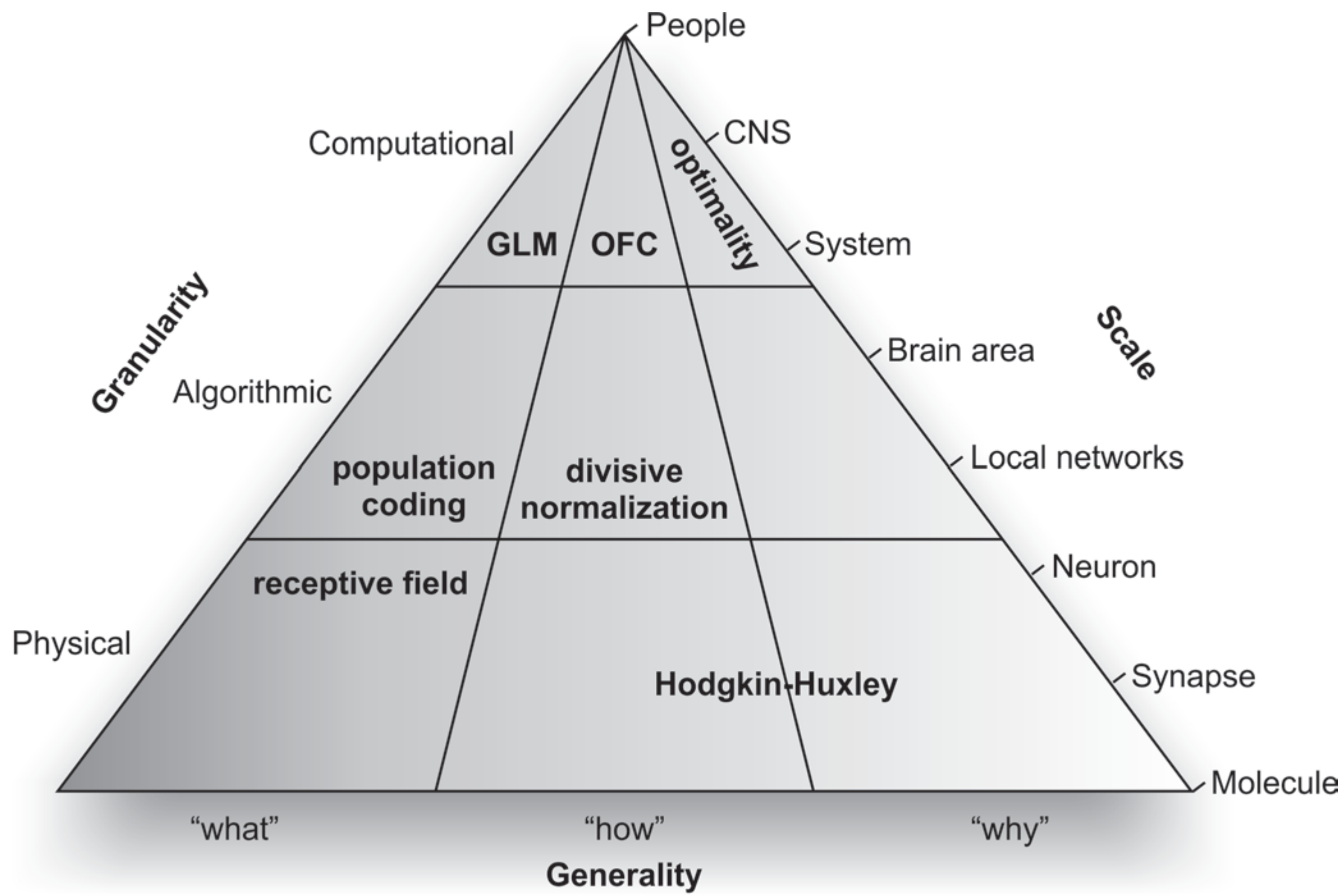

CoSMo
2017

Model classifications

- Models help answering different parallel questions



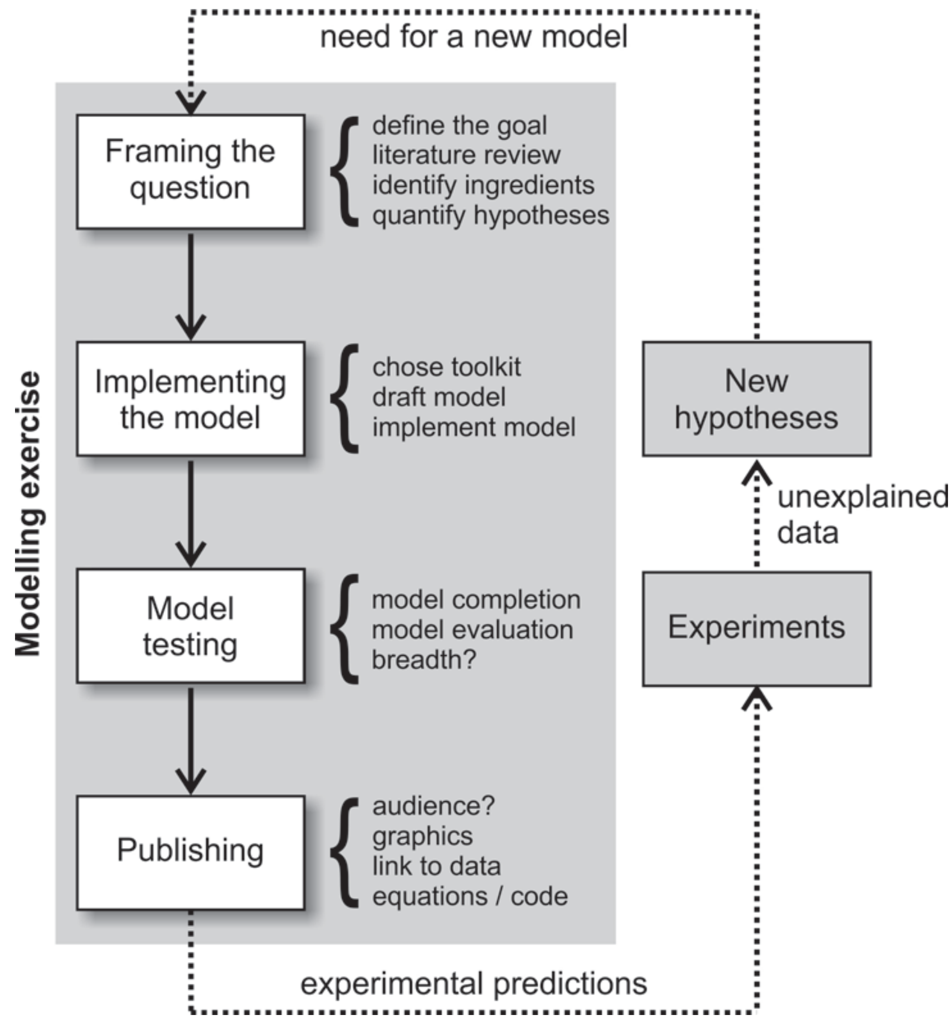
Model classifications

- Models help answering different parallel questions
  - Generality: inferential model classes
  - Granularity / scale: level of abstraction
- Knowing this interrelated hierarchy is crucial
  - Defines model goals
  - Defines evaluation framework (reviewers)
  - What can and should be expected from a model
  - Determines limitations

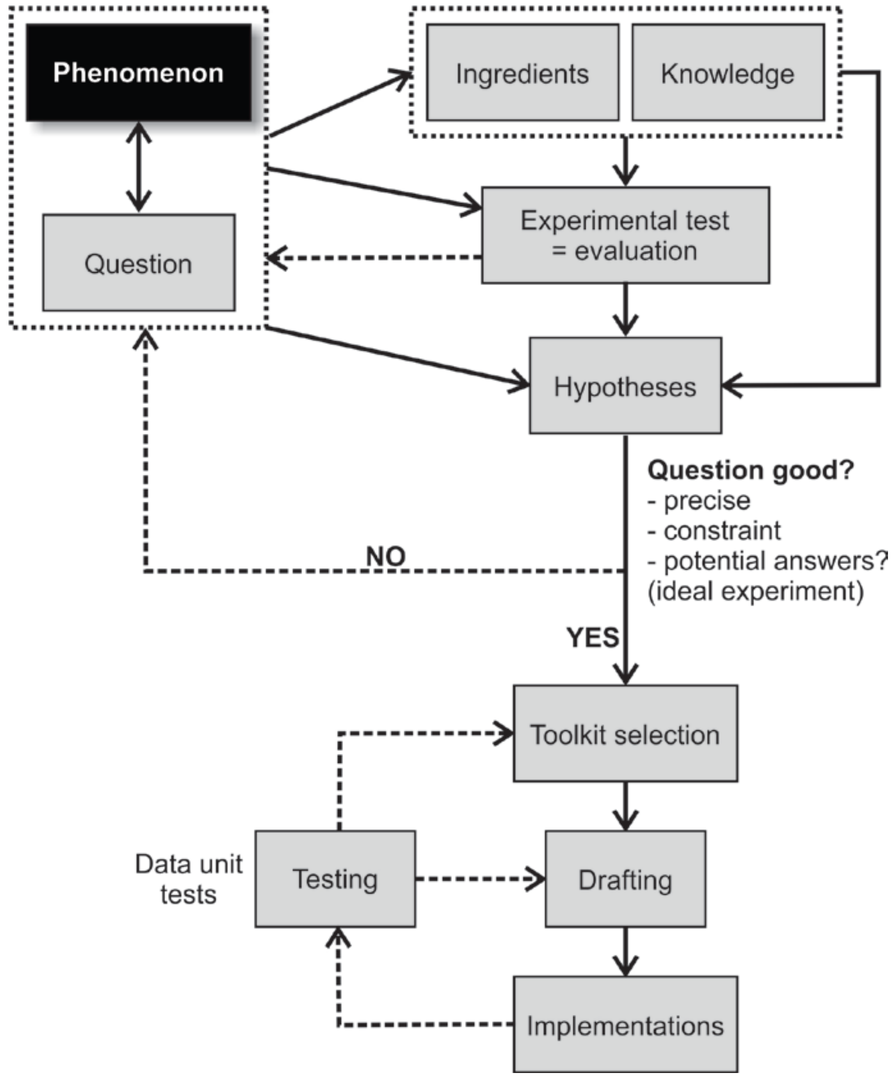
10 easy steps to model

A practical guide

Overview of the modelling exercise



Overview of the modelling exercise

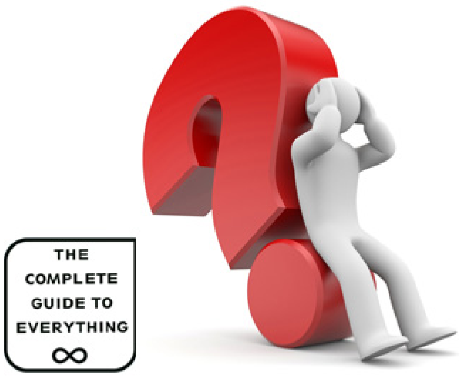


Framing the question

- Step 1: define an objective / goal / question
  - What exact aspect of data needs to be modelled?
    - Answer this question clearly and precisely!
    - Otherwise you will get lost (almost guaranteed)
    - Write everything down!
  - Also identify aspects of data that you do not want to address (yet)
  - Example
    - Bad question: "I would like to model motor control"
    - Good question: "How do time delays in sensory feedback influence motor control in a force field adaptation task"
  - Also: define the model evaluation method!
    - How will you know your model is good?
    - See later…

Framing the question

- Step 2: What's known / unknown?
  - Survey the literature
    - What's known?
    - What has already been done?
    - Previous models as a starting point?
    - What hypotheses have been emitted in the field?
    - Are there any alternative / complimentary models?
  - What skill sets are required?
    - Do I need learn something before I can start?
  - Ensures that no important aspect is missed
  - Provides specific data sets / alternative models for comparison (see also evaluation criteria)

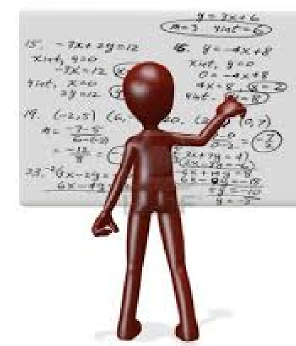


Framing the question

- Step 3: Determine the basic ingredients
  - What parameters / variables are needed in the model?
    - Constants?
    - Do they change over space, time, conditions…?
    - What details can be omitted?
    - Constraints, initial conditions?
    - Model inputs / outputs?
  - Variables needed to describe the process to be modelled?
    - Brainstorming!
    - What can be observed / measured? → latent variables?
    - Where do these variables come from?
    - Do any abstract concepts need to be instantiated as variables?
      - E.g. value, utility, uncertainty, cost, salience, goals, strategy, plant, dynamics
      - Instantiate them so that they relate to potential measurments!

Framing the question

- Step 4: Express hypotheses in math language (abstraction)
  - Relate ingredients identified in step 3
  - Do this before getting influenced by model structure / results
  - Hypotheses can be expressed in terms of relations between variables and state the original question from step 1 in a different form (in words)
    - What is the model mechanism expected to do?
    - How are different parameters expected to influence model results?
  - Assign variable names
  - Express hypotheses in terms of variables
    - Be explicit, e.g. $y(t)=f(x(t),k)$ but $z(t)$ doesn't influence y
    - Do the same with constraints, initial conditions, etc
  - Determines model approach and ingredients
  - The more precise the hypotheses, the easier the model will be to sell



Implementing the model

- Step 5: select toolkit / approach – level of abstraction
  - What is the most appropriate approach to answer your question?
    - What level of abstraction is needed?
    - Determine granularity / scale based on hypotheses & goals
    - **Stay as high-level as possible, but be as detailed as needed!!!**
  - Select the toolkit
    - Requires prior knowledge about flexibility / limitations of toolkit
    - Often more than one option possible
    - Some toolkits are more flexible, span a wider range of behaviour and/or are lumpable
    - Also determines how the model will be solved, i.e. simulated
      - Analytical? Numerical?
      - E.g. spatial, temporal resolution?

  - We now have everything we need to actually start modelling!

Implementing the model

- Step 6: Drafting
  - Keep it as simple as possible!
  - Draft on paper: flow diagram
    - Draw out model components (boxes)
    - What influences what? (arrows)
  - Consider each model box separately
    - Draft internal workings in terms of equations
    - This might require a lot of work…
    - Relate box inputs to box outputs!
    - Keep in mind that the model should include a way to relate model variables to measurements
  - You now have a first model ready to be implemented!

Implementing the model

- Step 7: implementation and adjustments
  - Start with the easiest possible implementation
    - Test functionality of model after each step before adding new model components (unit tests)
    - Simple models can sometimes accomplish surprisingly much…
  - Add / remove different model elements
    - Gain insight into working principles
    - What's crucial, what isn't?
    - Every component of the model must be crucial!
  - Make use of tools to evaluate model behavior
    - E.g. graphical analysis, changing parameter sets, stability / equilibrium analyses, derive general solutions, asymptotes, periodic behaviour, etc.

Model testing

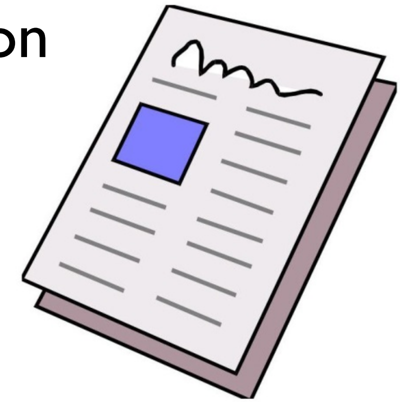
- Step 8: Model completion
  - When am I done? → hard question!!!
    - Determine a criterion
    - Refer to steps 1 (goals) and 4 (hypotheses)
      - Does the model answer the original question sufficiently?
      - Does the model satisfy your own evaluation criteria?
      - Does it speak to the hypotheses?
    - Can the model produce the parametric relationships hypothesized in step 4?
  - Precise question & hypotheses crucial for this!

  - If the original goal has not been met → back to drawing board!

Model testing

- Step 9: model testing and evaluation
  - By definition a model is always wrong!
  - Ensure the explicit interfacing with current or future data
    - model answers the questions/hypotheses/goals with a sufficient amount of detail
  - Quantitative evaluation methods
    - Statistics: how well does the model fit data?
    - Predictability: does the model make testable predictions?
    - Breadth: how general is the model?
  - Comparison against other models (BIC, AIC, etc.)
    - Not easy to do in a fair way…
  - Does the model explain previous data? Subsumption principle in physics!
  - A good model should provide insight that could not have been gained or would have been hard to uncover without the model
  - Model = working hypotheses → a good model should be falsifiable!

Publishing



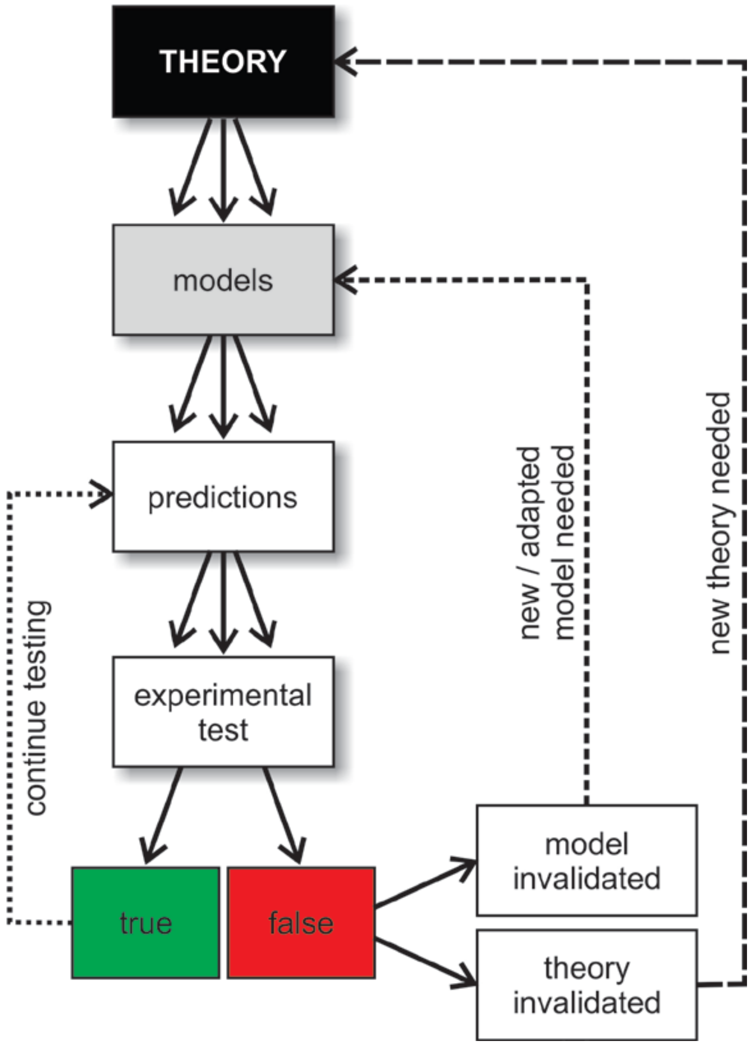
- Step 10: Communication through scientific publication
  - Know your target audience!
    - How much math details? How much explanation of math?
    - What's the message?
    - Should be experimentalists in most cases!!!
      - Provide intuitive explanations, analogies, etc.
      - Dora Angelaki: "a good modeller knows how to relate to experimentalists"
  - Clearly describe what the goals, hypotheses and performance criteria were
    - Prevents from false expectation of what the model should be doing
  - A graphical representation is worth 1000 words (or more)
  - Show model simulations in parallel to data
    - Much more convincing!
  - Publish enough implementation details
    - A good model has to be reproducible!

A few more considerations…

Lumping vs. abstraction

- Abstraction = process of information reduction to only retain the relevant underlying essence of a concept and / or render a concept more generalizable
- Lumping = particular instance of abstraction
  - Certain details irrelevant for a given research question are averaged out, discarded or merged together
    - E.g. Marr I = lumped system
  - Lumping allows focussing on a certain level of explanation
- However, ultimately models should span different levels of abstraction!
  - Otherwise information can be lost
    - E.g. spike coding & information transmission vs. rates (Sophie Denève)
  - This is hard!!!

Theory, models and data



Happy modelling!