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Evaluation of self-organizing systems using quantitative measures

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Overview

1. Modeling of systems
2. Quantitative measures
3. Approximation methods
4. Example: Synchronization of sensor nodes
5. Example: Evacuation

Modeling approaches

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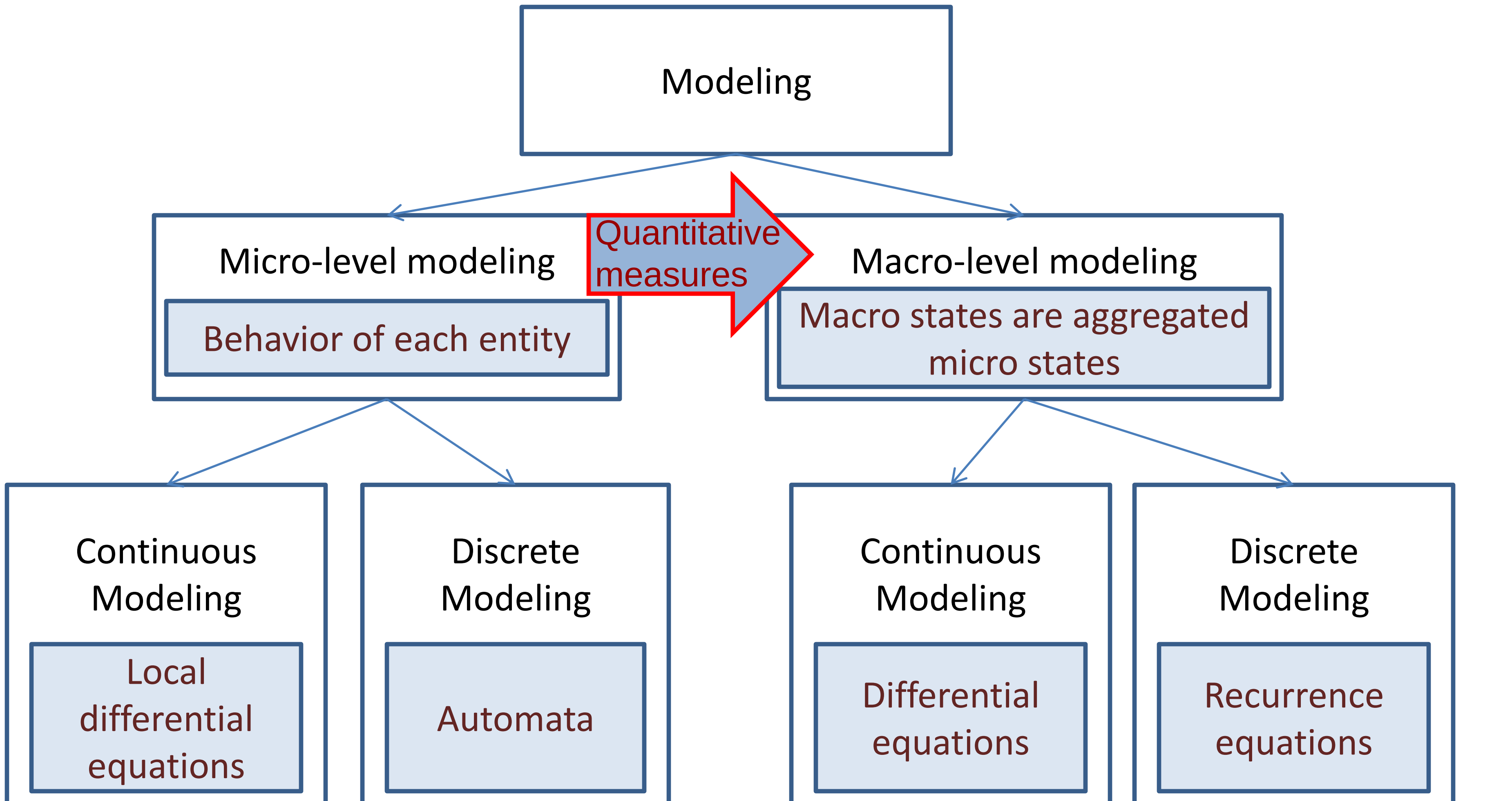
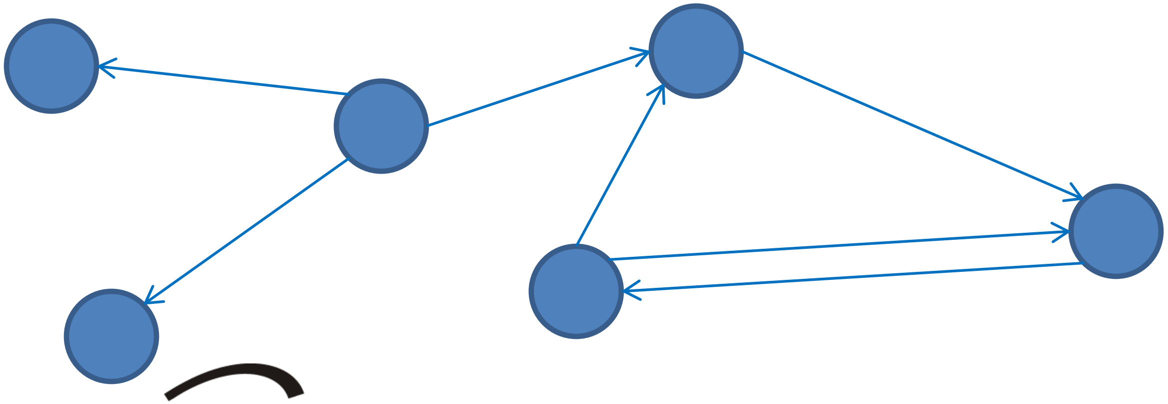


Discrete Micro-Level Modeling

- **Topology** can be described by a **directed graph G = (V, K)**
- **Behavior** can be described by local rules for each node



From Micro-level to Macro-level: Quantitative Measures

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To measure **self-organizing properties** of a system, we need to determine the quantity of information in the system.

Statistical **Entropy** of a random variable X:

$$H(X) = -\sum P(X=w) \log_2 P(X=w)$$

With this concept we can measure for each point of time

- the information in the whole system
- the information on the internal edges
- the information on the input edges
- the information on the control edges
- the information on the output edges

Quantitative Measures

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Quantitative measures can be obtained (partly based on information entropy):

Levels of

- emergence
  - How many globally coherent patterns are induced by local interactions?
- autonomy
  - How much control data from external entities are needed to keep the system running?
- target orientation
  - Is the high level goal, that the system designer had in his mind, reached by the system?
- adaptivity
  - Is the high level goal still reached after changes in the environment?
- resilience
  - Is the high level goal still reached after unexpected impacts on the system (e.g. break down of nodes, attacks by an intruder, …)?
- homogeneity
  - Do all nodes have the same behavior?
- global state awareness
  - How much information does a single node have about the global state?

Emergence

To measure the **level of emergence**

$\varepsilon \in [0, 1]$

of a system, we compute the dependencies between the values on the edges $k \in K$.

At time t we compare the information contained in all edges with the sum of the information contained in each single edge:

$$\varepsilon_t = 1 - (H(Conf_t|_K) / \sum_{k \in K} H(Conf_t|_k))$$

where $Conf_t$ is the global state containing all local states and all values on the edges.

Level of emergence of the whole system S:

$\varepsilon(S) = Avg(t \mapsto \varepsilon_t)$, where Avg is the average value of the map

$\varepsilon \approx 1$ high level of emergence (many dependencies)

$\varepsilon \approx 0$ low level of emergence (few dependencies)

Target orientation

Before a new system is designed, we have a goal of the system in our mind:

The system should fulfill a given purpose.

In the model, the goal can be described by a valuation of configurations:

$b : Conf \to [0, 1]$ (Conf is the set of all global states)

Level of target orientation at time t:

$TO_t = \boldsymbol{E}(b(Conf_t))$, where $\boldsymbol{E}$ is the mean value of the random variable

Level of target orientation of the whole system S:

$TO(S) = Avg(t \mapsto TO_t)$

$TO(S) \approx 1$ means that the system runs through many good configurations

$\Rightarrow$ high level of target orientation

$TO(S) \approx 0$ means that the system runs through many bad configurations

$\Rightarrow$ low level of target orientation

Approximations

- **Problem: Scalability**
  - In large systems, it might be difficult to compute the quantitative measures.
  - The global state space (the set of all configurations) grows exponentially with the number of the entities in the system.
  - To be able to analyze global properties of the system, entropies of global random variables like $H(Conf_t)$ are difficult to calculate analytically.
  - Therefore we need methods to approximate the needed values.

Approximations

- **Simulation runs** can be used to to approximate probabilities and entropies.
- R : Number of simulation runs.
- Each simulation run leads to a **time series**, which is the configuration sequence $c_0 \rightarrow c_1 \rightarrow c_2 \rightarrow \dots$ produced by the simulation run.
- The **probability** of a value $a \in A$ on a single edge $k \in K$ at time $t > 0$ can be approximated by the **relative frequency** $rel_{t,k,a}$ by counting the number of time series, which contains the value a on the edge k at time t.
- For **probabilities of global valuations** like $P(Conf_t = c)$ or $P(Conf_t|_K = a)$ the **range of values** for these random variables is too large, so the relative frequencies received from simulation runs are to inaccurate for the approximation of probabilities.
- For such global probabilities, we investigate **different approximation methods**.

Approximations

Classification

- The probability space is divided into different **classes**.
- The **relative frequency** for each class is calculated from the time series.
- The probability for a single element of the class can be approximated by the **relative frequency divided by the size of the class**.
- For $P(Conf_t|_K = a)$ the classification can be done by choosing a **subset** $K_0 \subseteq K$ and build $|A|^{|K_0|}$ equivalence classes $[b] := \{ a \in A^K \mid a|_{K_0} = b \}$ for $b \in A^{K_0}$, where the size of each class is $|[b]| = |A|^{|K \setminus K_0|}$.
- Now the **relative frequencies** $rel_{t,K_0,b}$ are calculated for each class [b] and the probability $P(Conf_t|_K = a)$ is approximated by

$$P(Conf_t|_K = a) \approx 1/|[b]| \cdot rel_{t,K_0,b} \quad \text{for} \quad b = a|_{K_0}$$

Approximations

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Classification

- Example:
  - $A = \{ 0, 1 \}$
  - $K_0 = \{ k \}$
  - Then we have two equivalence classes of configurations:
    - In the first class are all configurations c with $c_K(k) = 0$
    - In the second class are all configurations c with $c_K(k) = 1$

- After calculating the approximations of the probabilities, we get an **approximation of the quantitative measure**.

Approximations

Parzen window approach

- For a random variable X with a sample set W = { w_1, … .w_R } (observations of X) we can use the kernel density estimator based on a **Gaussian kernel**

$$p(a) = \frac{1}{R}\sum_{j=1}^{R}\frac{1}{(2\pi h^2)^{dim/2}}\exp(-\frac{1}{2}\frac{dist(a,w_j)^2}{h^2})$$

with

$$\begin{aligned} dim = &\ \text{dimension of the random variable } X \\ a \in &\ \mathbb{R}^{dim} \\ p(a): &\ \text{approximation of the density of } X \text{ at } a \\ R: &\ \text{number of samples for } X \\ dist(a,w_j): &\ \text{Euclidean distance between } a \text{ and } w_j \\ h: &\ \text{user-defined parameter for changing variance and bias} \end{aligned}$$

Approximations

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Parzen window approach

- By integrating over the density function p, we can calculate **probabilities** for the random variable X.
- In our case, we consider discrete systems, so the random variables (e.g. $Conf_t$) are **discrete**.
- If we assume that the random variable only yields **integer values** for each component, then we can use $P(X = c) = P(dist_\infty(X, c) \leq ½)$ for the approximation, where $dist_\infty(a, b) = \max\{ |a_i-b_i| : i = 1, 2, ..., dim \}$ is the distance induced by the maximum norm.
- Since the set $\{ a \mid dist_\infty(a, c) \leq ½ \}$ is a hypercube of size 1, the value $P(dist_\infty(X, c) \leq ½)$ can be approximated directly with the **density function** p, i.e. $P(X = c) \approx p(c)$.
- This approximation can then be used to get approximations of the entropies $H(Conf_t)$ and $H(Conf_t|_K)$.

Approximations

Restriction of the set of initial configurations

- When we have a system, in which large parts are **deterministic**, then a restriction of the set of the initial configurations reduces the complexity.
- Let $\Gamma_0 \subseteq \Gamma$ be a set of **initial configurations**.
- Then the **time series** are received from simulation runs starting in Γ_0.
- If all automatons are **deterministic**, two simulation runs with the same initial configuration would lead to the same time series, so for each initial configuration c_0 at most one simulation run is needed.
- If some automata are **stochastic**, different initial configurations might lead to different time series.

Approximations

Restriction of the set of initial configurations

- The entropy $H(Conf_t|_K)$ (and analogously $H(Conf_t)$) can then be derived by using the **relative frequency** as an approximation for the probability $P(Conf_t|_K = a)$:

$$H(\mathrm{Conf}_t\,|_K) = -\sum_{\underline{a}\in A^K} P(\mathrm{Conf}_t\,|_K = \underline{a}) \log_2 P(\mathrm{Conf}_t\,|_K = \underline{a})$$

$$\approx -\sum_{\underline{a}\in A^K} rel_{t,\underline{a}} \log_2 rel_{t,\underline{a}}$$

Approximations

- All these approximation methods are based on **time series.**
- By using **simulation runs**, time series consisting of the configuration sequences can be obtained.
- Instead of calculating the measures analytically in the model, it is possible to get approximations of the measures directly from the set of **time series**.
- Since the model is not needed anymore, this can be **generalized to arbitrary time series** of configurations: For each set of configuration sequences, the quantitative measures, which were defined analytically only for the model, can be approximated by considering only the time series.
- This allows the usage of **experimental data** from the real world without the need of the model: By measuring the parameters of interest in the real world system, we get some time series, which can be used for the calculation of the quantitative measures.

Example:
Slot synchronizing in wireless networks

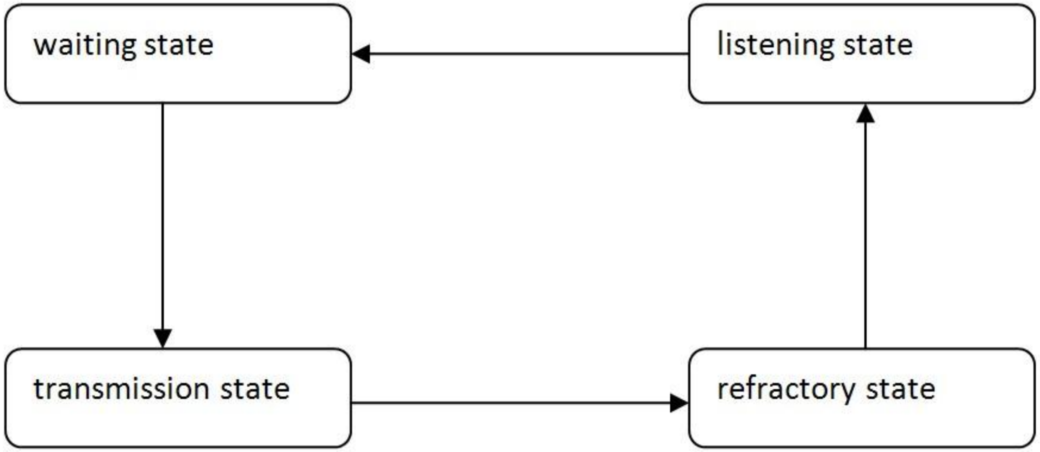
Wireless network:

- For communication, time is divided into slots.
- There is no central clock, which defines when a slot begins.
- The nodes try to synchronize the slots.

Example:
Slot synchronizing in wireless networks

Slot synchronization algorithm of Tyrrell, Auer and Bettstetter:

- At each point of time, each node is in one of four different states:
- In the transmission state, the node transmits a pulse to it's neighbors to indicate the beginning of a slot.
- In the listening state, the node can receive and decode pulses from it's neighbors and it adjusts its phase function ϕ according to these pulses. The listening state ends, when the threshold $\phi_{max} = 1$ is reached.
- In the waiting state and in the refractory state, the node does nothing.
- The length of an uncoupled cycle is 2T with T>0.



Example:
Slot synchronizing in wireless networks

Simulation results show:

- Two groups of synchronizations are built.
- Inside each group we have good synchronization: Each object of the group fires a pulse at nearly the same time like the other objects of the group.
- The second group fires T time units after the first group.
- By using slots of length T we get a good slot synchronization

Target orientation

Calculation of the level of **target orientation**:

The goal is to minimize the time differences between the beginning of the slots of the nodes.

$dist_c(v,w)$: Slot distance of nodes v, w $\in$ V in configuration c

$$b(c) = 1 - \frac{\sum_{v,w \in V} dist_c(v,w)}{|V^2| \cdot T/2}$$

After fixing the system parameters, we can approximate the level of target orientation using simulation runs.

$|V| = 30$, $T = 100$, $T_{dec} = 15$, $T_{Tx} = 45$, $T_{refr} = 35$, $T_{wait} = 40$, $\alpha = 1.2$, $\beta = 0.01$,

$R = 300$, $t = 1000$

Target orientation: $TO_t(S,\Gamma) \approx \frac{1}{R} \sum_{j=1}^{R} b(\mathrm{Conf}_{t,j}) \approx 0.996$

Emergence

Level of Emergence:

$\varepsilon_t = 1 - (H(Conf_t|_K) / \sum_{k \in K} H(Conf_t|_k))$

The values $H(Conf_t|_k)$ can be approximated by the **relative frequencies**.

For $H(Conf_t|_K)$ we have different methods for **approximation**.

Emergence

Level of Emergence:

Classification:

$$H(\mathrm{Conf}_t|_K) \approx -\sum_{[b]\,\mathrm{class}} rel_{t,K_0,[b]} \log_2 \left(\frac{1}{|[b]|} \cdot rel_{t,K_0,[b]} \right)$$

The result depends on the size of the classes.

$\lvert K_0 \rvert$	870	860	700
$\lvert [b] \rvert$	1	2^{10}	2^{170}
$\varepsilon_t(\mathcal{S}, \Gamma)$	0.988	0.980	0.773

Emergence

Level of Emergence:

Parzen Window:

$H(Conf_t|_K) \approx \quad p(a) = \frac{1}{R}\sum_{j=1}^{R}\frac{1}{(2\pi h^2)^{dim/2}}\exp(-\frac{1}{2}\frac{dist(a,w_j)^2}{h^2})$

The result depends on the user defined parameter h for the variance and bias:

h	0.478	0.479	0.4795	0.48
$\varepsilon_t(\mathcal{S},\Gamma)$	0.778	0.956	0.981	0.991

Emergence

Level of Emergence:

Restriction of initial configurations:

$$H(Conf_t|_K) \approx -\sum_{\underline{a}\in A^K} rel_{t,\underline{a}} \log_2 rel_{t,\underline{a}}$$

We set the number of simulation runs equal to the number of initial configurations.

$\lvert\Gamma_0\rvert = R$	10	1000	2000
$\varepsilon_t(\mathcal{S},\Gamma)$	0.99	0.984	0.982

Other applications

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- It is planned to test the approximation methods for two applications of the project **SOCIONICAL** fundet by the EU.
- SOCIONICAL focuses on the specific example of **Ambient Intelligence** (AmI) based smart environments.
- A key component of such environments is the ability to monitor user actions and to **adjust its configuration** and functionality accordingly.
- Thus, the system reacts to human behavior while at the same influencing it.
- The project will study global properties and emergent phenomena that arise in AmI based socio-technical systems from such local feedback loops and their coupling on two concrete **scenarios**:
  - emergency scenario
  - traffic scenario

Example: Evacuation scenario

- **Scenario:** Evacuation in a building
  - Each person wears a life belt:
    - Ambient Intelligence (AmI) device, which is able to communicate with other life belts to improve the evacuation.

Example: Evacuation scenario

- **Topology**
  - Each node in the graph represents one person wearing a life belt.
  - Each edge in the graph represents a communication channel
  - Since the persons move around, the topology changes during time
    - $\Rightarrow$ Graph $G_t = (V, E_t)$ depends on time t
  - In a simple scenario, external nodes are not needed. The system will self-organize.
    - In a more complex scenario, external nodes can be introduced to model changes in the environment (e.g. break down of a part of the building, etc.)

Example: Evacuation scenario

For the **target orientation** we need a valuation of configurations:

$b : \text{Conf} \rightarrow [0, 1]$

- In the evacuation scenario the good configurations are those where many people have already escaped:
  - b(c) = #escaped/N N = number of persons

- Consider a run of the system starting at time t = 0 ending at t = T.
- $TO_t = \boldsymbol{E}(b(\text{Conf}_t))$ is a nondecreasing function
- **Goal:** Try to maximize TO_T
- Different rule sets can be compared.
- Rules with different parameters can be compared.

Example: Traffic scenario

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- **Scenario:**
  - There was an **accident** on a highway
  - Other cars **slow down**, when they are approaching the scene of accident.
  - Possibility for **AmI device**:
    - Some cars may contain a device, which **send information** (e.g. velocity, acceleration, etc.) to other cars to improve safety.
    - The device can give **hints to the driver** (e.g. slow down) before he reaches the scene of accident
  - **Question:** How does the AmI device change the traffic flow around the scene of accident?

Example: Traffic scenario

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- **Level of target orientation**
  - From the point of view of the drivers, it would be good, if the **variance** of the velocities is low.
  - Define **good configurations** by the valuation
    - $b(c) = Var_{normal}(v)/Var\,(v)$
      - where $Var_{normal}(v)$ is the **variance** of velocity in the system without accident (can be calculated analytically, so no simulation runs are needed)
    - Then the **level of target orientation** can be approximated by using the time series received from the simulation runs.

Example: Traffic scenario

- **Level of emergence**
  - Can the traffic jam induced by the accident be seen as an emergent pattern of the system?

Evaluation of the scenarios

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- For the analysis with quantitative measures in the **evacuation scenario**, the University of Halle-Wittenberg is currently adapting a simulation software to produce the necessary time series.
- For the analysis with quantitative measures in the **traffic scenario**, the University of Munich is currently adapting a simulation software to produce the necessary time series.
- University of Passau is currently working on a software for the **evaluation of the quantitative measures** for the time series of simulation runs.

Conclusion

The mathematical modeling can be used for a wide variety of systems:

- Technical systems
- Biological systems
- Physical systems

and many more.

The models can help to analyse the behavior of complex systems.

Quantitative measures provide a link from the micro level to the macro level:

- They describe **global properties of the system**
- They can be used for the **analysis** of real world systems.
- They can be used for **design**, **engineering** and **optimization** of new systems.

Thank you for your attention

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