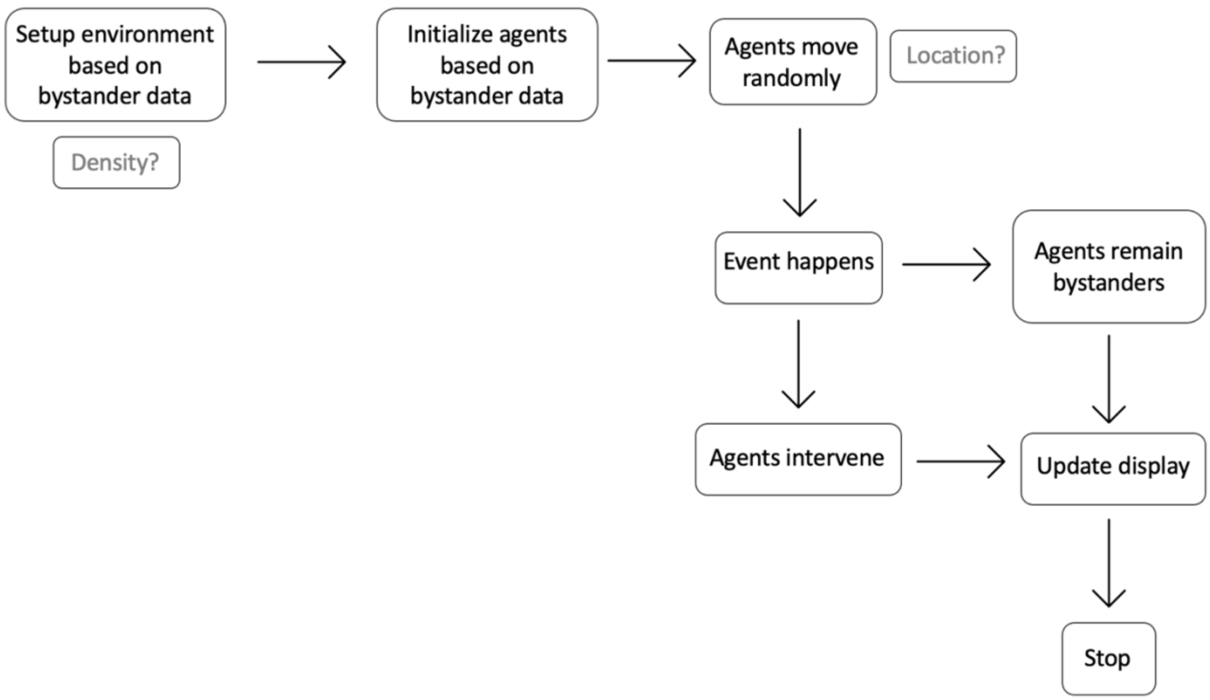


Figure A1: Model flow diagram.

**2 Design Concepts**

**2.1 Basic principles**

The model is a visualization of the bystander effect. Analyzing this model can help identify variables that influence the likelihood of individuals intervening in violent incidents.

**2.2 Emergence**

The key outcome from this model will come from comparing the number of individuals who decide to intervene in violent incidents with the total number of bystanders present. The number of people who intervene is determined by variables affecting the individual agents, such as agents' proximity to the incident and their gender.

**2.3 Adaptation**

This model implements adaptation in the case where agents either remain bystanders or become interveners. The decision to become an intervener is based on the imported data.

**2.4 Objectives**

This model does not use objectives.

**2.5 Memory**

This model does not implement memory.

**2.5 Learning**

This model does not implement learning.

**2.6 Prediction**

This model does not implement prediction within the agents.

**2.7 Sensing**

This model does not implement sensing between the agents.

**2.8 Interactions**

Agents are not aware of other agents. However, intervener agents become aware of the event patch after 10 ticks and head toward it.

**2.9 Stochasticity**

Stochasticity is used in initializing the starting locations for agents outside of a 2-meter radius of the event patch. Agents marked as having close proximity will start within the 2-meter radius. After their proximity is determined the agents' starting location within that area is random.

**2.10 Collectives**

This model does not implement collectives.

**2.11 Observation**

There are a few key outputs being observed by the model: (1) the total number and percentage of people who have intervened, (2) the gender composition of interveners, (3) the number of interveners in close proximity to the event, (4) the number of interveners who had a social relationship with a conflict party member, (5) any actions the interveners took, and (6) the environmental factors of the event. The total interveners, proximity, and environment are updated at the model setup. The gender composition, social relationship, and action type are updated after the event patch turns on and agents intervene.

**3 Details**

**3.1 Implementation**

The model is implemented in Netlogo 6.2.2

**3.1 Initialization**

The first step of initializing the model is to load in all the appropriate data. Using this data, the display density and initial event variables are set, and the agents are generated. A high-density environment is created by decreasing the number of patches in the display, while keeping the total area of the display the same. Next the event patch and proximity radius are created allowing the agents to be generated. Agents marked as having close proximity will start within a 2-meter radius of the event patch and all other agents will start outside of that radius.

### 3.2 Input data

There is one external data source used as input for this model, however, it has been split into two CSV files for the purpose of the model. The data was obtained from Liebst's et al. (2019) study on social relationships and the bystander effect and is hosted by The Center for Open Science (OSF). This data was collected from surveillance camera recordings of police reported public violent assaults in central Copenhagen between 2010 and 2012. The dataset contains information on each intervener involved in an incident, but it does not contain information on the apathetic bystanders. Each incident is identified with a unique code. This code was used to split the dataset into two separate files, event data and intervener data. The event data is used to set the environment, event variables, and bystanders. The intervener data is used to generate the interveners and during the model run, set their traits. Preprocessing consisted of translating the dataset from Dutch to English, categorizing actions as escalatory, de-escalatory, or both, calculating the number of apathetic bystanders, and splitting the dataset.

### 3.3 Submodels

**setup**: This function executes four actions before the model can run: (1) it loads the data, (2) sets the event and proximity patches, (3) calls the set-event-variables, generate-bystanders, and generate-interveners functions, and (4) sets the plot.

**set-event-variables**: This function uses the number of bystanders the user input to access the event data and set the constant event variables. These variables include density, location, day, and time. This function also creates the density of the display.

**generate-bystanders**: This function accesses the event data to create and randomly place the appropriate amount of apathetic bystanders outside of a two-meter radius of the event patch.

**generate-interveners:** This function accesses the individual data to create and randomly place the intervener agents for the event specified by the user. If the intervener is identified as being in close proximity to the event it is placed within a two-meter radius of the event patch, otherwise it is placed anywhere outside the two-meter radius.

**go**: This function has four major steps: (1) all agents move about randomly, depending on the events location, (2) after nine ticks the event patch turns on, (3) after 10 ticks the set-interveners function is called, and (4) the model stops after all interveners are within 1.5 meters of the event patch.

**set-interveners:** This function accesses the individual data to set the color, shape, and fill of the interveners based on their individual traits.

**move-inside-bar:** This is the move function for when the location of the event is inside a bar. If the tick count is less than 10, agents randomly rotate 360 degrees and move forward .3 steps per tick. If the tick count is greater than 10, bystanders continue to randomly rotate 360 degrees and move forward .3 steps, while interveners head towards the event patch.

**move-outside-bar:** This is the move function for when the location of the event is outside a bar. If the tick count is less than 10, agents randomly rotate 270 degrees and move forward 1 step per tick. If the tick count is greater than 10, bystanders continue to randomly rotate 270 degrees and move forward 1 step, while interveners head towards the event patch.

**move-public-street:** This is the move function for when the location of the event is a public street. If the tick count is less than 10, agents randomly rotate 90 degrees and move forward 2 steps per tick. If the tick count is greater than 10, bystanders continue to randomly rotate 90 degrees and move forward 2 steps, while interveners head towards the event patch.

**move-station:** This is the move function for when the location of the event is a station. If the tick count is less than 10, agents randomly rotate 180 degrees and move forward .5 steps per tick. If the tick count is greater than 10, bystanders continue to randomly rotate 180 degrees and move forward .5 steps, while interveners head towards the event patch.

**move-shop:** This is the move function for when the location of the event is a shop or restaurant. If the tick count is less than 10, agents randomly rotate 360 degrees and move forward .2 steps per tick. If the tick count is greater than 10, bystanders continue to randomly rotate 360 degrees and move forward .2 steps, while interveners head towards the event patch.

**snap-shot:** This function can be used in place of the go function. When a snapshot is taken the event patch turns on, the set-interveners function is called, and bystanders change shape to an X. This function does not use movement.

**References**

Grimm, V., Railsback, S., *et al*. (2020). *The ODD Protocol for Describing Agent-Based and Other Simulation Models: A Second Update to Improve Clarity, Replication, and Structural Realism*. Journal of Artificial Societies and Social Simulation 23 (2) 7. http://jasss.soc.surrey.ac.uk/23/2/7.html

Liebst, L. S., Philpot, R., Bernasco, W., Dausel, K. L., Ejbye-Ernst, P., Nicolaisen, M. H., & Lindegaard, M. R (2019). intervention_data.dta (Version: 1). Center for Open Science (OSF). https://osf.io/8wk4d/

Liebst, L. S., Philpot, R., Bernasco, W., Dausel, K. L., Ejbye-Ernst, P., Nicolaisen, M. H., & Lindegaard, M. R. (2019). Social relations and presence of others predict bystander intervention: Evidence from violent incidents captured on CCTV. Aggressive behavior, 45(6), 598–609. https://doi.org/10.1002/ab.21853