# Modelling With Differential Equations

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- Aims:
  - Basic concepts





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- Advanced possibilities





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- Software workflow





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- Why are they useful?
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- Known inputs
- Uncertainty / unknown inputs
- Complexity state dependent parameters, random effects, etc.



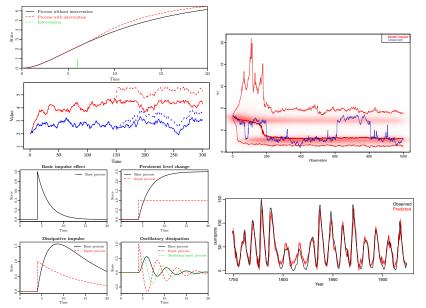
$$\frac{\mathrm{d}y}{\mathrm{d}t}=b$$

$$\dot{y} = b$$

$$y(t) = y_{t0} + bt$$











$$\dot{y} = Ay + b$$

$$y(t) = e^{At}y_{t0} + (e^{At} - 1)A^{-1}b$$





$$\underline{\mathbf{d}\begin{bmatrix}\mathsf{eta1}\\\mathsf{eta2}\end{bmatrix}(t)} = \left(\underbrace{\begin{bmatrix}-0.3 & 0\\0.4 & -0.1\end{bmatrix}}_{\mathbf{A}}\underbrace{\begin{bmatrix}\mathsf{eta1}\\\mathsf{eta2}\end{bmatrix}(t)}_{\boldsymbol{\eta}(t)} + \underbrace{\begin{bmatrix}1\\0\end{bmatrix}}_{\mathbf{b}}\right) \mathbf{d}t$$

$$\underbrace{\begin{bmatrix} \mathbf{Y}1 \\ \mathbf{Y}2 \\ \mathbf{Y}3 \end{bmatrix}(t)}_{\mathbf{Y}(t)} = \underbrace{\begin{bmatrix} 1 & 0 \\ 0.8 & 0 \\ 0 & 1 \end{bmatrix}}_{\mathbf{\Lambda}} \underbrace{\begin{bmatrix} \mathsf{eta1} \\ \mathsf{eta2} \end{bmatrix}(t)}_{\boldsymbol{\eta}(t)} + \underbrace{\begin{bmatrix} 1.5 \\ 0 \\ -2 \end{bmatrix}}_{\boldsymbol{\tau}} + \underbrace{\begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ \epsilon_3 \end{bmatrix}(t)}_{\boldsymbol{\epsilon}(t)}$$













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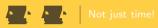


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- In multivariate systems, zeroes only imply 'no effect' in differential equation formulation.
- Coupled with appropriate estimation routines allows relatively unconstrained theory specification and testing.

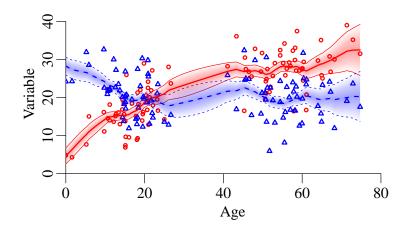






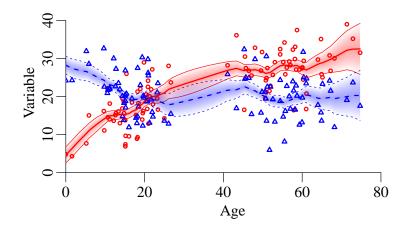


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- Besides time, age is an obvious candidate for us.





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- Good reasons to use: More flexible than typical regression / SEM approaches. Random / time varying effects on any parameter. Estimation works under problematic conditions, many parameters etc.
- Good reasons to avoid: More flexible than typical regression / SEM approaches. Less developed workflow, doesn't cope with high dimensions in variable domain.