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«EMR-Based Cupcake Production Line: modeling for diagnostic»

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UQTR ÉCOLE D'INGÉNIERIE Génie mécanique

- Outline -

«Introduction»

- In manufacturing industry, production line is composed of:
  - Electric machines
  - Hydraulic/pneumatic machines
  - Conveyers
  - Oven
  - Chiller
  - Etc.

- Any manufacturing process involves one or more machines

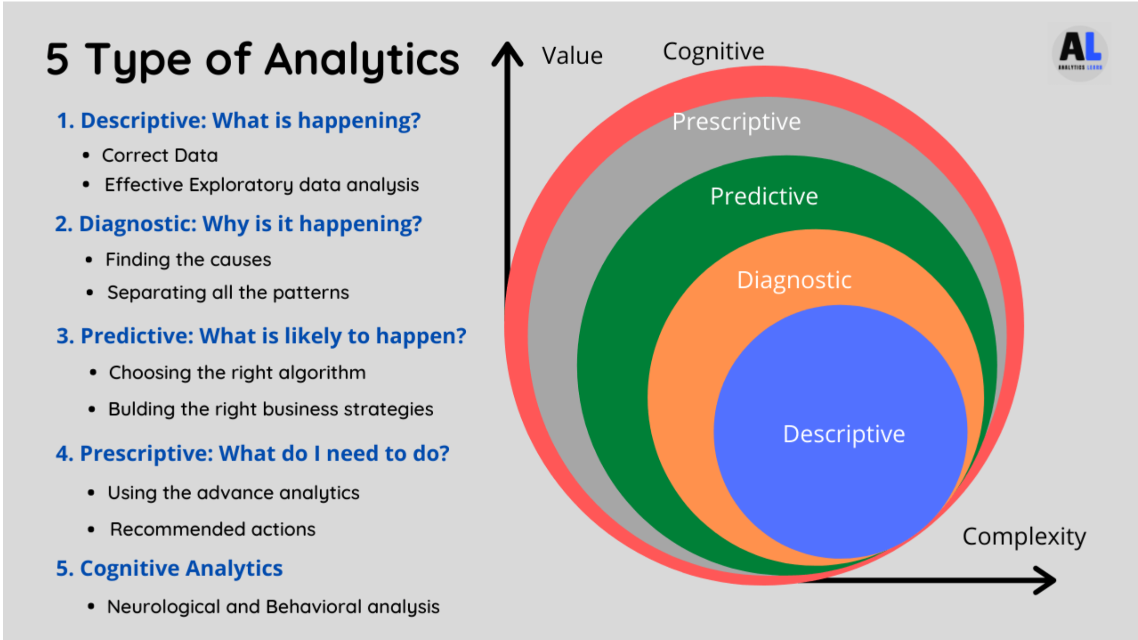
- A machine can be modelled in different ways.

- However a multiphysics model based on power and energy exchanges between different modules is well suitable to analyze causality.

- Bond Graph and EMR (Energetic Macroscopic Representation) are two well-known approaches for modelling a machine

- A fundamental concept of multiphysics modelling is based on causal representation.

- After descriptive analytics which deals with stochastic modeling, the next step is the diagnosis analytics. The predictive analytics is the stage afin diagnostic analytic.
- In manufacturing processes, we are interested to understand:
  - "WHY THERE IS A FAILURE ?"
  - "WHAT IS THE MOST PLAUSIBLE EXPLANATION OF A WORSE KPI ?"
- To answer these questions using data, a diagnostic analytics framework is required because:
  - We are not really sure of the answer.
  - There are several possible answers and may be one of them is the most likely good one.



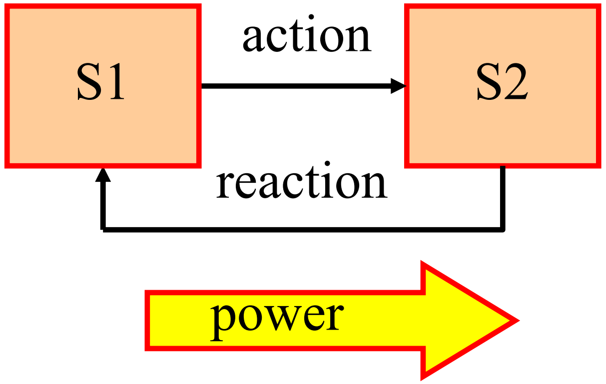
- What is diagnosis analytics in manufacturing ?

- Diagnosis analytics is a complex data analysis to:
  - Identify anomalies
  - Discover some causal links across multiple datasets that can help to answer, "why this happened?"

- Probability framework with inferences and time-series data analytics can be useful to do diagnosis.

- EMR combined with Probabilistic framework is a an interesting approach for diagnostic and predictive modeling

- When two physical modules are interacting :
  - Each action from one of these modules will induce a reaction from the other module.
  - Each reaction of one of the modules is necessary due to an action from the other module.



- Each basic physical component is designed to impose a specific signal within its primarily engineering domain
- To represent the interaction, two generalized quantities are defined:
  - The flow: this quantity represents something that has a displacement in its physical domain
  - The effort: this quantity represents some potential of a variable within its physical domain

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- Each module of a machine can be decomposed (in general) into the following basic components:
- Source (i.e: battery)
- Power dissipation component (i.e: electrical resistor, mechanical friction, etc.)
- Flow accumulator (i.e: electrical capacitor, mechanical spring, etc.)
- Effort accumulator (i.e: electrical inductor, mechanical inertia, etc.)
- Power converter or power transformer (ex. electric motor, electric transformer, gearbox, etc.).
- Interconnexion component.

«Case study: Cupcake production line»

https://youtu.be/qnNF78cGQX4

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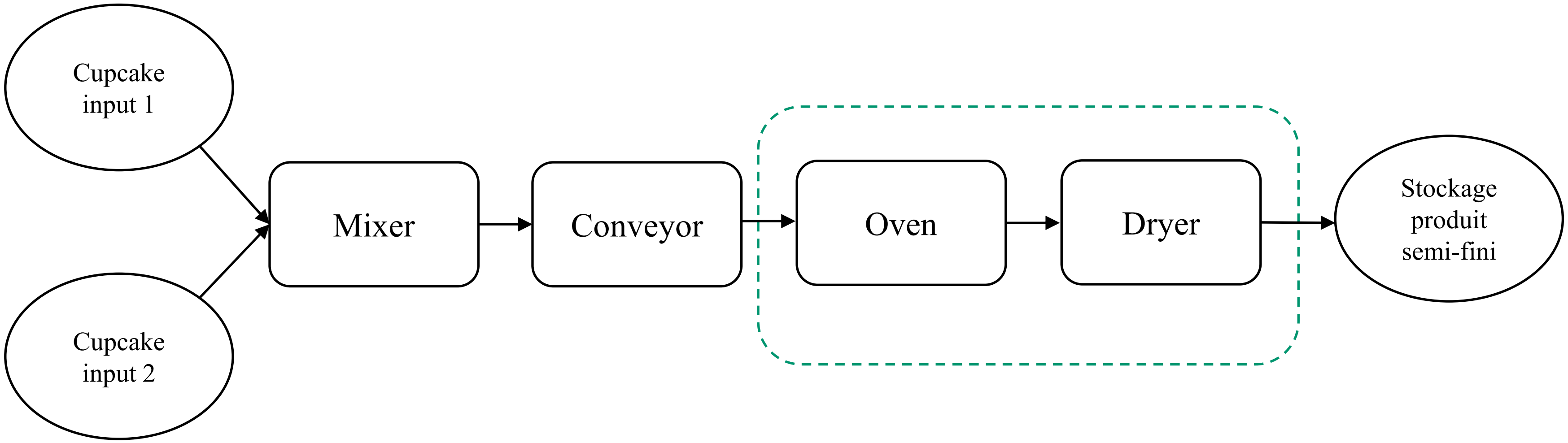
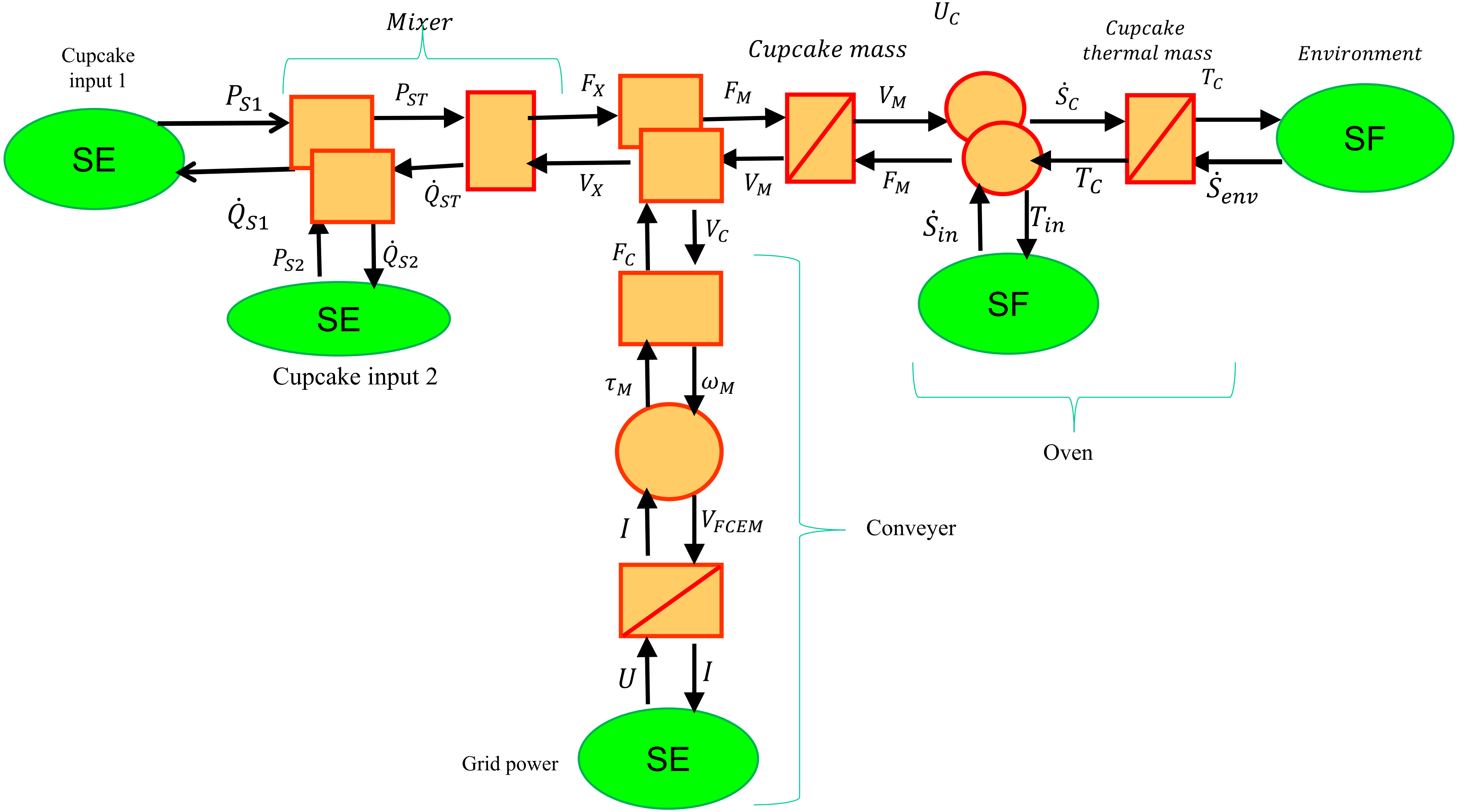


Causal model to control the cupcake temperature T_C



Despite the best control loops we could implement, what will be the most likely cause of a deviation between the temperature $\boldsymbol{T\_C}$ and a target (reference) temperature $\boldsymbol{T\_R}$?

In order word, assume that $\varepsilon\_T = \boldsymbol{T\_R} - \boldsymbol{T\_C}$ and it is desirable to keep $\|\varepsilon\_T\| \leq E$ where E is a given small and positive value.

For all possible N causes $C\_i \; : i \in \{1,2,3,\ldots,N\}$, compute all $P((\|\varepsilon\_T\| > E) \left| C\_i \right.)$

«Markovian Network»

- One of the most use frameworks to infer the causality is the Bayesian network.
- Bayesian network:
- Allows learning probabilistic models from data.
- Is a structured, direct graphical representation (with edges and vertices) of probabilistic relationships between random variables.
- Can represent conditional independencies. Missing edges indicate conditional independence.
- Efficient representation of joint probability distribution function
- Bayesian network is NOT suitable to handle cyclic graph.
- Markov network is more appropriate.

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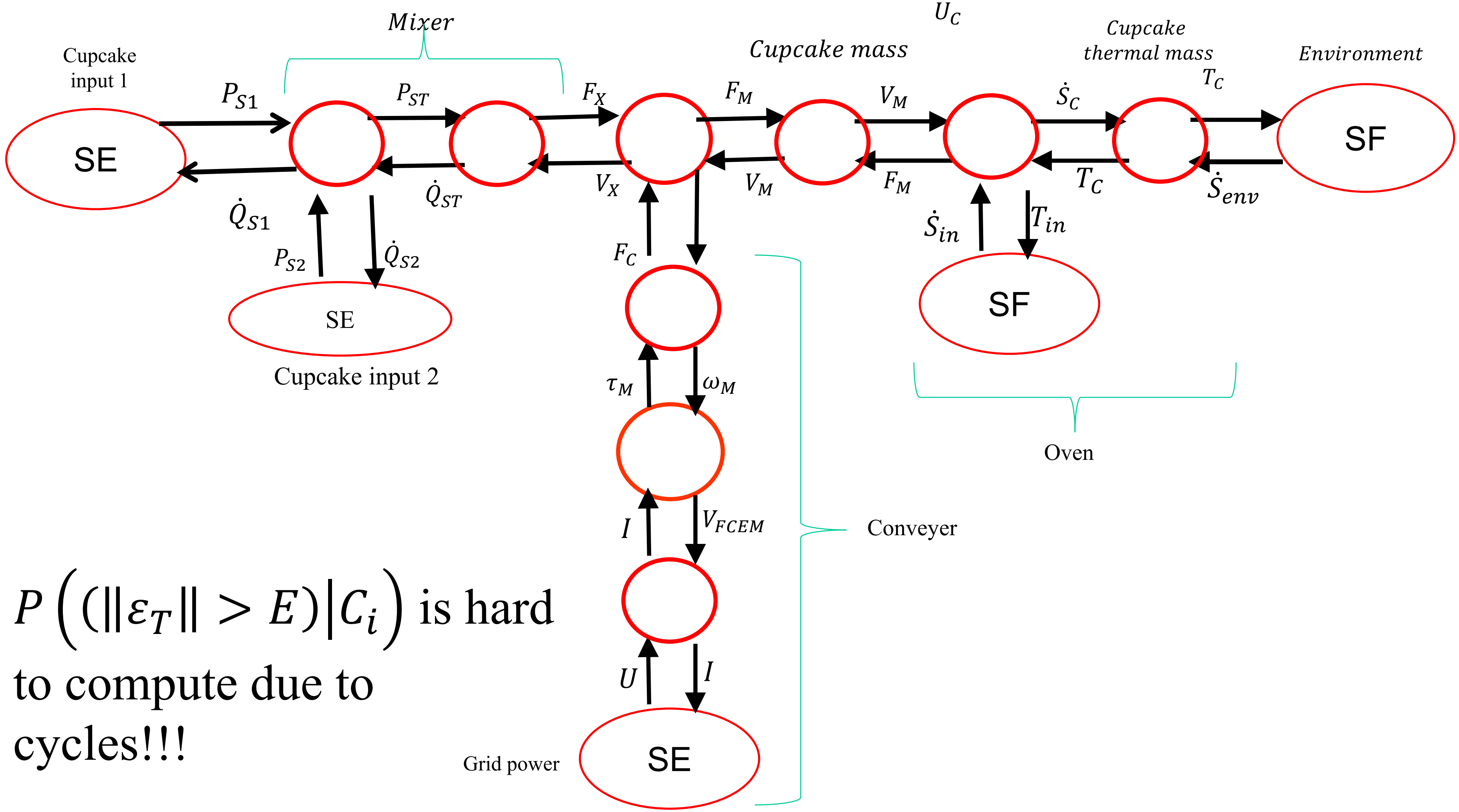
- What is a Markov network ?

- A network that obeys Markov property

- Markov property:
  - Assume that a discrete random variable can be in one of a finite set of states.
  - Assume that the probability distribution of transition is known
  - To predict the most likely state, if the only information required is the current state, then the variable is following Markov order 0 property.
  - If the immediate past state and the current state are reqired to find the most likely next state, the variable is following Morkov order 1 property.

From causality network to Markov network



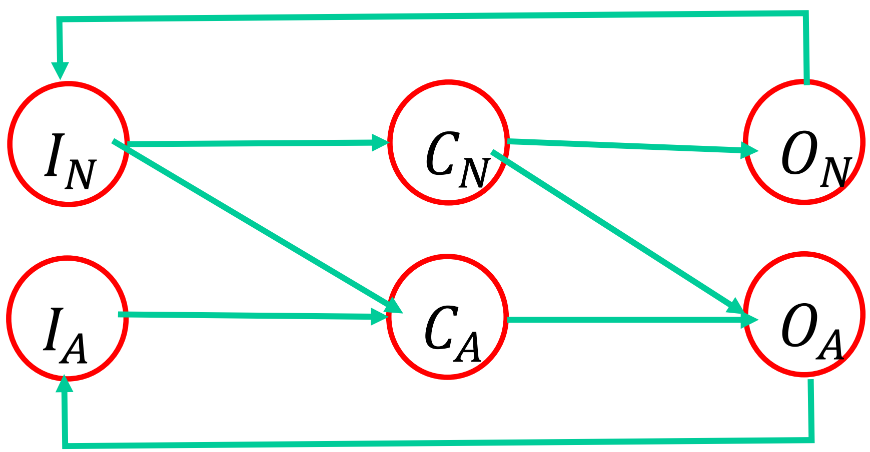
$P\left((\|\varepsilon_T\| > E) \middle| C_i\right)$ is hard to compute due to cycles!!!

Markov network: simplification

- Any bloc in to the EMR has at least a finit set of INPUTS, a finit set of TRANSFER FUNCTIONS and one OUTPUT

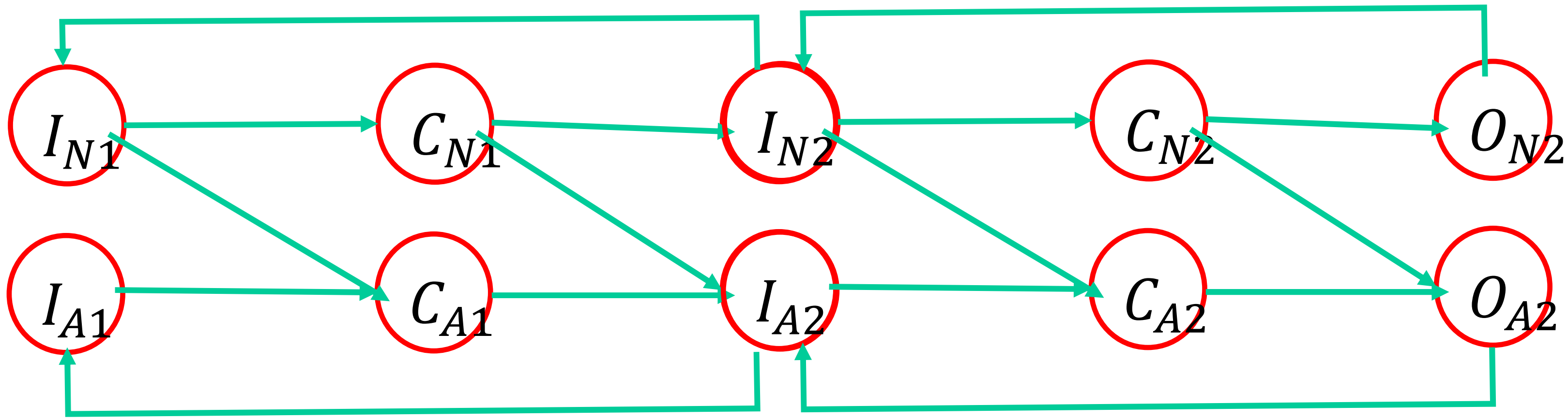
Now let assume a bloc with 1 input, 1 output and 1 transfer function

- The output can take two states:
  - O_N: output values are "normal"
  - O_A: output values are "anormal"
- The input can take two states:
  - I_N: input values are "normal"
  - I_A: input values are "anormal"
- The component itseft with its transfer function can take two states:
  - C_N: component behaviour is "normal"
  - C_A: component behaviour in "anormal"



Markov network: simplification

- The input of a bloc is the output of the previous bloc
- The output of a bloc is the input of the next bloc



- Knowing transition matrix, we can compute any probability

« Biographies and References »

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