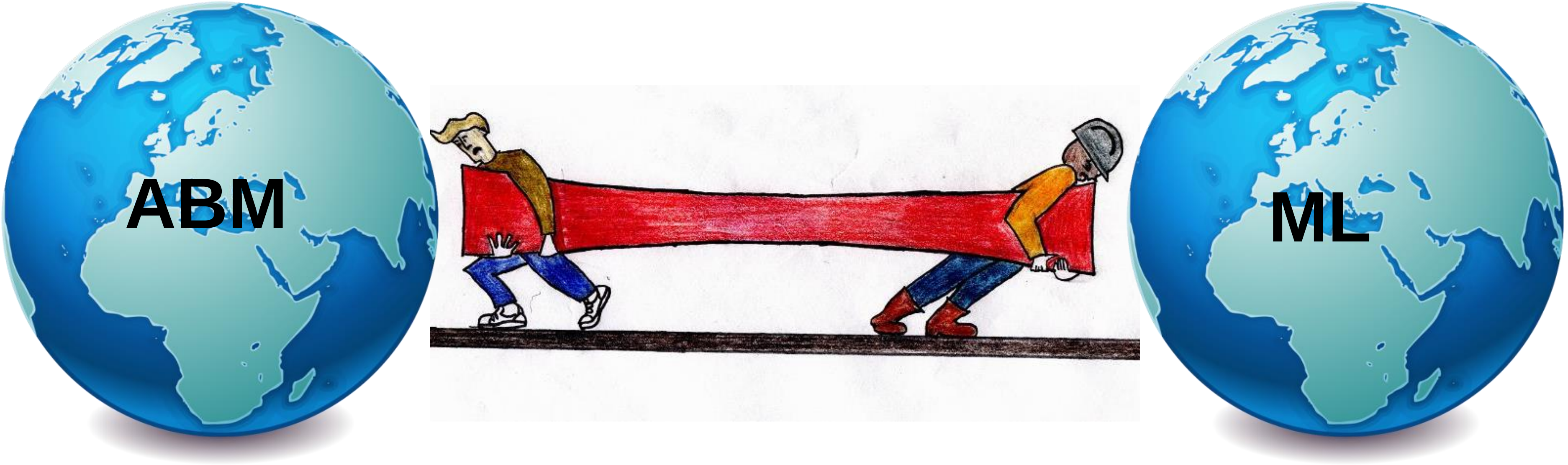
Integrating Agent-Based Modelling and Machine Learning

Ellen-Wien Augustijn
Shaheen Abdulkareem

UNIVERSITY OF TWENTE.
FACULTY ITC

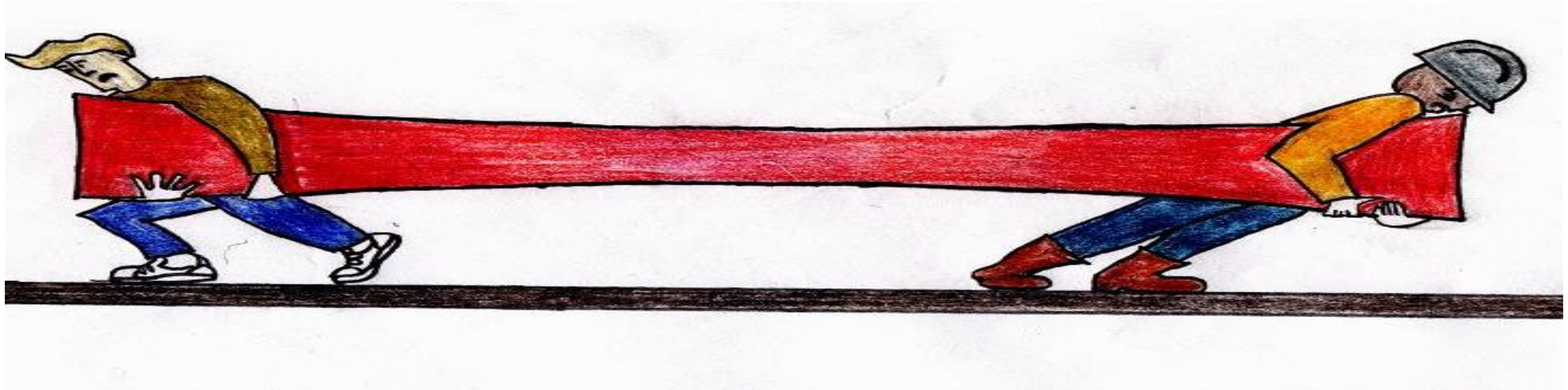
ADVANTAGES OF INTEGRATING ABM AND ML

- The integration of Agent-Based Modelling (ABM) and Machine Learning (ML) provides many promising opportunities:
  - ABM perspective: agent-awareness (observation of changes in environment states), agent-learning and for validation of ABMs.
  - ML perspective: Involving domain and human intelligence, data fusion and preparation, adaptive learning. ABMs are a way of creating datasets that otherwise would not be available



HOW CAN ABM AND ML BE INTEGRATED?

VIEWED FROM THE ABM PERSPECTIVE:



COMBINING ABM AND ML

PREPROCESSING

Motivation?
- Poor or Missing Data

Techniques applied?
- Prediction

Technical difficulty?
- Low as no integration is required

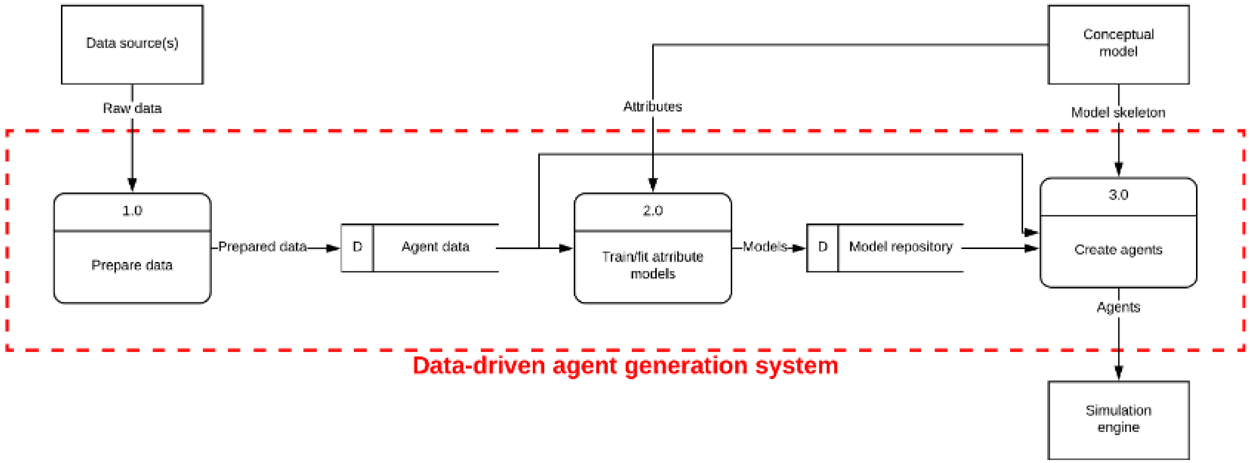
Motivation?
- Extraction of agents, agent variables, and agent behavior rules

Techniques applied?
- Clustering..

Technical difficulty?
- Low as no integration is required

EXTRACTING AGENT TYPES AND ATTRIBUTES

- Conceptual model defines the agent types, attributes and behavior signatures
- Behavior rule generation requires historical data to include the real-world entity's behavioral actions (e.g., interactions with other entities over time).



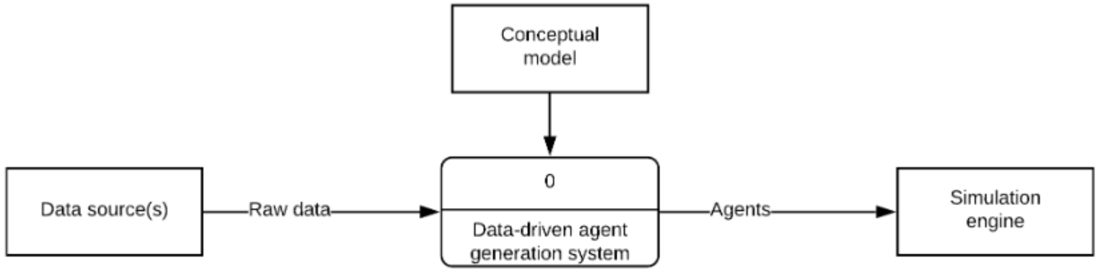


Figure 1: Contextual Data Flow Diagram of the proposed data-driven approach.

Source: Big Data, Agents, and Machine Learning: Towards a Data-Driven Agent-Based Modeling Approach.

ATTRIBUTE INITIALIZATION CASE

Approach:

- *Direct initialization* passes values without modification (e.g., agent age).
- *Look-up-based initialization* transforms attribute data into specific values in process using a look-up table (e.g., ‘age’ transforms to ‘age range’)
- *Model-based initialization* organizes and transforms data into an input that is suitable to be used in the attribute value inference model (machine learning or statistical).

Problems:

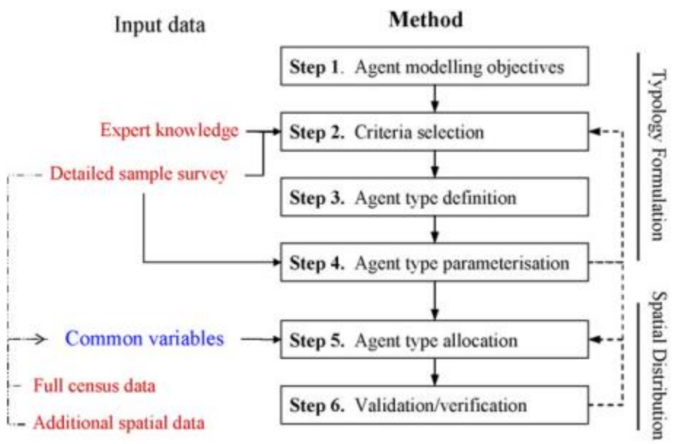
- Requires detailed quantitative data (survey data is often difficult)
- Requires large datasets (surveys are often too small)
- Requires temporal data (Behavior can change over time)
- Requires spatial data (behavior can change due to the location of the agent)

Source: Big Data, Agents, and Machine Learning: Towards a Data-Driven Agent-Based Modeling Approach.

AGENT TYPOLOGY – EMPIRICAL AGENTS

- Typology is an artificial way to define different groups based on specific criteria in order to organize and analyze reality (McKinney, 1950; Jollivet, 1965).
- The criteria to construct a typology, primarily depend on the objectives of its implementation (Escobar and Berdegue´ , 1990)

- Agent typology for Empirical ABM models can be based on:
  - Lab Experiment data
  - Survey
  - Census data
  - Interviews
  - Stakeholder information
  - etc



https://spinlab.vu.nl/wp-content/uploads/2016/09/Valbuena_etal_2008_AEE.pdf

EMPIRICAL AGENT TYPOLOGY

- Surveys are a sample of the population, you need to upscale using census data to the real population
- Perform a clustering to “group” survey entries to come to agent types
- Need to address the spatial aspects

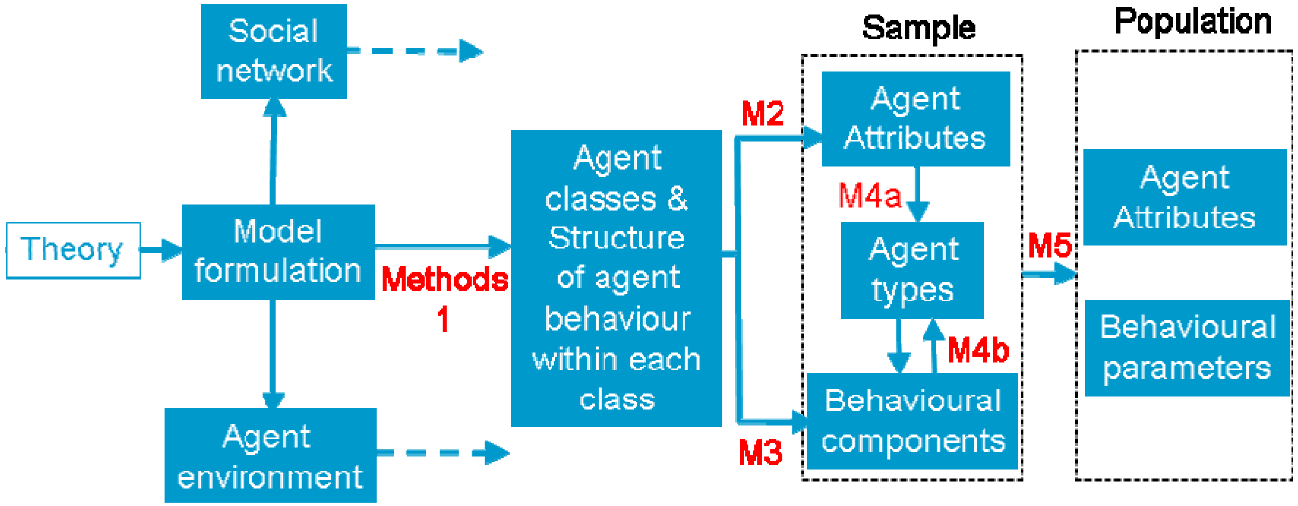


Figure 1: Framework for parameterisation of ABM

https://publications.csiro.au/rpr/download?pid=csiro:EP101780&dsid=DS4

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Motivation?
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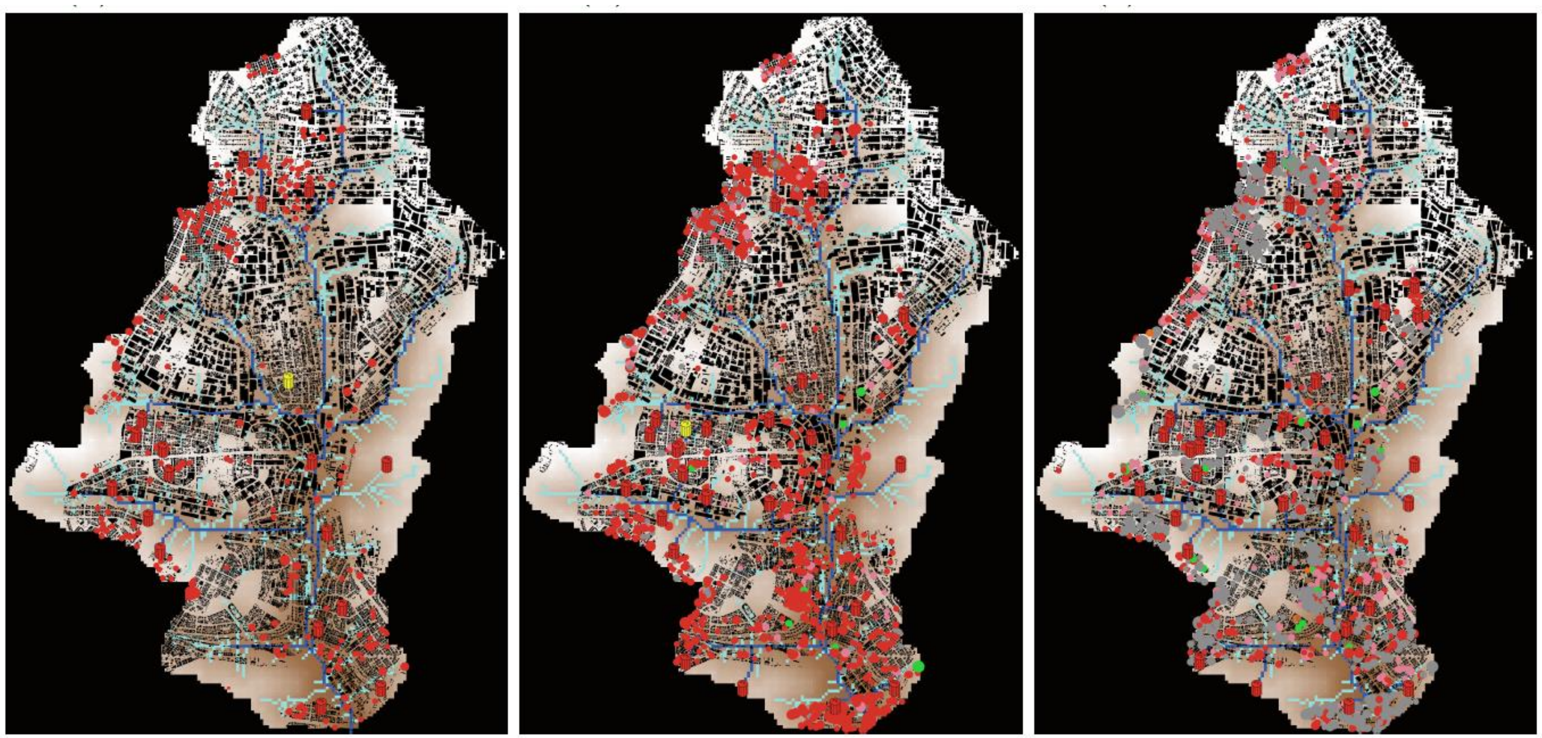
Motivation?
- Intelligence

Techniques applied?
- Depends

Technical difficulty?
- High as ABM and ML need to be fully integrated

AN EXAMPLE – CHOLERA MODEL GHANA



(d) *Run 2: After 15 days* (e) *Run 2: After 30 days* (f) *Run 2: After 45 days*

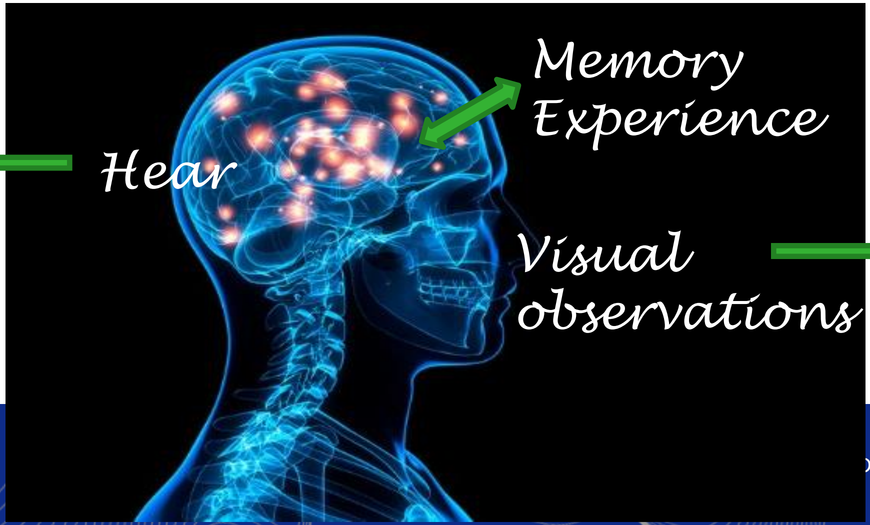
The circles represent infected households, the colour represents the type of transmission: grey=HEHD, brown=HEHP pink=EH, orange= VT, lime=HH.

How Do Agents Take Decisions

- ABMs: results are contingent on agents' behavior
- Agents base their decision on the **perception of information** from their environment
- Which **information** to include? How to assess risk based on it?
- How much do we learn from previous experiences and from others?

Media

Our social contacts



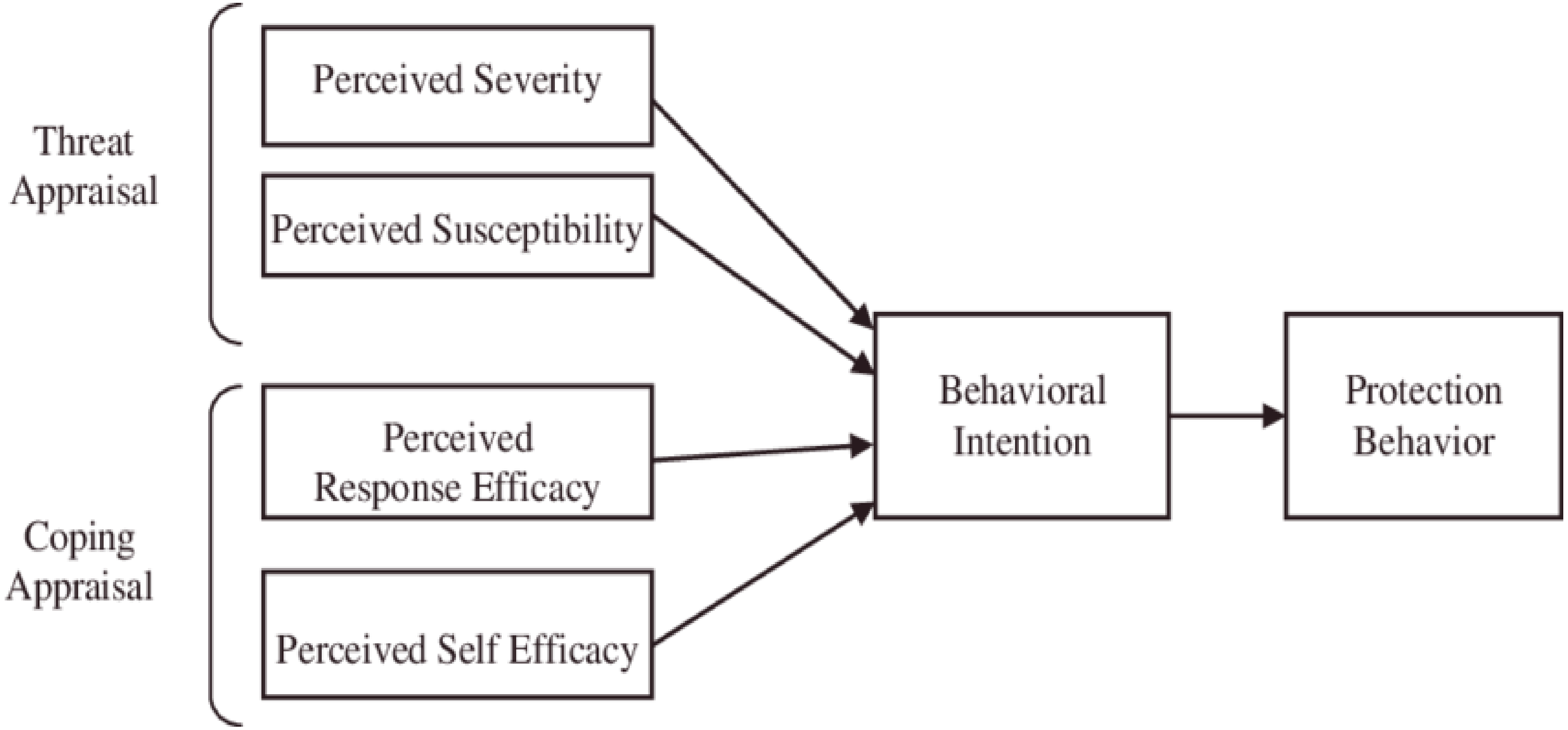
Spatial Environment

Focus Of this Research

1. How do we make decisions under risk ? – **Protection Motivational Theory (PMT)**
2. How does the spatial environment impact agent behavior – **Visual Pollution**

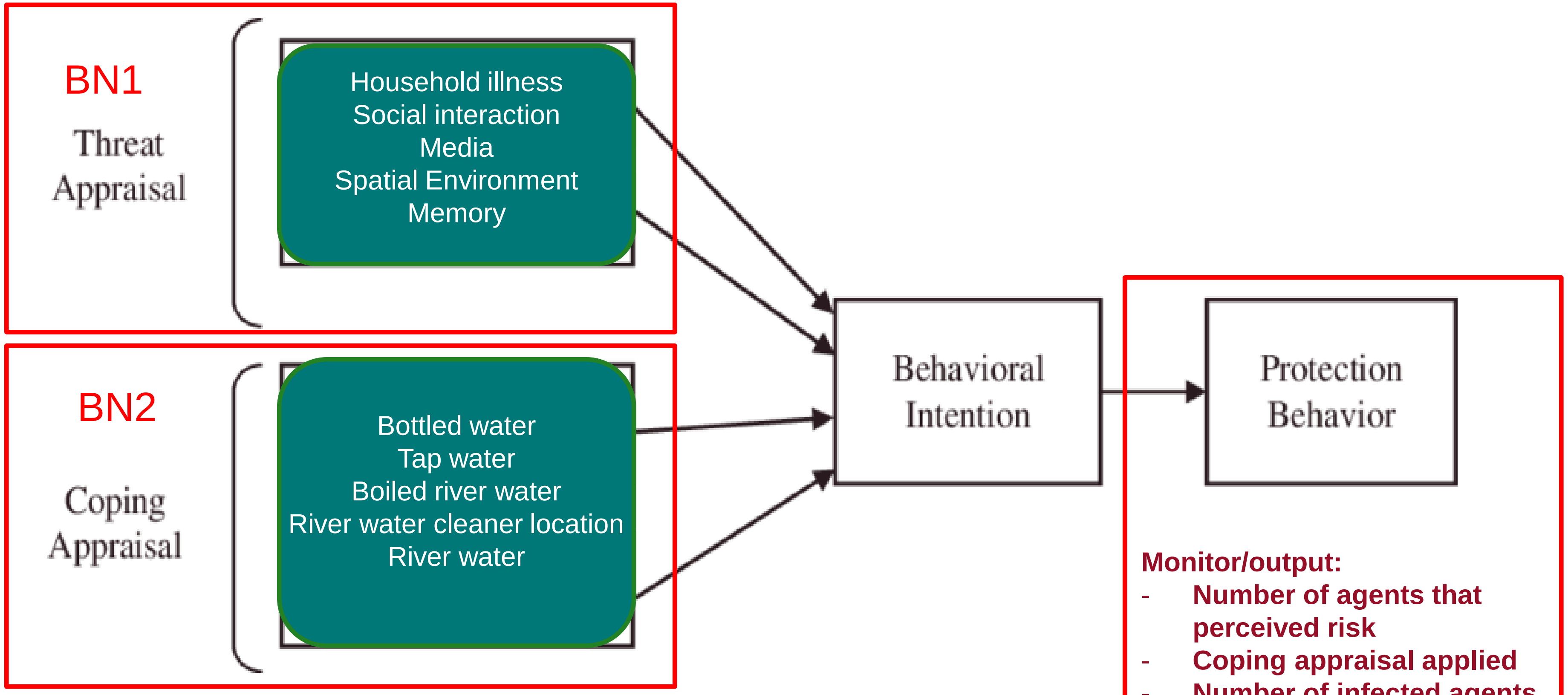
Implemented in an existing **cholera model for Kumasi** Ghana → what type of water will agents use given there is cholera?

Protection Motivation Theory (PMT)



Rogers. R. W. (1983). Cognitive and Physiological Processes in Fear Appeals and Attitude Change: A Revised Theory of Protection Motivation. In *Social Psychophysiology: A Sourcebook* (pp. 153–177).

Protection Motivation Theory (PMT)



Monitor/output:
- **Number of agents that perceived risk**
- **Coping appraisal applied**
- **Number of infected agents**
- **Distributed infection and risk perception over space**

ADJUSTMENTS MODEL

- **Visual pollution** is calculated as:

$$f(VP) = \sum_{i=0}^{N} \frac{xg}{d}$$

N: number of dumpsites around the water collection points

x: is the distance from the dumpsites to the water point

g: is the amount of garbage produced by each household

d: is the distance between the dumpsite and the water point

- New Agent: **Media** - It is activated when the number of days exceeds a threshold value (22 days)
- **Social contacts** were added (random selection based on water-point sharing)
- **Memory**: record risk perception previous time step

Implementation Threat And Coping Appraisal

BN1 contains five nodes from the information sources to evaluate RP: *memory* (*Me*). *visual pollution (VP)*. *household health status (HH)*. *Media (M)* and *communication with neighbor households (CNH)*. Media and communication with other households are combined into "Epidemic Evidence" (*EE*).

$$P(T|Me.VP.HH.EE) = \frac{P(Me.VP.HH.EE|T)\,P(T)}{P(Me.VP.HH.EE)}$$

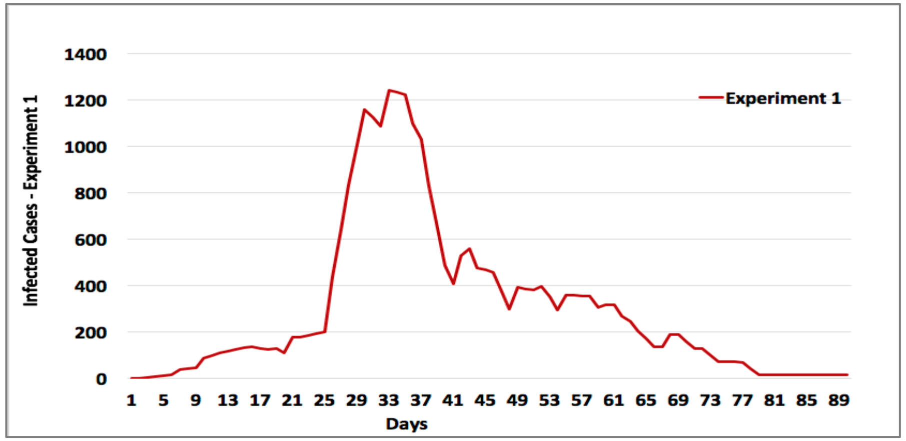
BN2 is calculated as:

$$P(D|I.E.OE.NE) = \frac{P(I.E.OE.NE|D)\,P(D)}{P(I.E.OE.NE)}$$

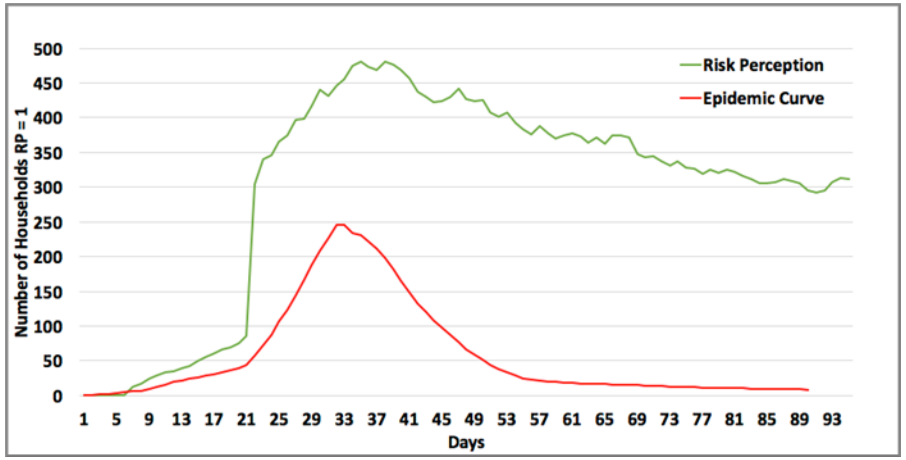
The perceived adaptation efficacy will differ per decision: Walking to another has a lower efficacy compared to boiling. Perceived self-efficacy (i.e. perceived effectiveness that enables an agent to perform the preventive measure) is varied for each decision. Perceived costs of the options (income level).

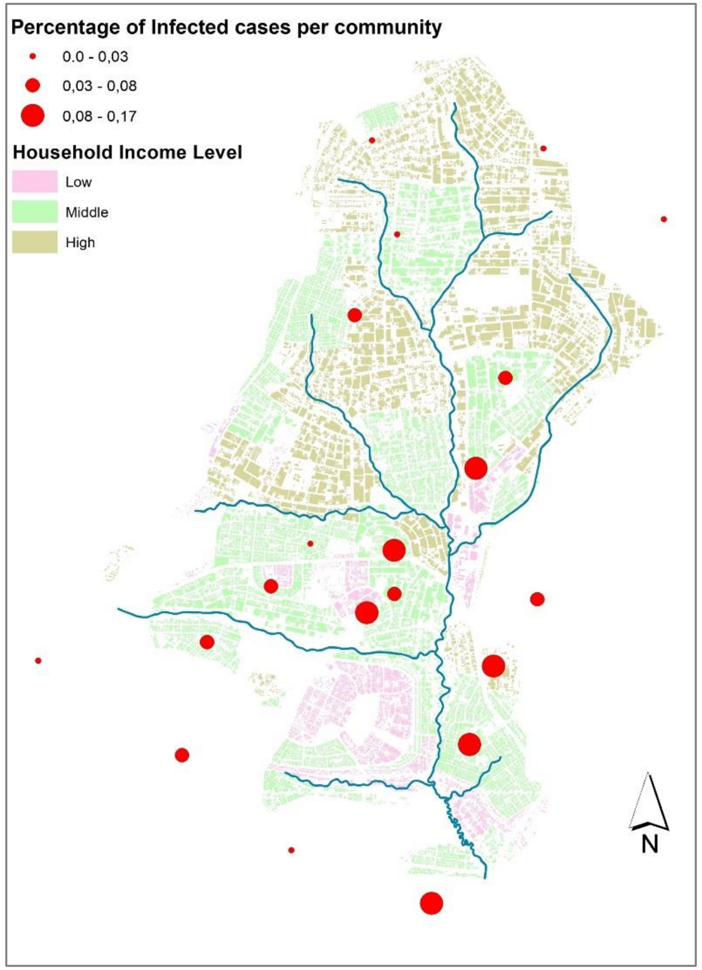
Results – infection over time

Experiment: No PMT

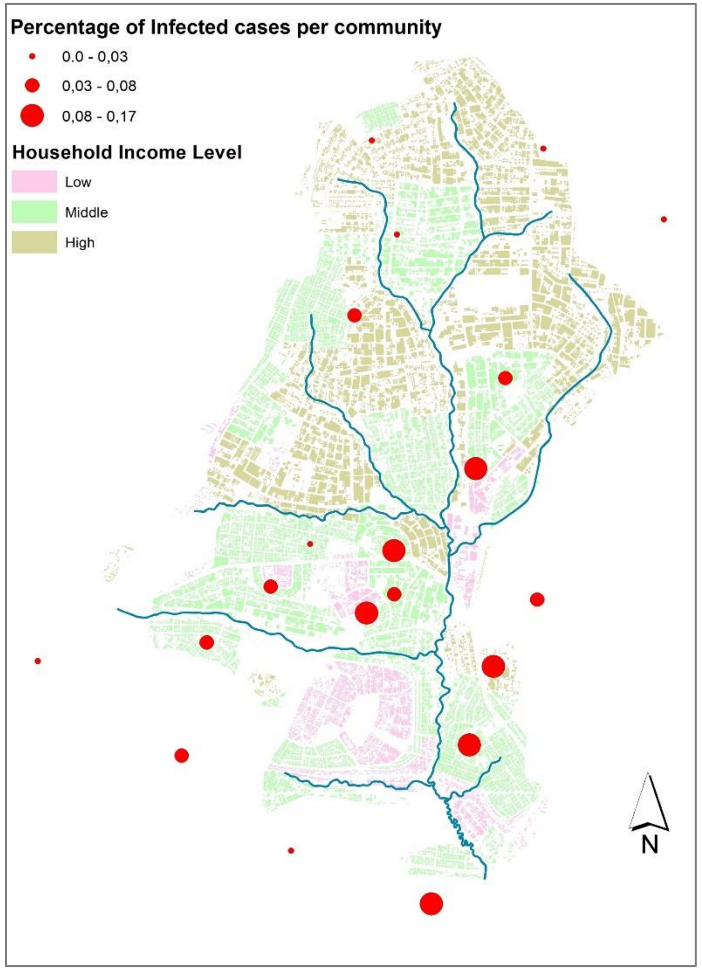


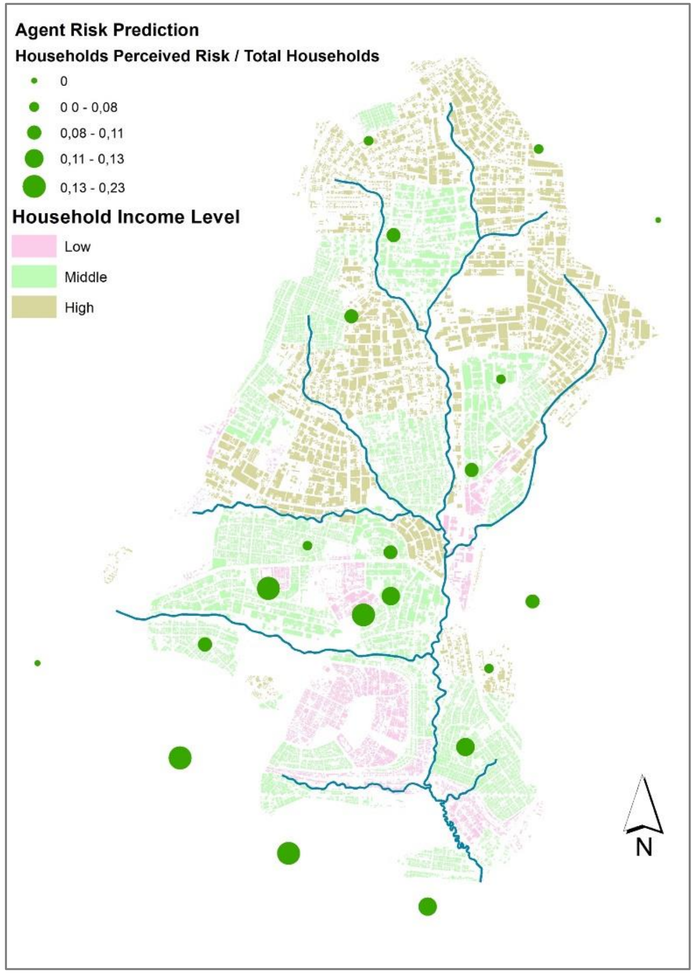
Experiment: PMT





Results – Perceived risk





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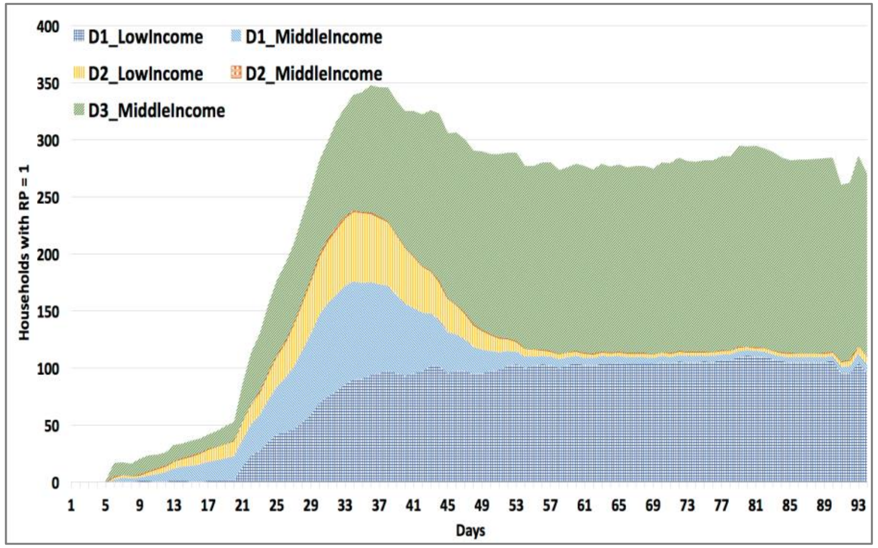
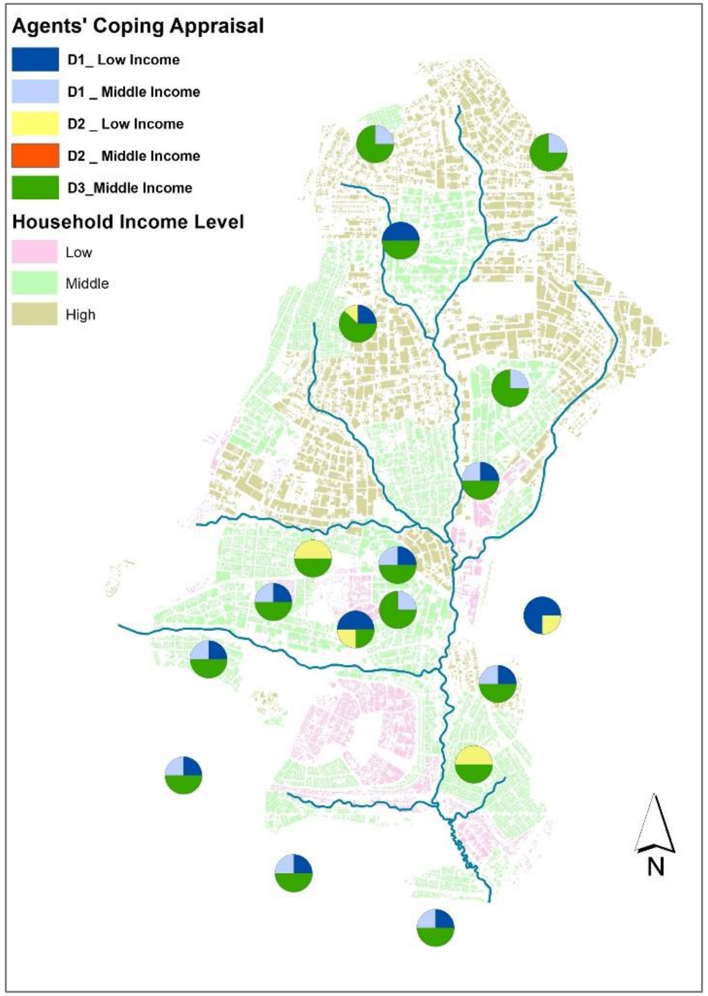
Results – Coping appraisal

Coping Appraisal – Decisions:

- D1: Take water and use it as it is
- D2: Walk to cleaner river water location
- D3: Boil river water





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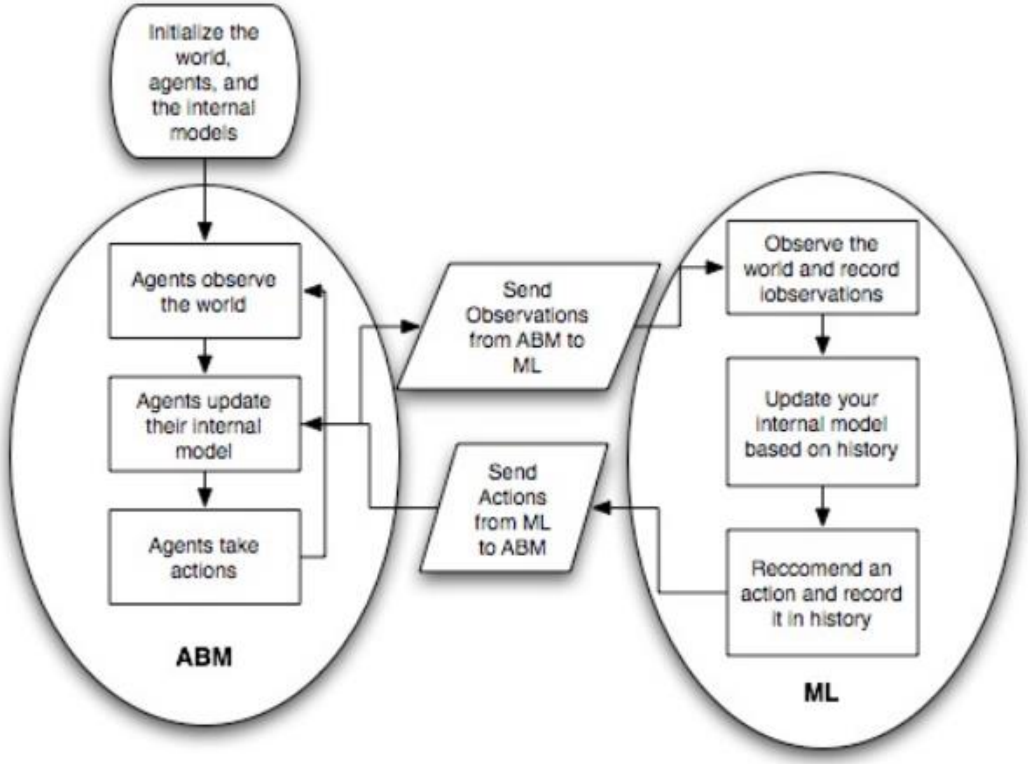
BEHAVIORAL RULE GENERATION

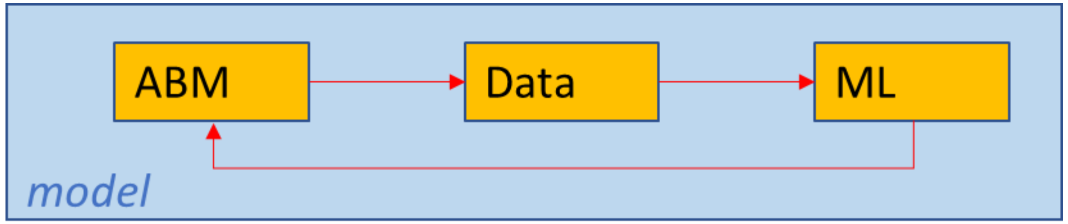


Source: W. Rand

- Behavioral data is organized and transformed in a way that each action and related parameters are captured as a single record. These records are then used in training a machine learning model.
- In the training, the expected output of the model is given as the action parameter whereas other parameters are provided as input.
- This model is then encapsulated as a function and turned into agent programming language statements

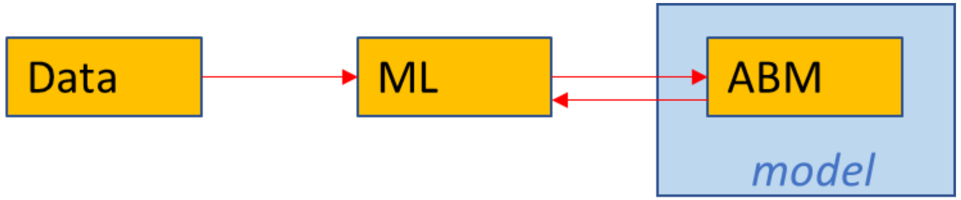
Source: Big Data, Agents, and Machine Learning: Towards a Data-Driven Agent-Based Modeling Approach.

Architecture A



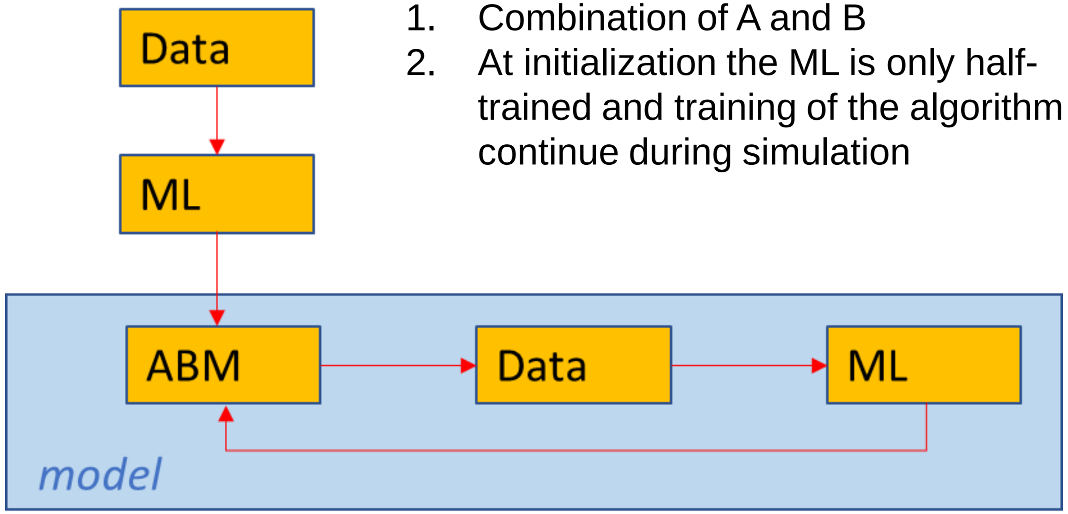
1. You have no empirical data, but your agents perform a task leading to a positive or negative feedback (**reinforcement learning**)
2. Data is collected and will feed into an ML that will slowly learn how to correctly predict
3. The result of the ML steers agent behavior

Architecture B



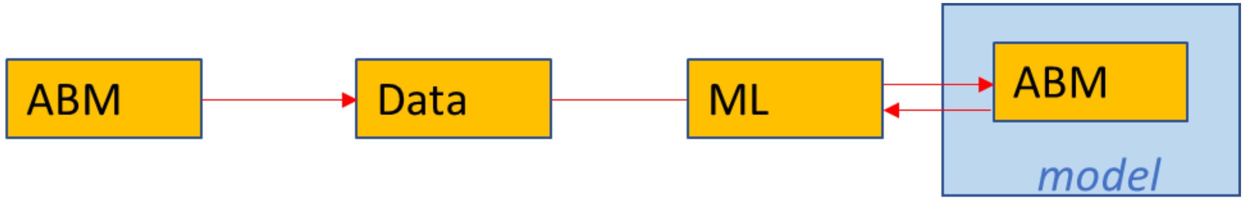
1. You use empirical data to train an ML algorithm
2. You run your ABM to generate a data record and map this back to your trained ML
3. The result is communicated back to the ABM

Architecture C



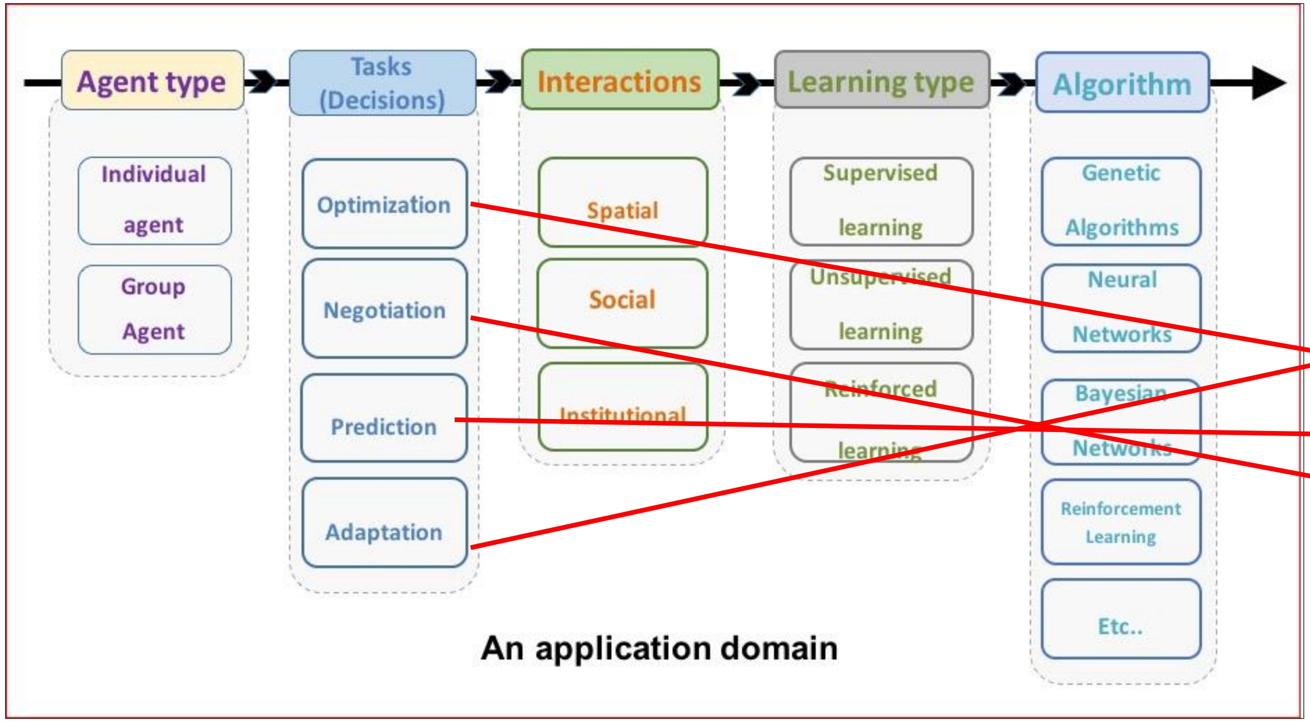
1. Combination of A and B
2. At initialization the ML is only half-trained and training of the algorithm will continue during simulation

Architecture D



1. Same as B but no data is available at the start, and will have to be generated by running the ABM

LEARNING TASKS

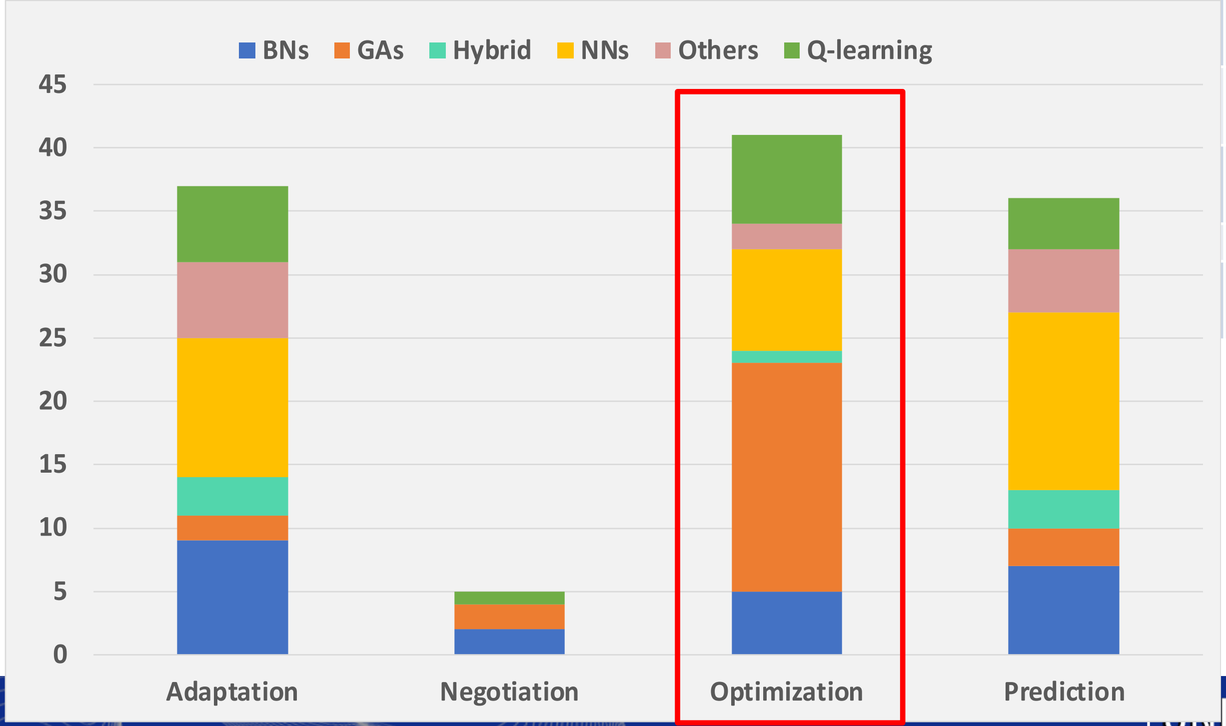


Elements of the updated ODD protocol
1. Purpose 2. Entities, state variables, and scales 3. Process overview and scheduling
4. Design concepts • Basic principles • Emergence • Adaptation • Objectives • Learning • Prediction • Sensing • Interaction • Stochasticity • Collectives • Observation
5. Initialization 6. Input data 7. Submodels

OPTIMIZATION

- Optimization concerns the search for the best action or decision from a set of alternatives based on one or several criteria.
- Often uses GAs.
- Examples of GA used to support agents' optimization decisions vary from seeking a land-use allocation that scores as the best on multiple social and environmental criteria (Manson, 2005); to iterative optimization of household travel schedules (Meister et al., 2005); or to optimize the performance of battle agents (Lim et al., 2005).

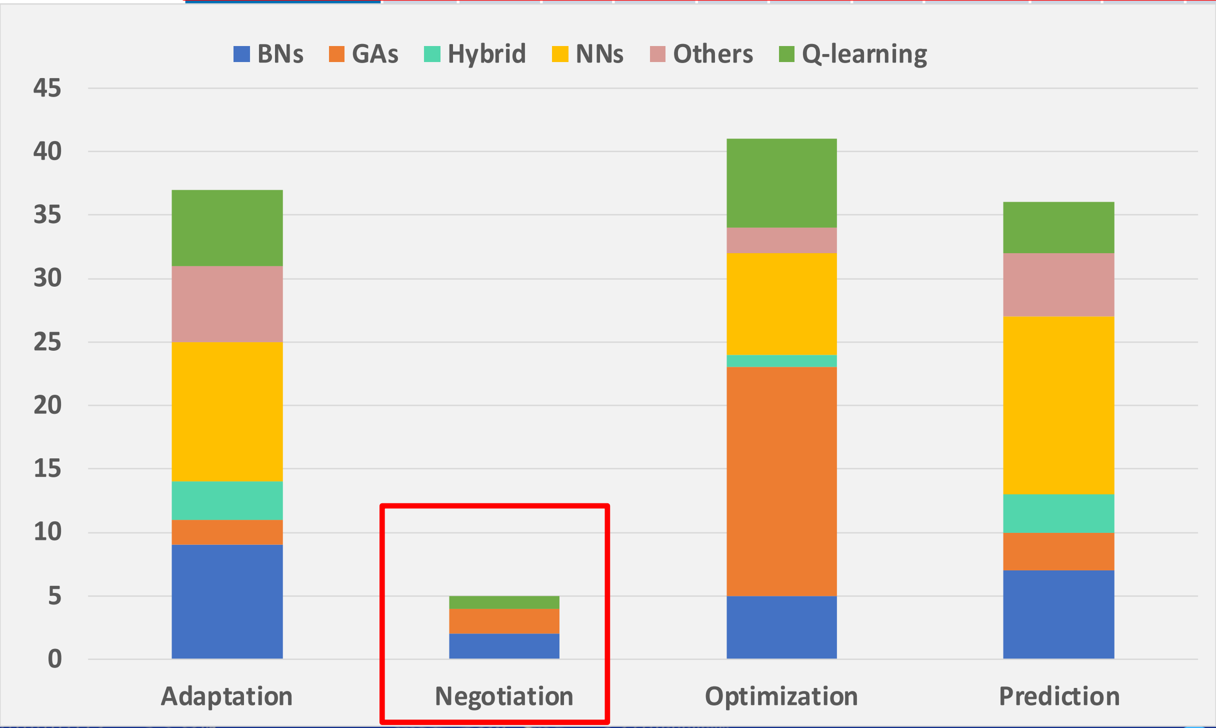
	GA		NN		BN		Q-Learning		Other		Hybrid		Total
Task	No.	(%)	No.	(%)	No.	(%)	No.	(%)	No.	(%)	No.	(%)	No.
Optimization	18	44	8	20	5	12	7	17	2	5	2	2	41
													4
													36
													37
													119



NEGOTIATION

- Negotiation is a dialog with a purpose of reaching an agreement that may bring mutual advantages to involved actors.
- Negotiation is often implemented using GA, but also using BN, and Q-Learning.
- Examples are negotiations in e-commence (Choi et al., 2001), in a land renting auction (Balmann and Happe, 2001), in defining transaction prices among firms in a supply chain (Russ and Walz, 2009) and game theory (Kattan et al., 2013

	GA		NN		BN		Q-Learning		Other		Hybrid		Total
Task	No.	(%)	No.	(%)	No.	(%)	No.	(%)	No.	(%)	No.	(%)	No.
Optimization	18	44	8	20	5	12	7	17	2	5	2	2	41
Negotiation	2	40	0	0	2	40	1	20	0	0	0	0	4
												8	36
												8	37
												7	119

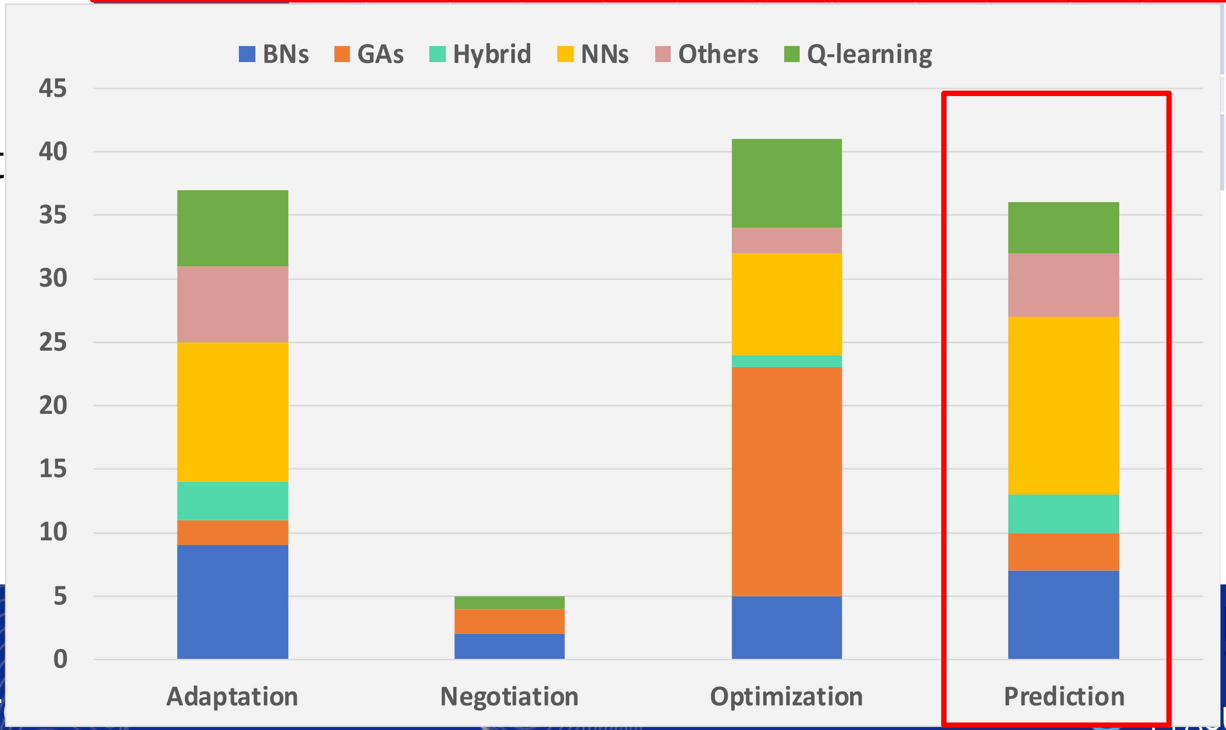


Sources: Shaheen Abdulkareem

PREDICTION

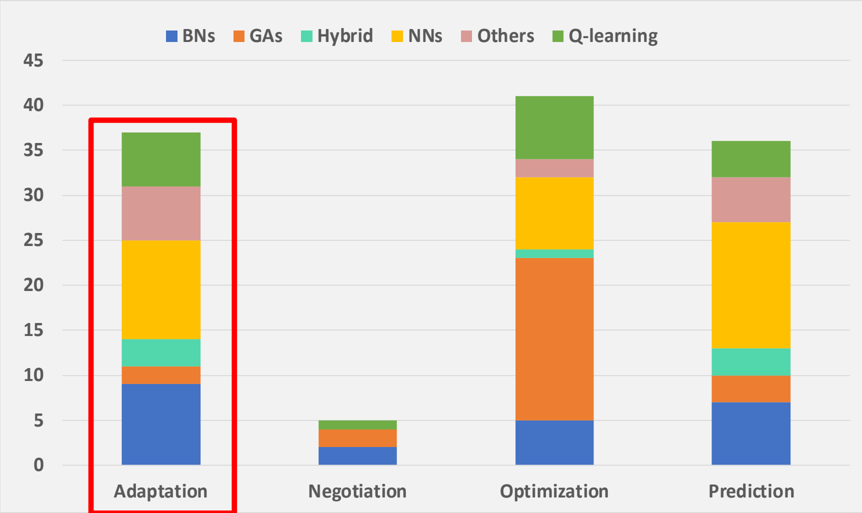
- Prediction is an attempt to forecast the future. The type of information predicted by agents in simulation models ranges from specific outcome values to actions of other agents
- A range of learning algorithms is used to implement this decision, but NN are used most.
- There are many financial applications in which agent predict prices and stock market (Oprea, 2002); (Plikynas and Aleksiejūnas, 2007) (Rekik et al., 2014). Kaya & Alhajj (2005) augment their hunter agents with a hybrid of RL and FL to predict actions such as next location of other hunters following the same prey.

	GA		NN		BN		Q-Learning		Other		Hybrid		Total
Task	No.	(%)	No.	(%)	No.	(%)	No.	(%)	No.	(%)	No.	(%)	No.
Optimization	18	44	8	20	5	12	7	17	2	5	2	2	41
Negotiation	2	40	0	0	2	40	1	20	0	0	0	0	4
Prediction	3	8	14	39	7	19	4	11	5	14	3	8	36
													37
													119



ADAPTATION

- Adaptation is an alteration of behavior or attributes of an agent in response to changing surroundings (spatial environment, a society of other agents).
- ABM developers use NNs, BNs and Q-learning to model adaptation.
- Examples:
  - NNs used to enable agents adapt and realistically change behavior with the experience of street robbery (Joubert et al, 2022), or to adapt to the behavior of individual or institutional land users (Zhao et al, 2019).
  - BNs is used to steer the adaptive behavior of agents to analyze the role of risk perception in water management systems (Hyun et al, 2019), or to adapt the behavior of agents under uncertain information real estate market (Shen et al, 2016).



	GA		NN		BN		Q-Learning		Other		Hybrid		Total
Adaptation	2	5	11	30	9	24	6	16	6	16	3	8	37

COMBINING ABM AND ML

POSTPROCESSING

1.Preprocessing of data using ML algorithms

2.Steering Agent behavior by using ML

3.Postprocessing outputs from ABMs by using ML

Motivation?
- Po

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- Pr

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- Lo
re

Motivation?
- Extraction of rules

Techniques applied?
- Clustering…

Technical difficulty?
- Low as no integration is required

Motivation?
- Intelligence

Techniques applied?
- Depends

Technical difficulty?
- High as ABM and ML need to be fully integrated

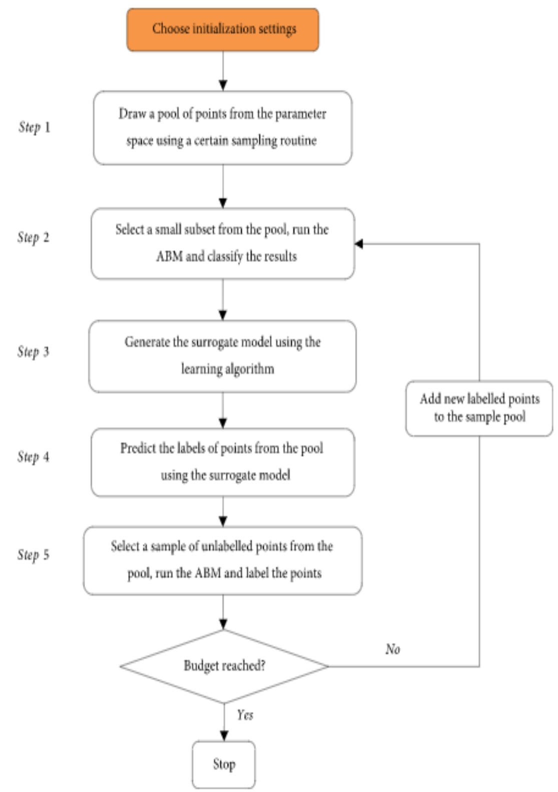
Motivation?
- Calibration, Validation

Techniques applied?
- Depends

Technical difficulty?
- Low as no integration is required

SURROGATE ANALYSIS APPROACH

Validation and Calibration of an Agent-Based Model: A Surrogate Approach



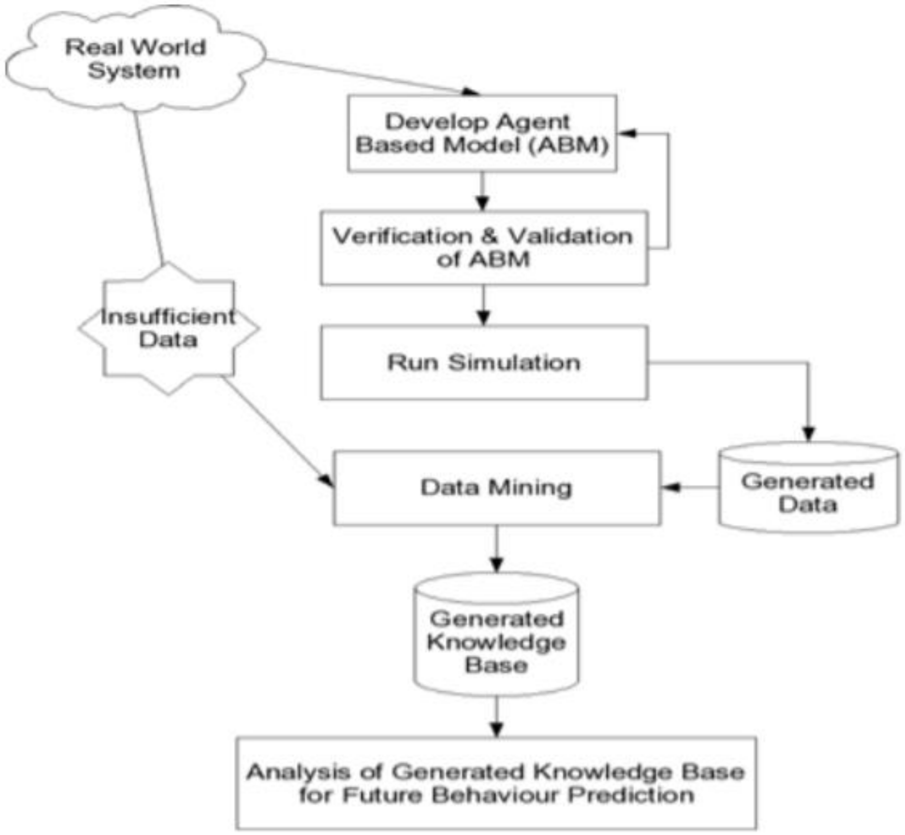
https://www.hindawi.com/journals/ddns/2020/6946370/

The main idea of this approach is to generate a surrogate model using a certain learning algorithm as the approximation of the original agent-based model. The surrogate model can reduce the dimensionality of the original model parameter vector and greatly simplify the form while maintaining the dynamic characteristics of the original system.

Step 1. Construct a relatively large pool of parameter combinations as a substitute set for the parameter space using a certain sampling routine.
Step 2. Randomly draw a small subset from the parameter pool and run the AB model. Each parameter vector is identified as positive or negative according to the calibration measurement and calibration criterion.
Step 3. The surrogate model is created
Step 4. Predict and label all parameter combinations in the pool according to the results of the surrogate model.
Step 5. Draw a small subset of unlabeled points in step 2 and run the ABM. The points are labelled and added to the training set to construct a new subset of training samples. The newly added parameter vectors are randomly selected from the positive labelled parameter combinations that are predicted by the surrogate model

POSTPROCESSING

- Data Preparation: output of the ABM should fit (same structure) compared to the empirical data
- Real data should be sufficient in size for ML
- Different ML algorithms can be applied to also compare the outcomes
- Make sure that you know what you are looking for exactly (patterns)



Baqueiro, O., Wang, Y.J., McBurney, P. and Coenen, F. 2009. Integrating Data Mining and Agent Based Modeling and Simulation. In: Berlin, Heidelberg. Springer Berlin Heidelberg, pp.220-231.

TEAM BASED LEARNING

Ellen-Wien Augustijn

Shaheen Abdulkareem

UNIVERSITY OF TWENTE.

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Team-Based learning 4

(Note: there are no videos to watch)

Question 1 – ODD protocol

Below you see a text fragments, extracted from a published ODD protocol. Identify where (in which part of the ODD protocol) you would place this text.

The model involves a population of reactive agents located in a simplified urban environment (composed of buildings and roads) over which a toxic cloud gradually spreads. The individual behaviours depend both on their degree of assimilation of the official emergency regulations and, for some of them, on their propensity to be influenced by their neighbours.

Elements of the updated ODD protocol
1. Purpose
2. Entities, state variables, and scales
3. Process overview and scheduling
4. Design concepts
• Basic principles
• Emergence
• Adaptation
• Objectives
• Learning
• Prediction
• Sensing
• Interaction
• Stochasticity
• Collectives
• Observation
5. Initialization
6. Input data
7. Submodels

Question 2 – ODD protocol

Below you see a text fragments, extracted from a published ODD protocol. Identify where (in which part of the ODD protocol) you would place this text.

Agents perceive their environment. They can situate themselves and have a limited visibility of neighbouring individuals. The C2 agents who run away from the cloud know the position of the source of the cloud and know the direction they have to take to run away from it. The C1 agents also know the location and take shelter as quickly as possible.

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Question 3 – ODD protocol

Below you see a text fragments, extracted from a published ODD protocol. Identify where (in which part of the ODD protocol) you would place this text.

The simulation starts with simple default parameters. The user selects the spatial configuration (Figure 2) and chooses between several environments: a random built-up environment (around 10% density), a regular grid (Manhattan lattice) or a pre-existing raster data set.

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OPTIONAL TOPIC

MARKOV CHAINS

X Post

Markov Chains

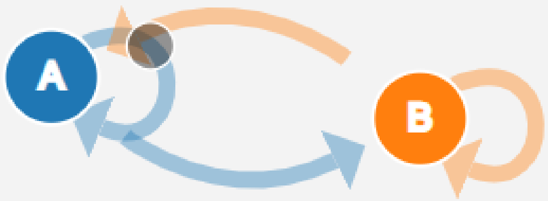
A visual explanation by Victor Powell
/w text by Lewis Lehe

Markov chains, named after Andrey Markov, are mathematical systems that hop from one "state" (a situation or set of values) to another. For example, if you made a Markov chain model of a baby's behavior, you might include "playing," "eating", "sleeping," and "crying" as states, which together with other behaviors could form a 'state space': a list of all possible states. In addition, on top of the state space, a Markov chain tells you the probabilitiy of hopping, or "transitioning," from one state to any other state---e.g., the chance that a baby currently playing will fall asleep in the next five minutes without crying first.

A simple, two-state Markov chain is shown below.

	A	B
A	P(A|A): 0.50	P(B|A): 0.50
B	P(A|B): 0.50	P(B|B): 0.50

speed



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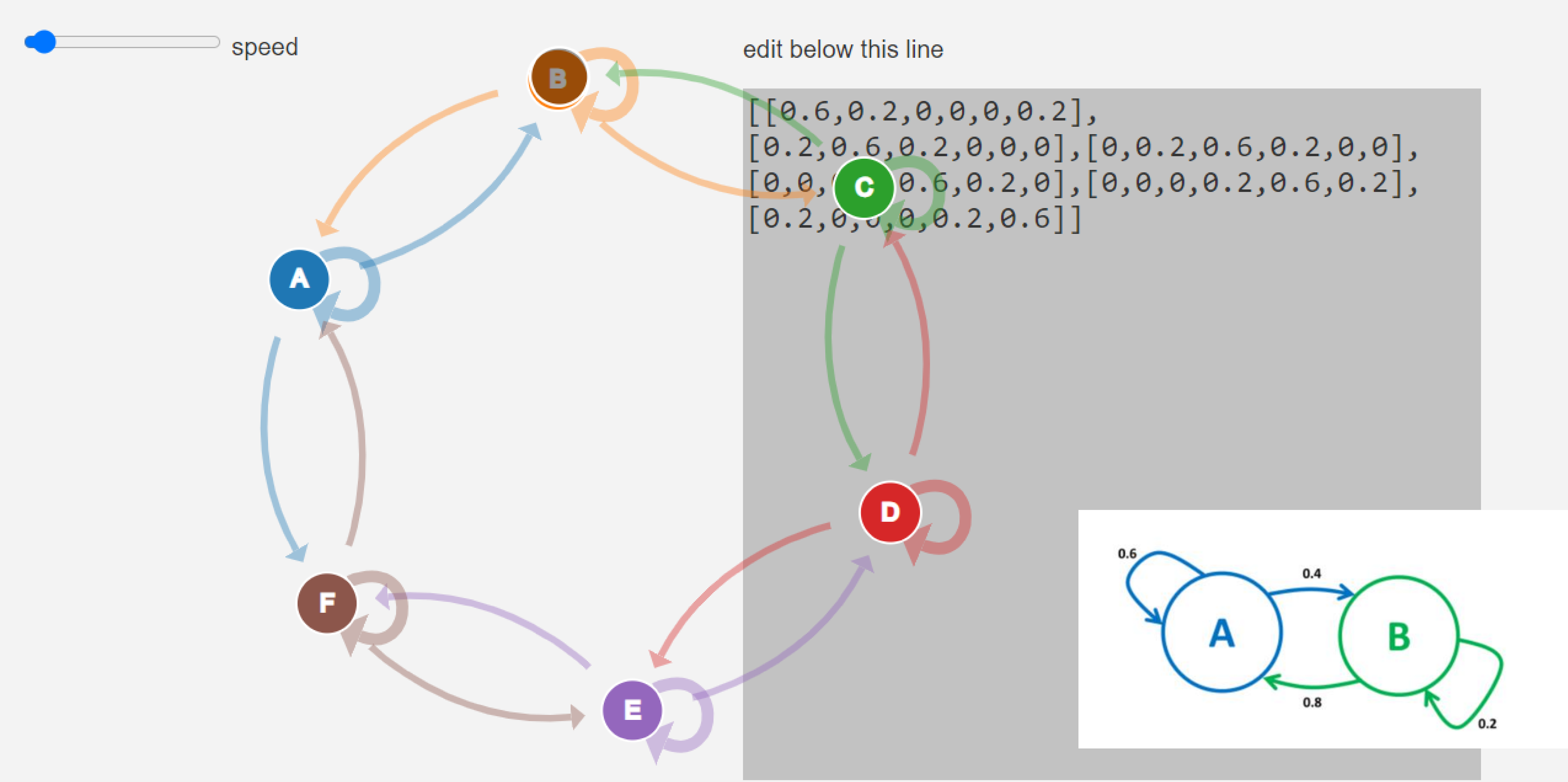
speed
edit below this line
[[0.6,0.2,0,0,0,0.2],
[0.2,0.6,0.2,0,0,0],[0,0.2,0.6,0.2,0,0],
0.6,0.2,0],[0,0,0,0.2,0.6,0.2],
0,0.2,0.6]]
B
A
C
D
F
E
0.6
0.4
A
B
0.8
0.2

Markov Chains

- Good for phenomena with autocorrelation: future state depends on the current state
- Requires understanding what the future state will be (when today it is sunny, it is more likely that the next day is sunny also)
- Weights come from your data

DTW = number of dry days followed by a wet day / total number of dry days = 5 / 14 = 35.71%

WTD = number of wet days followed by a dry day / total number of wet days = 5 / 16 = 31.25%

```
globals [ weather ]

patches-own [ growth ]
```

```
to setup
  clear-all
  set weather one-of [ "WET" "DRY" ]
  ask patches [
    set growth random 11
    set pcolor scale-color green growth 10 0
  ]
  reset-ticks
end
```

```
to go
  markov-rain
  grow-grass
  tick
  if ticks = 500 [ stop ]
end
```

```
to markov-rain
  ifelse weather = "WET" [
    if random-float 1.000 < WTD [
      set weather "DRY"
    ]
  ]
  [
    if random-float 1.000 < DTW [
      set weather "WET"
    ]
  ]
end
```

Check on current state