discrete_event_simulation

a practical example

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contents

1. what?
2. why?
3. how?
4. does it fly?

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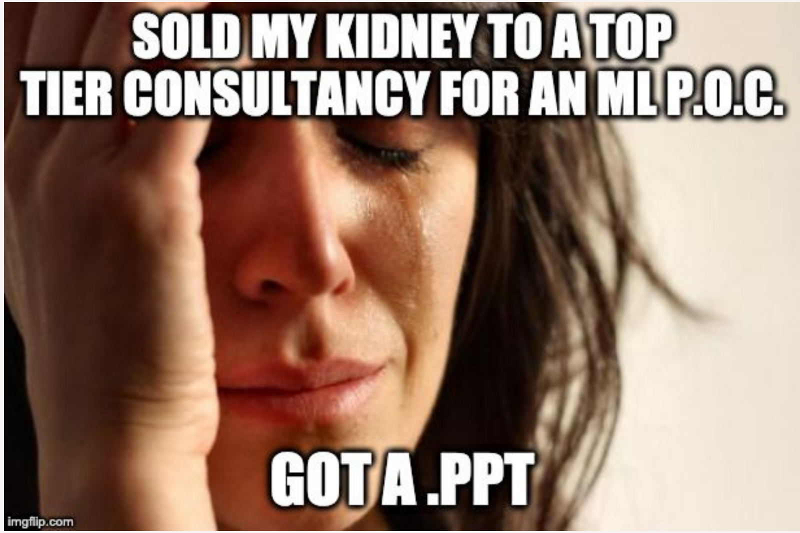
we?

December 2016



"Hold my Belgian ale"

"When everything you have is a hammer, everything looks like a nail."

~ Unknown carpenter, 33 A.D.

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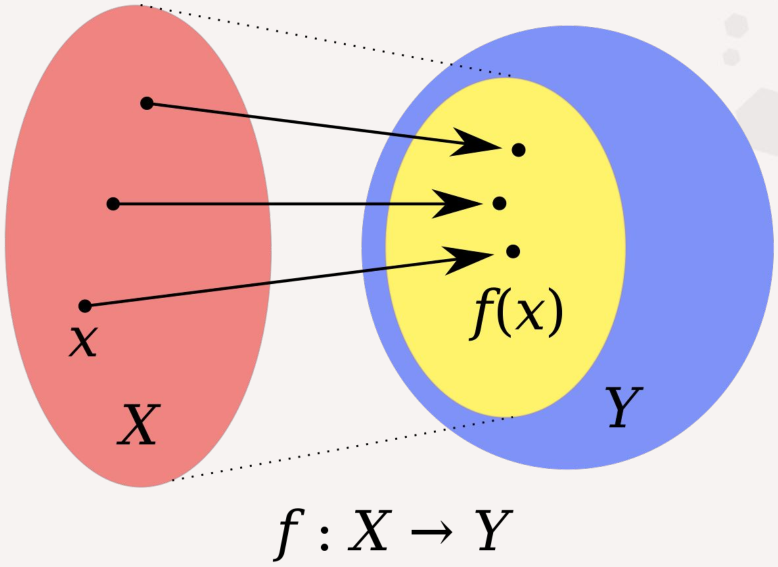
95% of models used today are just “fancy mappings” (at best!)



Time?
States?
Entity interplay?
Resources?

Time?

Ingenious solution!

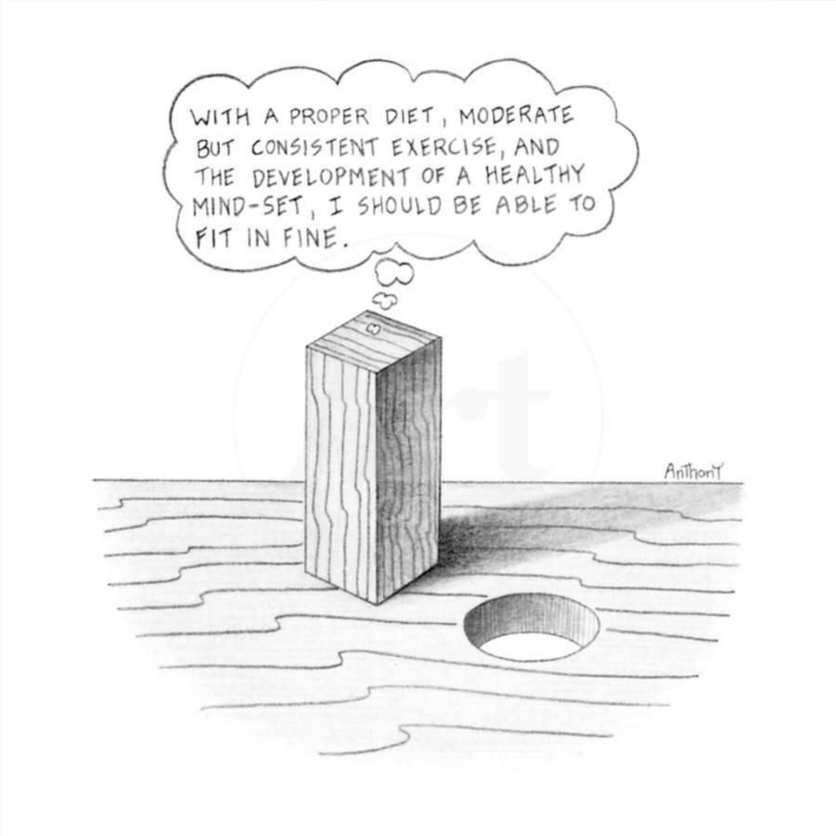
$X_t = [X_t, X_{t-1}, X_{t-2}]$

$\Rightarrow$ AR(I)MA(X) models

Still, different models for

$X_t \Rightarrow y_{t+1}, X_t \Rightarrow y_{t+5}, \ldots$

... can work, but a stretch



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Other issues

- How to encode prior/expert knowledge?
  - Forcing the model to learn something that can be parametrized in the process model is a waste.

- How to model complex interplay of entities and resources?
  - $X \Rightarrow y$ mappings are too naive for processes with multiple agents and resources.

- Model parameters “fused” to a specific process structure
  - How to test/predict outcomes of small structural changes in the process?

what if only...

... there existed a modelling approach

... and a library

... that made all of this ~~simple~~ **less painful**?

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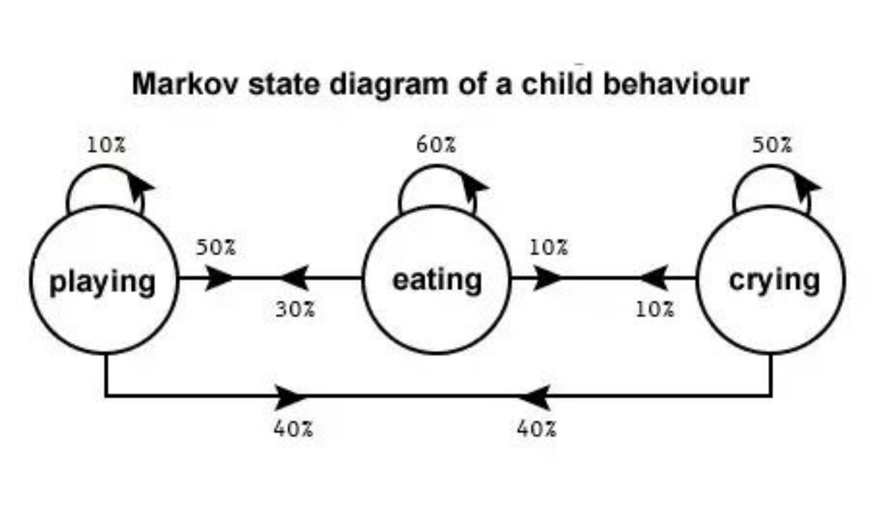
enter: discrete event simulation (des)

- A **discrete-event simulation** (**DES**) models the operation of a system as a (discrete) sequence of events in time. Each event occurs at a particular instant in time and marks a change of state in the system



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enter: discrete event simulation (des)

In other words: Replicating a real-world process in a virtual environment for the purpose of

- experimenting with different process inputs (e.g. working hours)
- better understanding the system behavior (e.g. bottlenecks)
- evaluating different scenarios to discover better processes (e.g. more resources)

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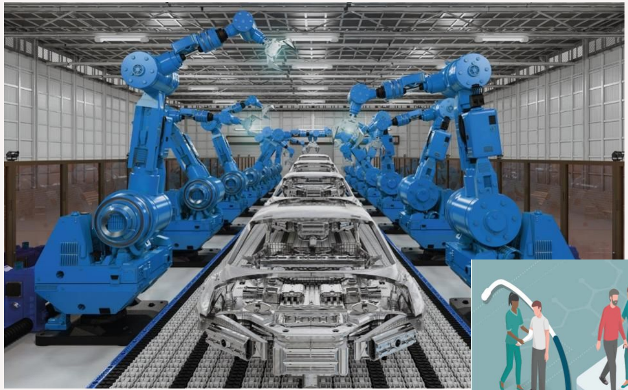
enter: discrete event simulation (des)



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how?

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process discovery

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Two options

1. Manual
   a. *Business analysis, interviews with stakeholders, data exploration*
2. Automated
   a. *Using Process Mining software*

Data based

General format is a table containing

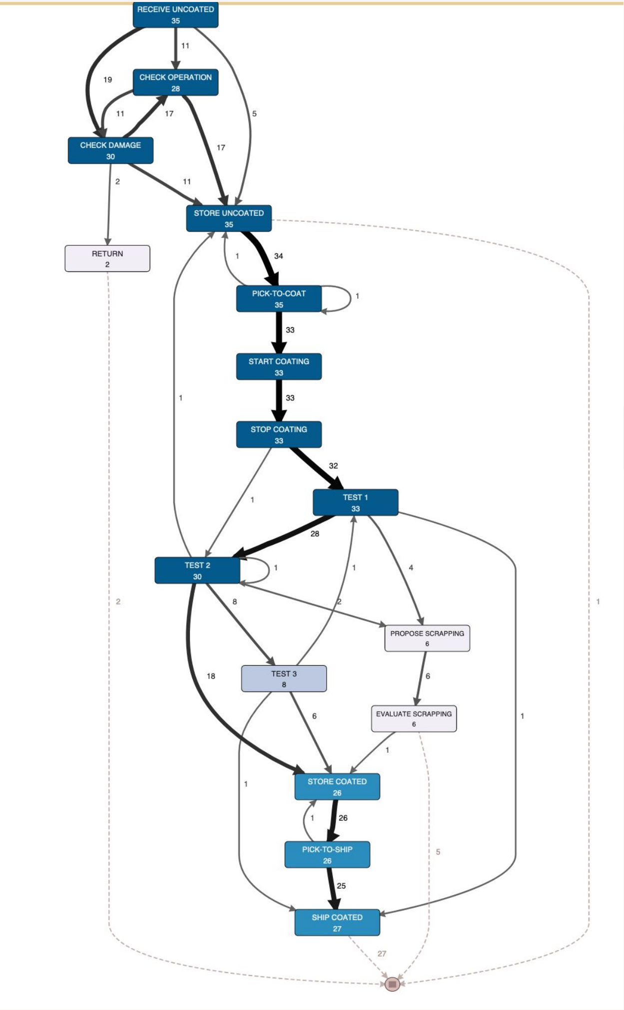
1. Entity of interest
2. Activity or resource occupied
3. Activity/resource start and end time

This allows us to reconstruct the trajectories.

Data

Case ID	Activity description	Timestamp	Resource	Location
Phone 3651	RECEIVE UNCOATED	2/03/2016 8:10	Arthur	INBOUND AREA
Phone 3651	CHECK OPERATION	2/03/2016 9:13	Arthur	INBOUND AREA
Phone 3651	CHECK DAMAGE	2/03/2016 9:25	Arthur	INBOUND AREA
Phone 3651	STORE UNCOATED	2/03/2016 10:08	Arthur	WAREHOUSE UNCOATED
Phone 3651	PICK-TO-COAT	15/03/2016 10:51	Jerome	WAREHOUSE UNCOATED
Phone 3651	START COATING	16/03/2016 15:14	Alix	COATING ROOM
Phone 3651	STOP COATING	16/03/2016 15:34	Alix	COATING ROOM
Phone 3651	TEST 1	17/03/2016 16:34	Edward	TESTING ROOM
Phone 3651	TEST 2	18/03/2016 10:34	Edward	TESTING ROOM
Phone 3651	TEST 3	18/03/2016 14:34	Edward	TESTING ROOM
Phone 3651	STORE COATED	18/03/2016 16:04	Jerome	WAREHOUSE COATED
Phone 3651	PICK-TO-SHIP	24/03/2016 9:33	Jerome	WAREHOUSE COATED
Phone 3651	SHIP COATED	24/03/2016 15:33	Jerome	OUTBOUND AREA

https://www.horsum.be/sites/default/files/wysiwyg-uploads/Process%20mining%20explained%20by%20an%20example%20-%20Episode%202.pdf



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Tools

Closed source

- DISCO
- Logpickr
- Blueprism
- Fluxicon

Open source

- PM4Py
- Apromore
- ProM Tools

des modelling in r

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simmer

simmer is a process-oriented and trajectory-based Discrete-Event Simulation (DES) package for R. Designed to be a generic framework like [SimPy]() or [SimJulia](), it leverages the power of [Rcpp]() to boost the performance and turning DES in R feasible.

Developers

Iñaki Ucar

Author, copyright holder, maintainer

Bart Smeets

Author, copyright holder

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Very (very) short tutorial

1. Define trajectory
2. Create resources
3. Create trajectory generators
4. Run the simulation N-times
5. Fetch and analyze results

```r
library(simmer)

set.seed(1234)

bank <- simmer()
```

```r
customer <-
  trajectory("Customer's path") %>%
  log_("Here I am") %>%
  set_attribute("start_time", function() {now(bank)}) %>%
  seize("counter") %>%
  log_(function() {paste("Waited: ", now(bank) - get_attribute(bank, "start_time"))}) %>%
  timeout(12) %>%
  release("counter") %>%
  log_(function() {paste("Finished: ", now(bank))})
```

```r
bank <-
  simmer("bank") %>%
  add_resource("counter") %>%
  add_generator("Customer", customer, function() {c(0, rexp(4, 1/10), -1)})

bank %>% run(until = 400)
```

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Basic grammar

```
seize(<resource>, <quantity>)
timeout(<n_intervals>)
release(<resource>, <quantity>)

set_attribute(<name>, <numerical_value>)
get_attribute(<name>)

leave()
rollback(<n_steps>)
branch(<condition>, <branch_1>, <branch_2>, ...)
```

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a real-world example

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The problem

- Our client is a the logistics department of a major brewery.
- Warehousing costs are very volatile and hard to predict using traditional BI approaches.
- Drivers of warehousing costs are
  - Volume of beer produced
  - Beer arrivals in and departures from warehouses
  - Total days all beers spent in each warehouse
- Movement profiles vary greatly by SKU

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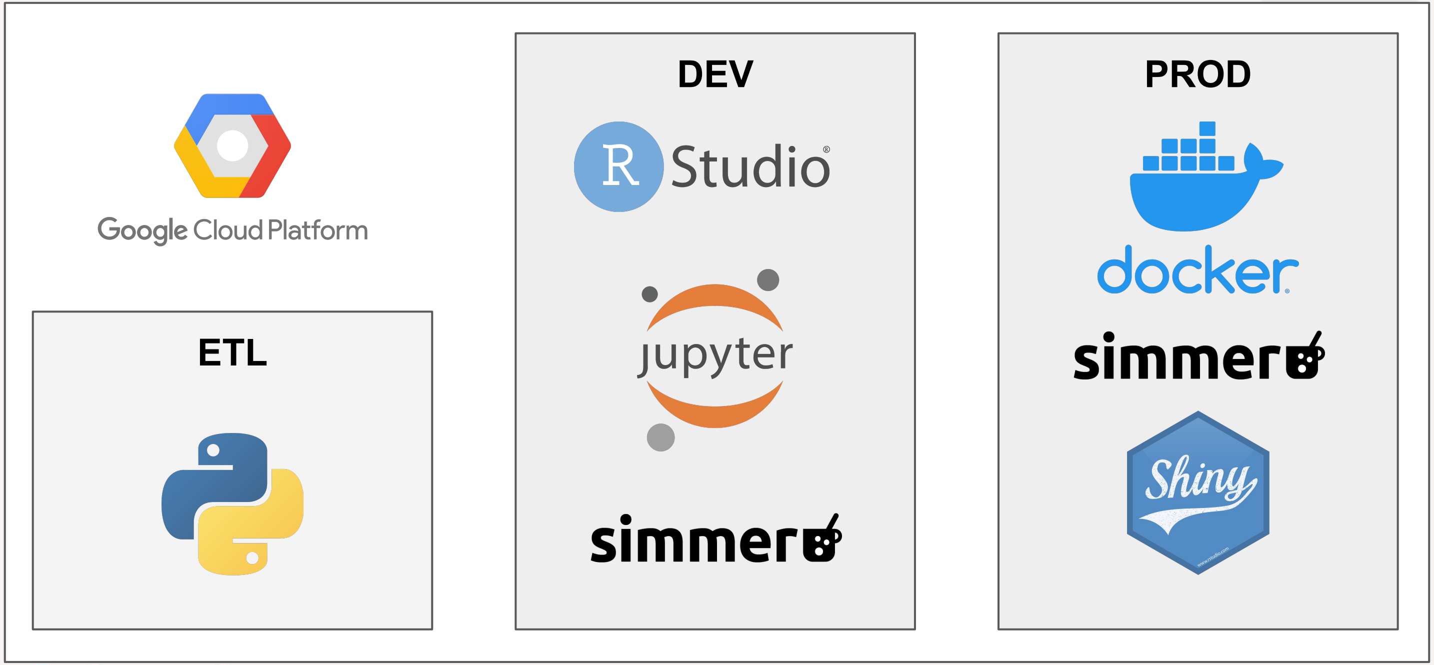
PoC architecture



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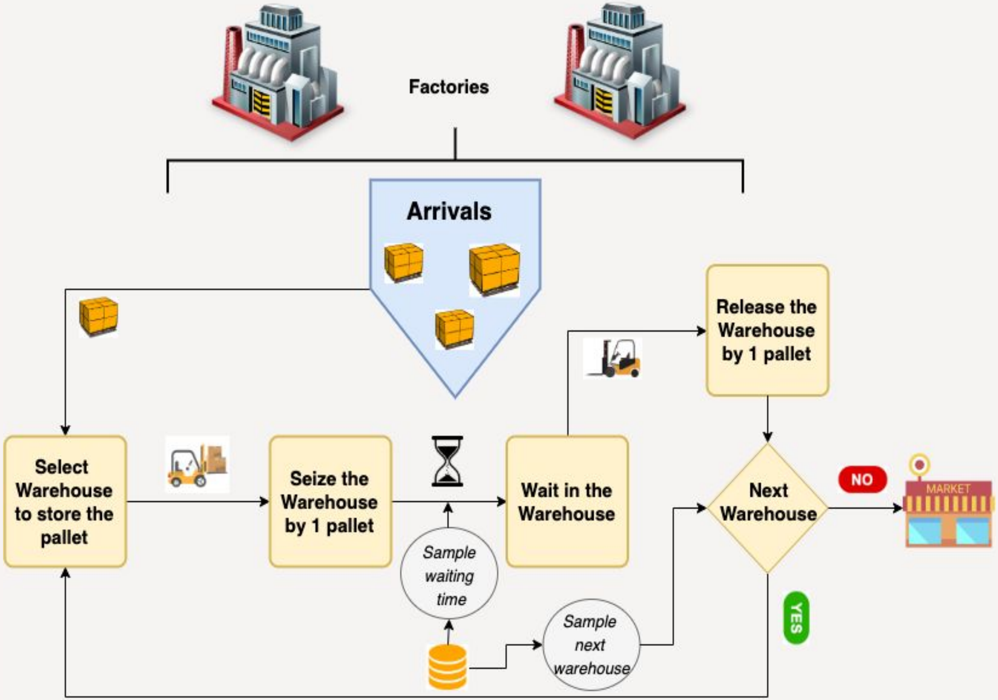
Process diagram



Resource

- Warehouses

Attribute

- The capacity of warehouse

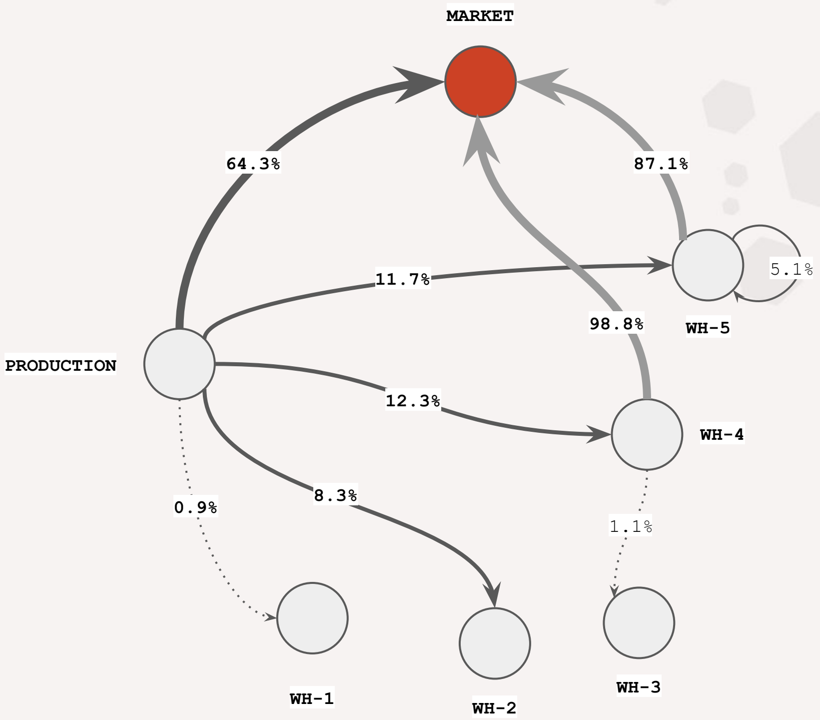
Variable

- Total stock in each warehouse

States

- Arrivals
- Selecting a warehouse
- Seizing the warehouse
- Waiting in the warehouse
- Releasing the warehouse

Parametrization: movement profile for SKU 123



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Performance

Key evaluation metric: 1 month cumulatives of:

- Moves into the warehouse (UNLOADS)
- Moves out of the warehouse (LOADS)
- Days spent in the warehouse (STORAGE DAYS)

Results:

- LOADS: 9% MAE
- UNLOADS: 8% MAE
- STORAGE DAYS: 4% MAE

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Conclusions

- DES allowed us to model the process in its “natural form”, leveraging the client’s business knowledge.
- Running N simulations in parallel allowed us to estimate worst and best case scenarios for a set of defined inputs (normally not available with classical models)

Improvement points

- Time-varying movement profiles (beer is very seasonal)

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recap

takeaways

- white/grey(ish) process modelling approach.
- requires process understanding.
- time consuming development, but granular output.
- ONE OF alternative approaches, not THE alternative -- be wise.

DISCLAIMER

- can be time consuming/overkill
    - Model design, documentation, validation, verification
- finite number of states / fixed graph
    - Not suitable for high-degree-of-freedom reinforcement learning

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thank you!

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