

CHIMERA

/kɪ'mɪərə, kɪ'mɪərə/

noun

Collaborative Healthcare Innovation through
Mathematics, Engineering and Artificial Intelligence

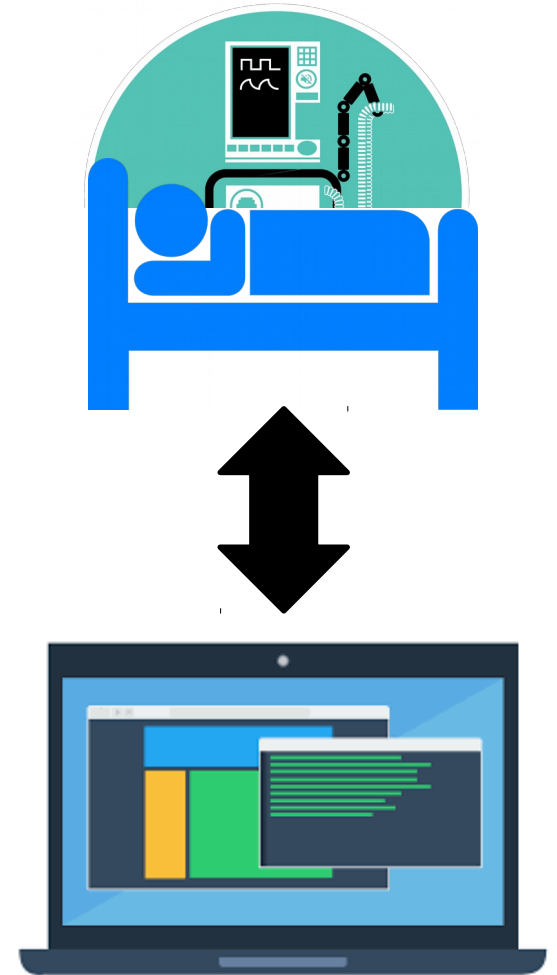
The Particular Problems of Critical Care

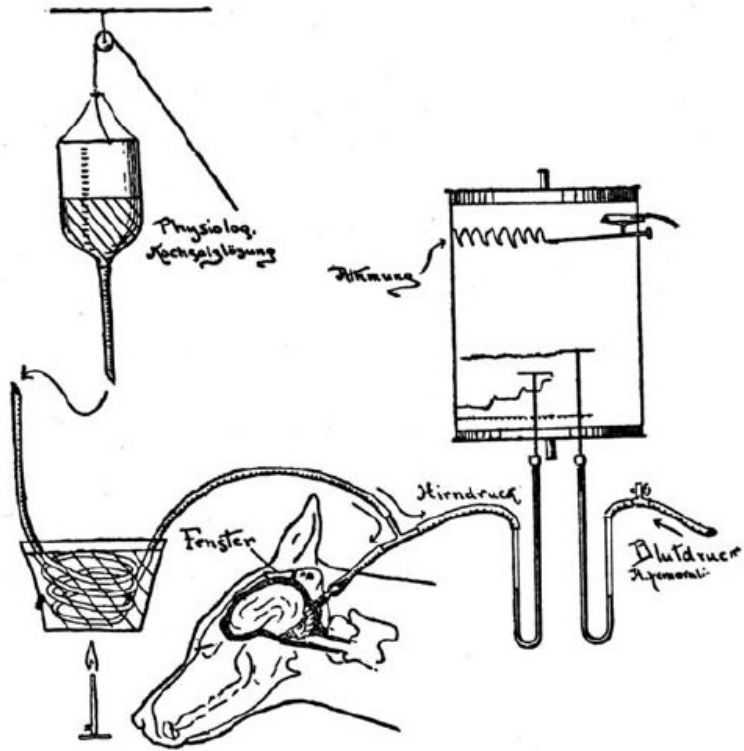
- Mechanical ventilation is the most important therapeutic intervention for patients with respiratory failure
- 100k ICU admissions undergo mechanical ventilation per year in the UK, with average daily cost of £1500
- Clinician workload is directly linked to patient outcomes. 1.7 human errors per patient per day, high mortality rates (30-40%)



Why use mechanistic models for respiratory illnesses?

- Very difficult to conduct clinical research on critically ill patients
- Many practical / ethical issues, clinical trials massively expensive, difficult to design, with high failure rates
- No single animal model typically replicates the complex pathophysiology of respiratory diseases
- Still difficult to “look inside” the lung
- Demand for more personalised treatment strategies
- Strong interest from Funding Agencies and Industry





Most physiology knowledge developed from animal experiments

This interpretation of physiology is applied to the complex environment of intensive care units





Continuous data generation in ICU patients...

... but only fraction of data used to make treatment decisions

		04/04/2019	04:00	05:00	06:00	07:00	08:00	09:00	10:00	11:00	12:00	13:00	14:00	15:00	16:00
Flowchart (Paeds)	Flowchart (Paeds)		25.000	25.000	25.000	25.000	25.000	25.000	25.000	25.000	25.000	25.000	25.000	25.000	25.000
Medication Administration Record	Weight (Working)														
Order Entry	Height (Working)														
Order Reminders	Head circumference (cm)														
Orders Overview	Tri Weekly Weight (Kg)														
Shift checklist	No. of Days on ITU		1	1	1	1	1	1	1	1	1	1	1	1	1
Vital signs	Date/Time Fit For Discharge														
Ventilation	Heart Rate	123	125	125	133	128	124	123	121	119	117	117	117	122	117
Spontaneous Breathing T...	Heart Rhythm	NSR	NSR	NSR	Sinus tach	Sinus tach	NSR	NSR	NSR	NSR	NSR	NSR	NSR	NSR	NSR
Blood gases	Art BP	111/53 (68)	90/53 (66)	89/51 (63)	103/69 (81)	101/43 (58)	104/58 (70)	99/50 (62)	97/48 (60)	86/45 (56)	87/46 (57)	81/45 (55)	80/42 (54)	83/45 (55)	
Physio	NBP	91/54 (64)													
Fluid Balance / Targets	Temp. 1	Oes. 37.0	Oes. 36.9	Oes. 36.9	Oes. 37.0	37.0	Oes. 37.0	Oes. 37.4	Oes. 37.4	Oes. 37.2	Oes. 37.2	Oes. 37.0	Oes. 36.9		
Fluids & Dietary Intake	Temp. 2	Ax. 37.0											Ax. 36.5		
Colloids	Temp. 3														
Drugs - Continuous Infus...	Bair Hugger														
Drugs - All Others	Respiratory Rate	22	25	25	25	22	22	20	18	20	18	18	18	18	17
Drug Levels	Capillary Refill	2-3 Secs		2-3 Secs		2-3 Secs	< 2 Secs		< 2 Secs		< 2 Secs		< 2 Secs		
Withdrawal score: Opioid...	General Colour	Normal		Normal		Normal	Normal	Normal	Normal	Normal	Normal	Normal	Normal	Normal	Normal
Output	CVP														
Pain	Intra-abdominal pressure														
Calcs	Cardiac Output														
PEWS	Cardiac Index														
	NIRS Channel Right Forehead														
	NIRS Channel 3 Somatic														
	Pupils, Left			2: Briskly		: Pinpoint	3: Briskly		3: Briskly		3: Briskly		3: Briskly		3: Briskly
	Pupils, Right			2: Briskly		: Pinpoint	3: Briskly		3: Briskly		3: Briskly		3: Briskly		3: Briskly
	Sedation Score			-5			-5		-5		-5		-4		-4

- Use real patient data
- Apply contemporary mathematical and computational techniques to develop an understanding of patient physiology during critical illness and recovery
- Improve methods for patient treatment
- Build an internationally-recognised, multidisciplinary and multisector Hub focused on these questions



WP1 – statistical learning from clinical data

WP2 – iteratively testing and improving biomechanical models








WP3 - learning biophysical model structure and parameters with neural networks

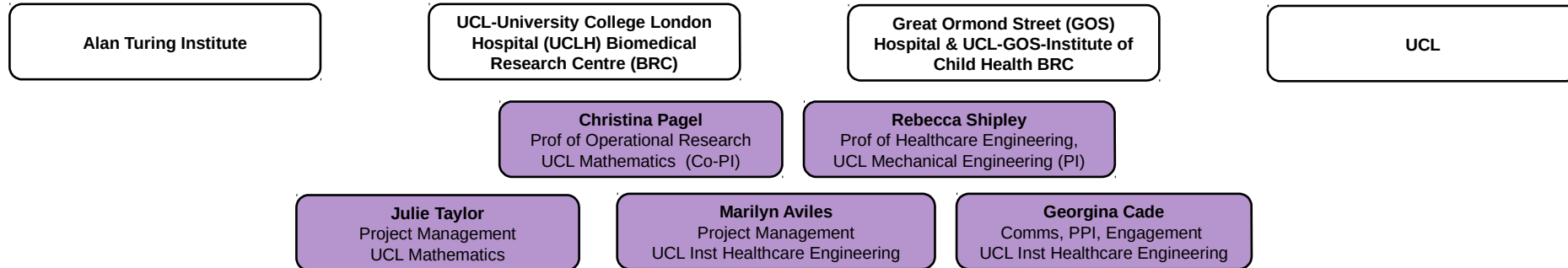
WP4 – multidisciplinary workshops, clinical and industry engagement








WP5 – data curation, infrastructure, open source data and model platforms

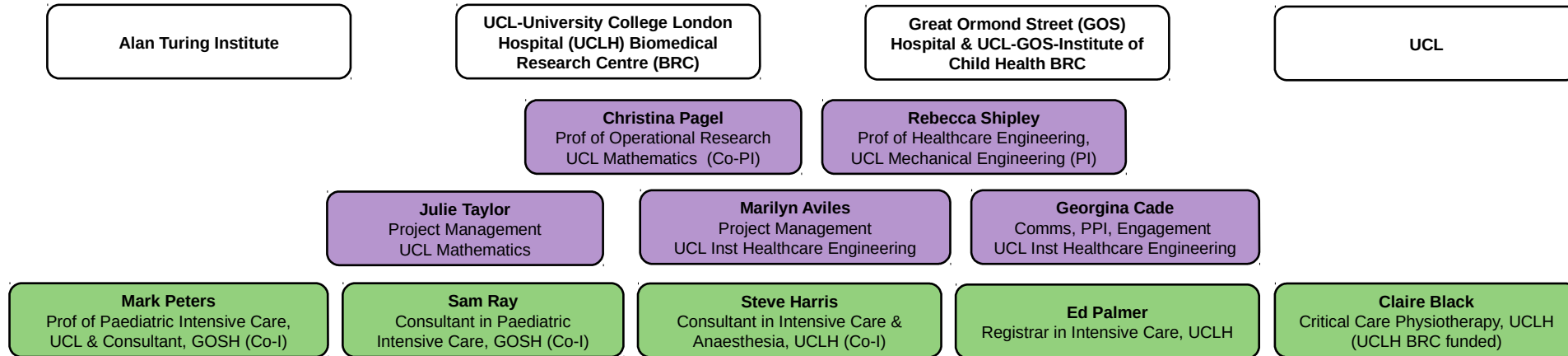
WP6 – patient and public engagement, dissemination










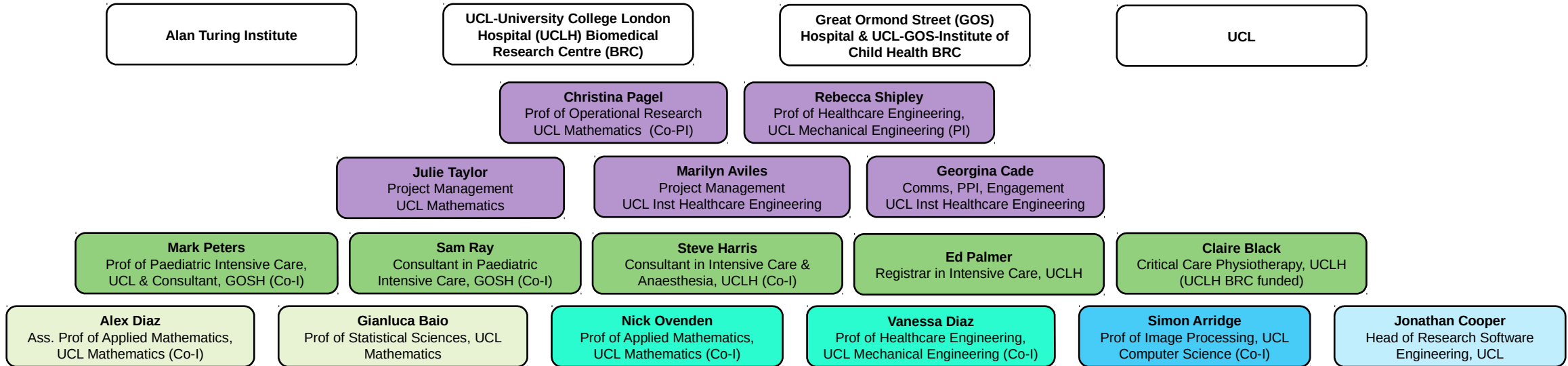
-  Project partners and host institution
-  Management, partnership building, engagement, dissemination (WP4,5,6)
-  Clinical partners
-  Statistical analysis and learning (WP1)
-  Biomechanical modelling (WP2)
-  Machine learning (WP3)
-  Critical care, clinical data (WP4,5)










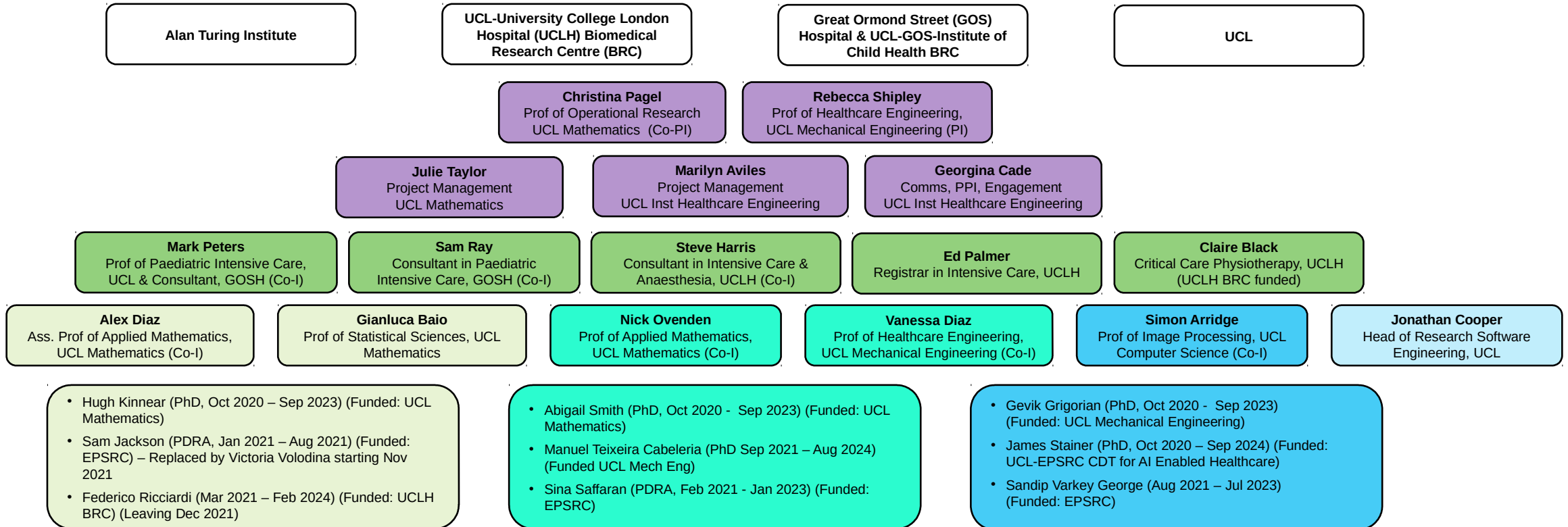
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- Officially started in Jan 2021
- PhDs and PDRAs all recruited
- Weekly meetings of investigator team since August 2020
- Fortnightly multidisciplinary meetings of full team in place since August 2020
- Monthly seminar series established – internal and external speakers
- UCL website: <https://www.ucl.ac.uk/chimera/>; Twitter: @uclchimera
- Have already developed new collaborations internal and external to UCL
- Meetings with other EPSRC Maths in Healthcare Hubs including ECR conference
- Events and workshops being held in 2022 – Turing Engagement Event, Clinical Engagement Event
- Established Research Data Services platform for data sharing of deidentified clinical data within UCL/ UCLH/ GOSH
- Ongoing developments in data governance and ethics approvals with UCLH and GOSH.

1. Constructed a Dynamic Bayesian Network to analyse the oxygen affinity state, represented by p50, in critically ill patients.
2. The proposed approach relates the control factors (lactate, ph, PCO_2) to each other and to p50 over adjacent time steps.
3. Demonstrated the importance of comprehensive uncertainty treatment, i.e. through the probabilistic coupling we have propagated the uncertainty about the control factors and accounted for this uncertainty in the predictions of the oxygen affinity state.

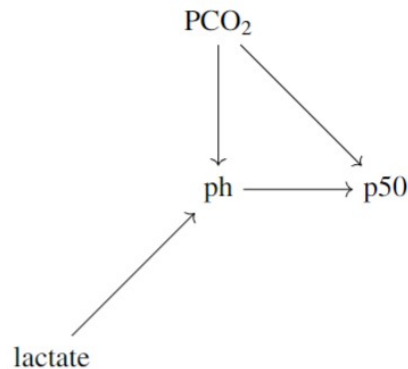


Figure: Directed acyclic graph to analyse the oxygen affinity state. Arrows represent causal effects.

- For individual patient, let $Y_t(i)$ be the value of clinical variable i at time t and the set $pa(Y_t(i))$ is the set of parents of $Y_t(i)$, these variables have an arrow to $Y_t(i)$.

The joint density for the whole network can be decomposed:

$$f(\mathbf{y}) = \prod_{t=1}^T \prod_{i=1}^n f(y_t(i) | pa(y_t(i)), D_{t-1}),$$

where D_{t-1} denotes the information available at $t - 1$. To model individual variables conditioned on its parents set, we use a Dynamic Linear Model.

To produce the short-term forecast, we propose to only consider the first two moments:

$$E[Y_t(i) | D_{t-1}] = E[E(Y_t(i) | pa(Y_t(i)), D_{t-1}) | D_{t-1}]$$

$$V[Y_t(i) | D_{t-1}] = E[V(Y_t(i) | pa(Y_t(i)), D_{t-1}) | D_{t-1}] + V[E(Y_t(i) | pa(Y_t(i)), D_{t-1}) | D_{t-1}]$$

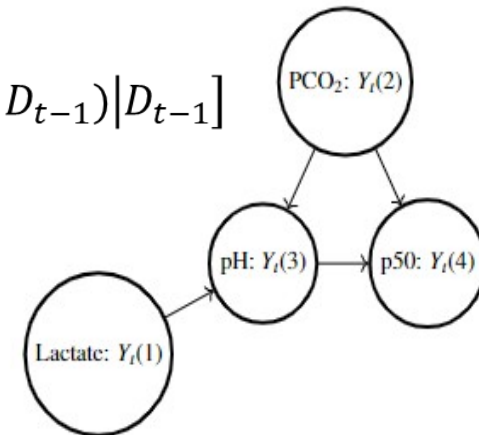


Figure 2: Naive DAG for the analysis of oxygen affinity state in ICU patients.

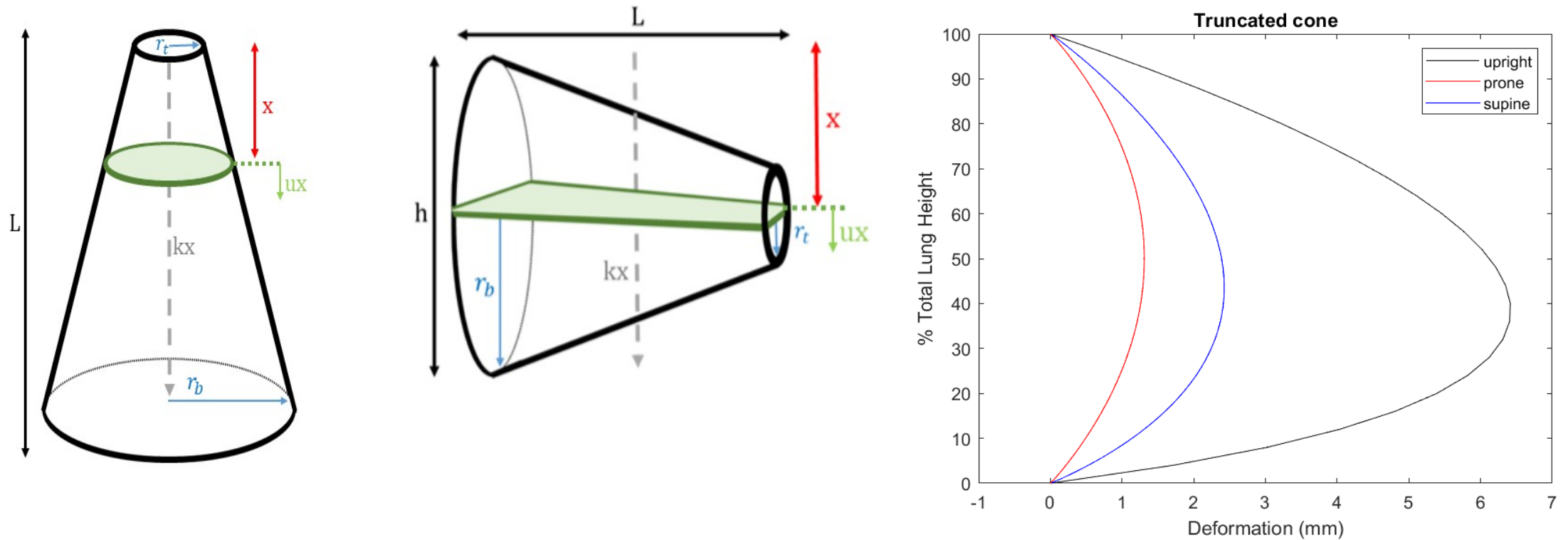
Future work

Incorporate information about medical treatment by suitable intervention into the model to explain abrupt structural changes.

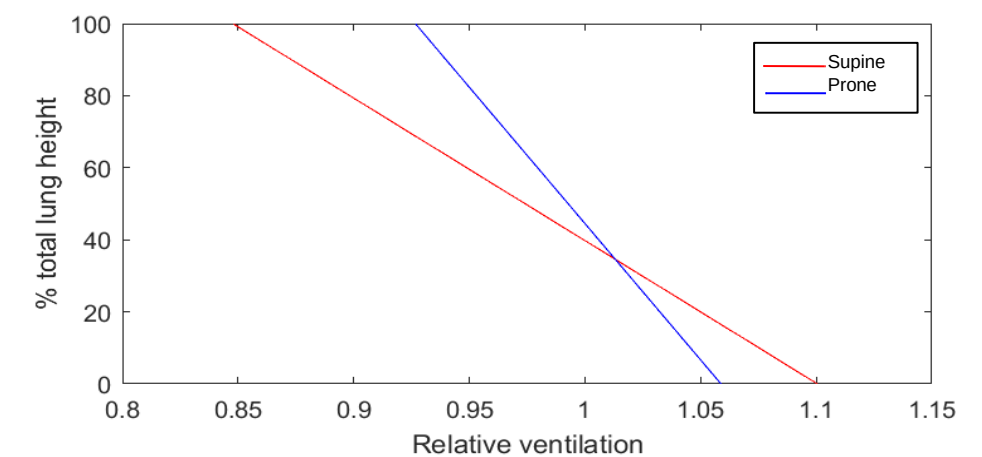
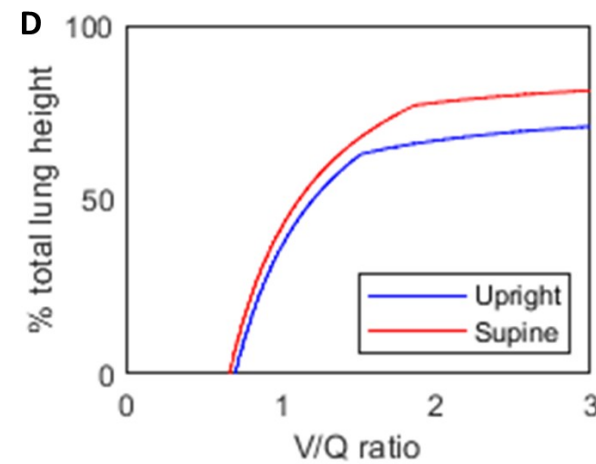
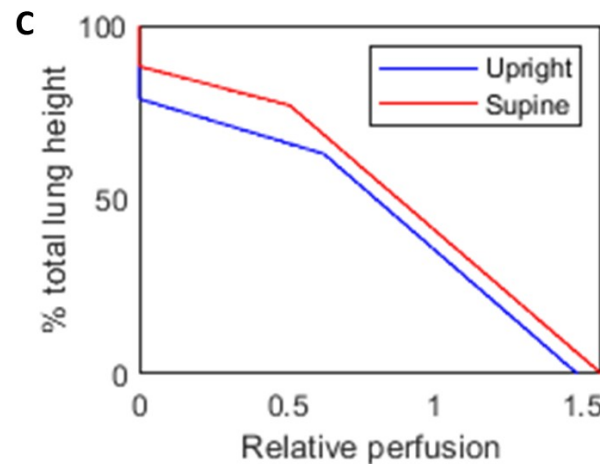
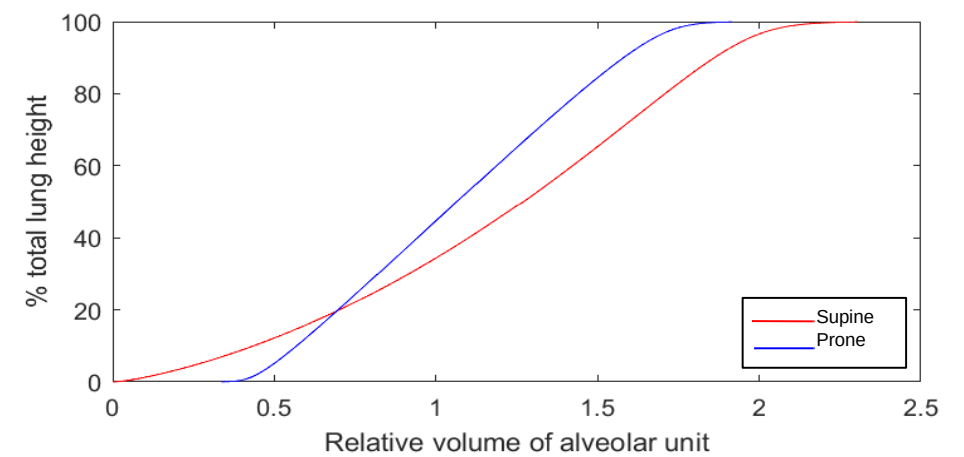
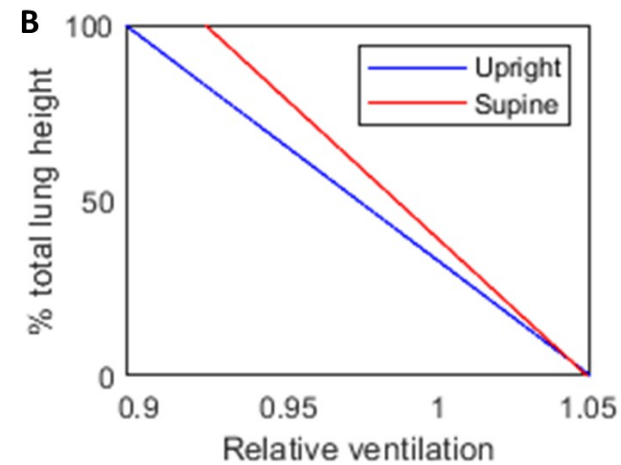
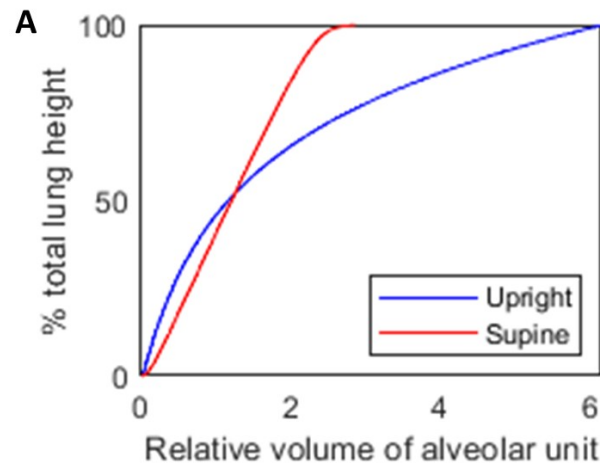
If such information is not available, modify the network model to handle these events automatically.

Specifying a Bayesian inverse problem to improve p50 values produced by a blood gas analyser machine for clinically ill patients.

Use of solid mechanics to simulate tissue deformation in the lung under its own weight.

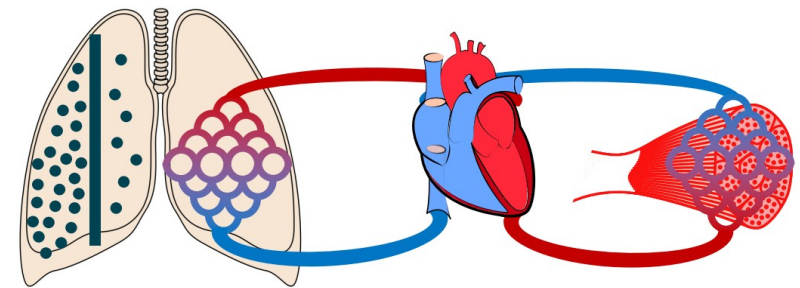
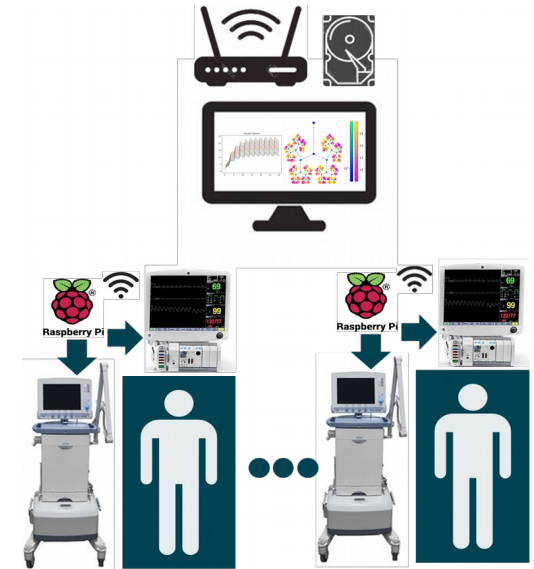


Calculation of regional ventilation and perfusion.



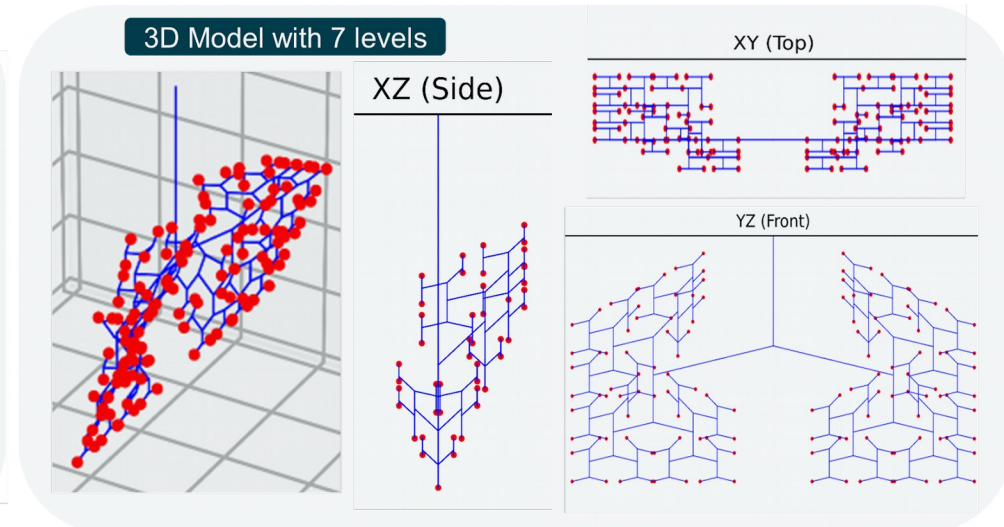
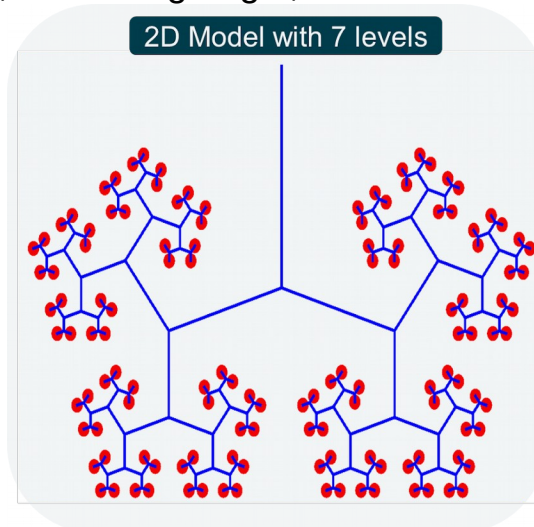
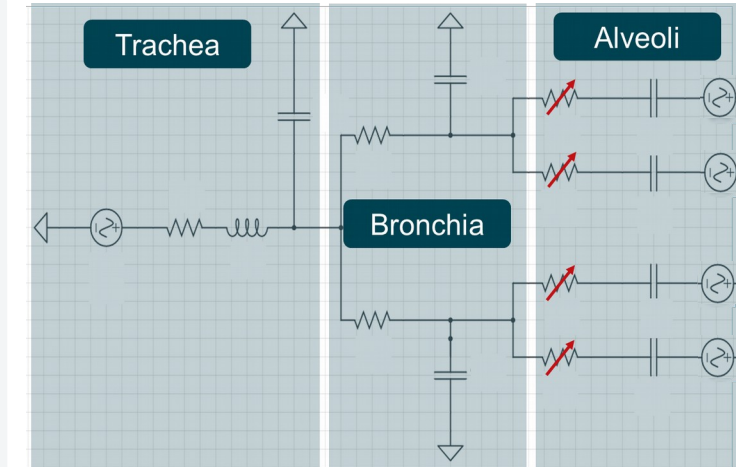
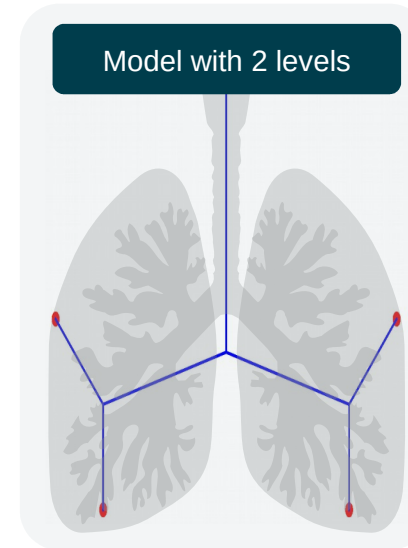


- A software that can be used at the bedside
- Implements a mathematical model of the cardiorespiratory system, optimised to the patient
- The effects of treatments can be simulated in real-time prior to being applied to the patient
- The evolution of the patient during ICU stay can be monitored
- Parameter estimation in real-time (ex. Blood gases and pH)



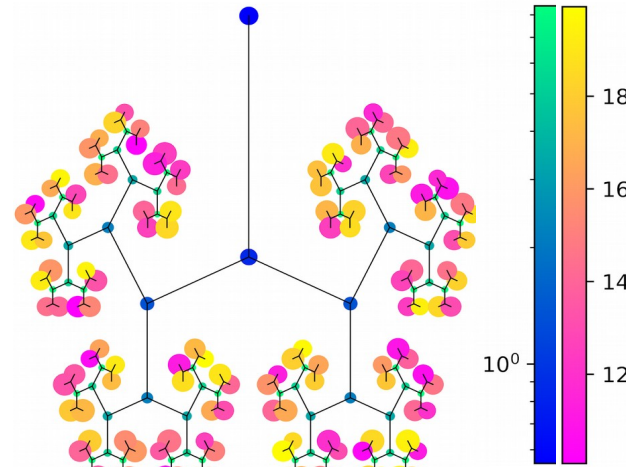
Lung Model

- Lumped parameter model of the lung incorporating branching of the bronchia,
- Systems of equations and 2D/3D models are generated automatically using a set of initial conditions:
 - # Levels, Length and Radius of the trachea, Branching angle, Length decay, Min/Max R and C
- The model can be imbued with extrinsic pressures at the alveoli level to simulate the effect of gravity and autonomic control features

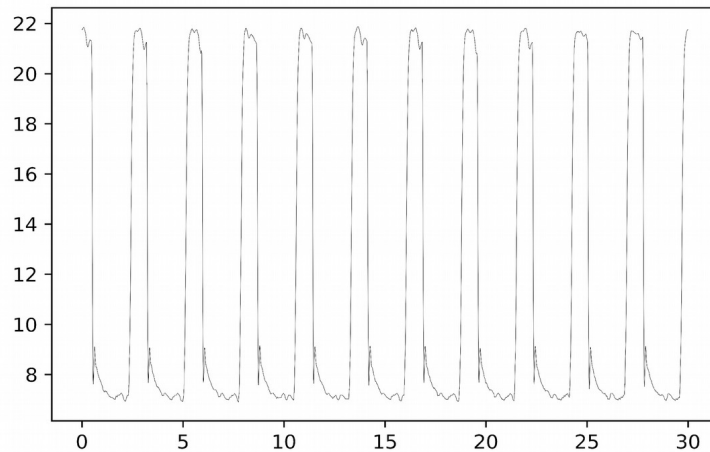


Preliminary Results

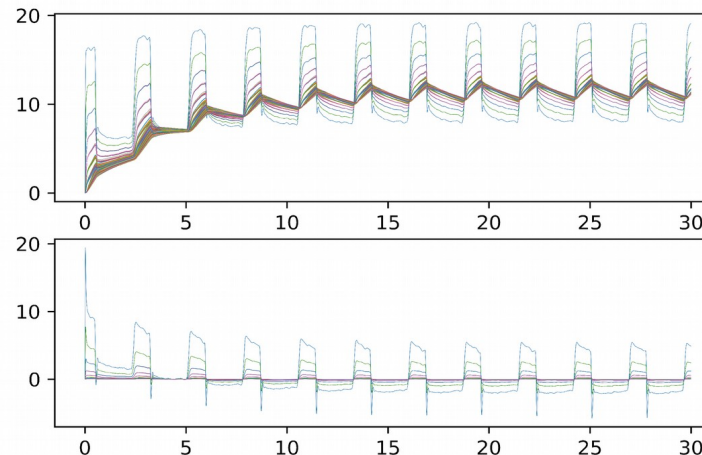
- length: 0.12
- radius: 0.01
- maxLevels: 7
- branchAngle: $\pi/2.5$
- lengthDecay: 1.6
- mode: random
- resStart: 10
- resEnd: 20
- capStart: 0.01
- capEnd: 0.02



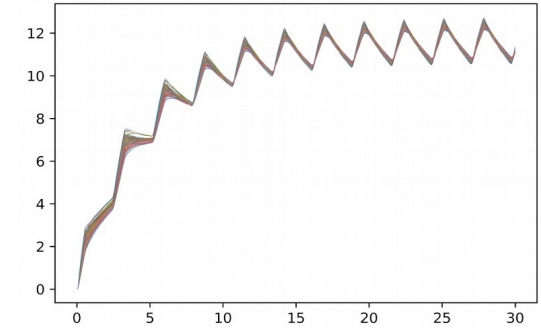
Input: Pressure wave from a ventilator



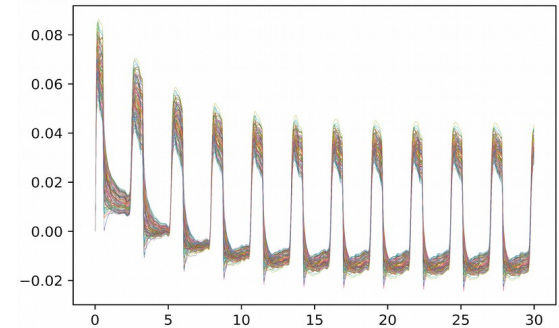
Pressure (top) and Flows of the lung



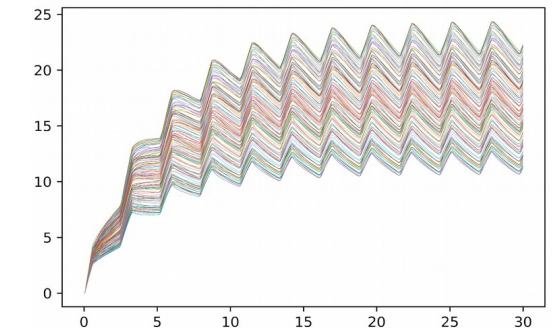
Alveoli Pressures



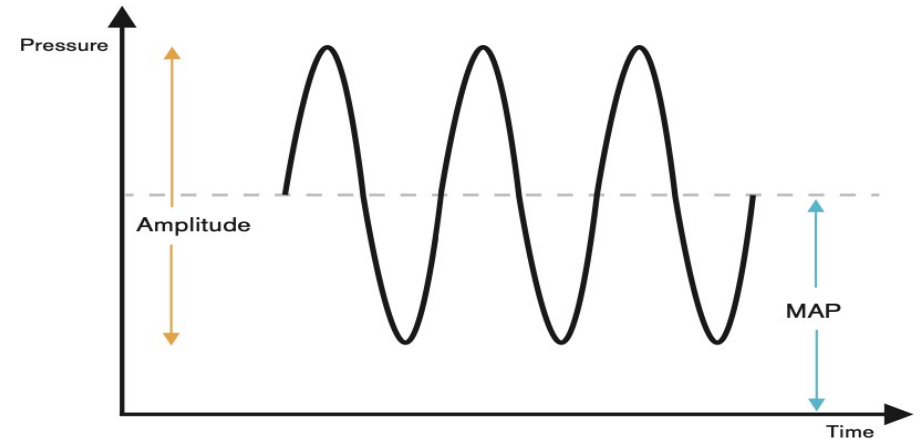
Alveoli Flows



Alveoli Volume

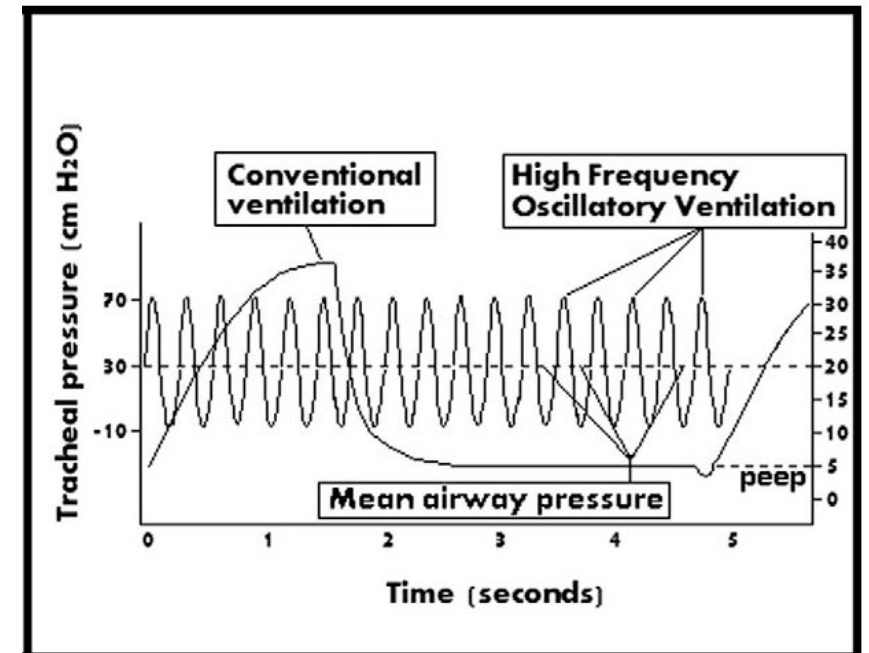


- HFOV is an alternative method of mechanical ventilation which can be used as a **'lung protective strategy'** in the management of some severe lung conditions.

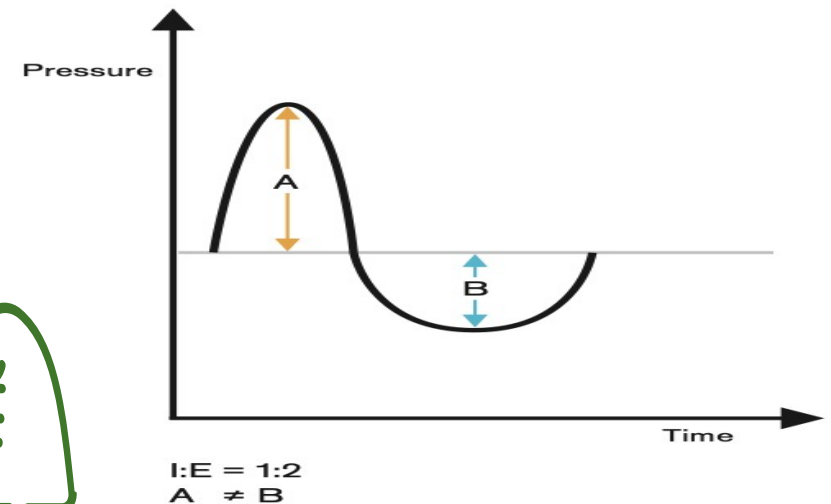
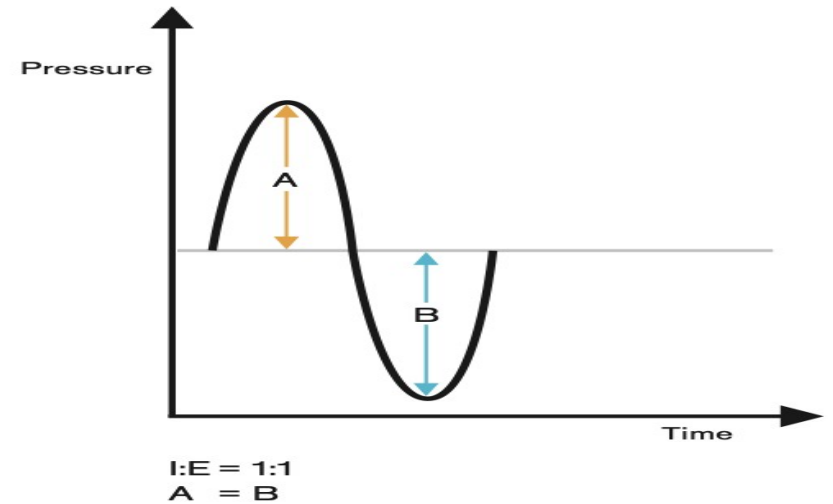
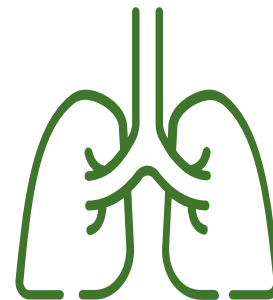


- How it works?

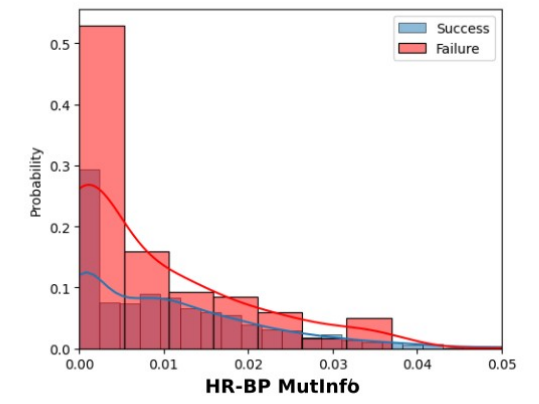
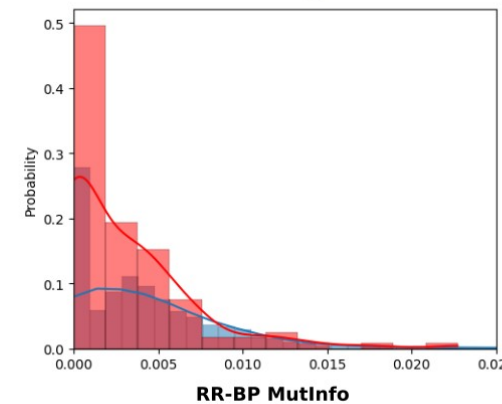
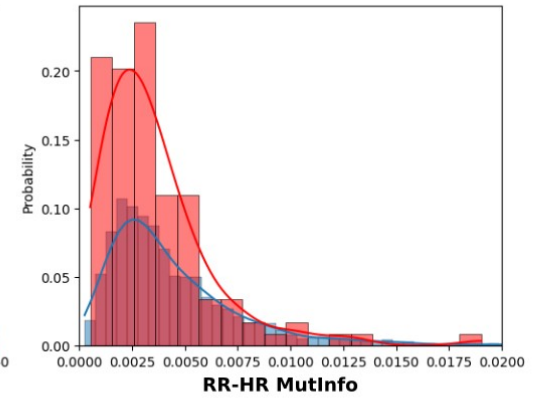
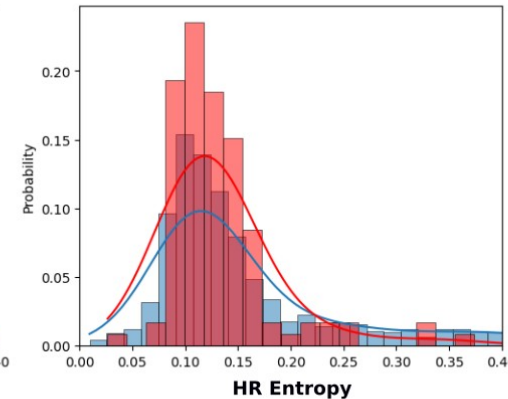
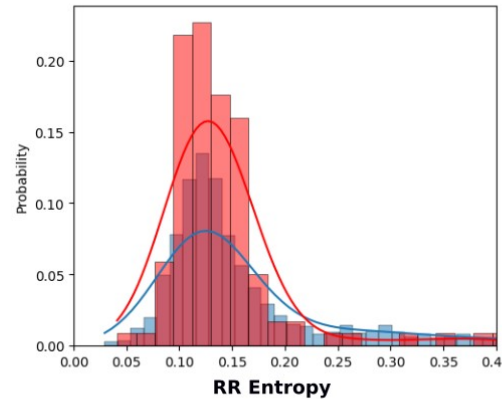
A constant distending airway pressure (MAP) is applied, over which small tidal volumes (less than dead space) are superimposed at a high respiratory frequency (3-15 Hz).



- Gas mixing during CV is primarily dependent on direct ventilation, requiring tidal volumes larger than the deadspace.
- In sharp contrast to CV, HFOV offers highly effective oxygenation and clearance of waste gas, despite use of sub-dead-space tidal volumes.
- The efficiency of HFOV in ventilating the lung at very low tidal volumes is attributed to highly effective mixing of fresh and exhaled gases in the airways and alveolar compartment.

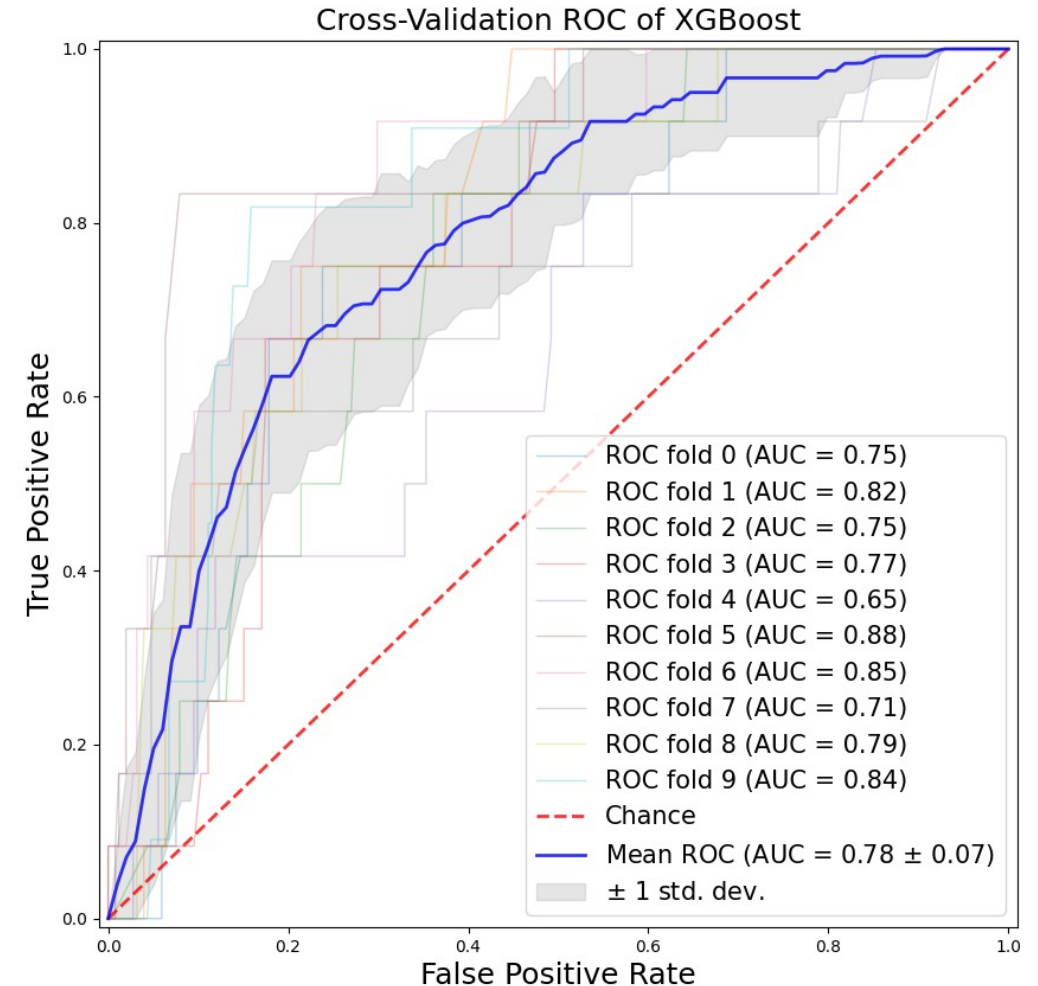


- Calculate nonlinear measures of ICU time series 24 hours before extubation.
- Compare between failed and successful extubation groups
- ICU time series data
 - Heart rate (HR)
 - Respiratory rate (RR)
 - Blood pressure (BP)
- Nonlinear measures
 - Fractal dimension
 - Multiscale entropy
 - Mutual information
- 5 of 9 measures showed a difference between the groups.
 - Entropy of RR and HR
 - Mutual information between
 - HR and RR
 - HR and BP
 - RR and BP



- Predict extubation outcome using machine learning models
- Models compared between feature sets
 - Without complex measures (Basic)
 - With complex measures (Added)

Model	AUC (Basic)	AUC (Added)
Support vector machine	.73 ± .04	.74 ± .04
Artificial neural network	.72 ± .05	.74 ± .01
Random Forest	.74 ± .05	.75 ± .05
Light Gradient Boosting Machine	.77 ± .04	.77 ± .04
Extreme Gradient Boosting Machine	.74 ± .01	.78 ± .07



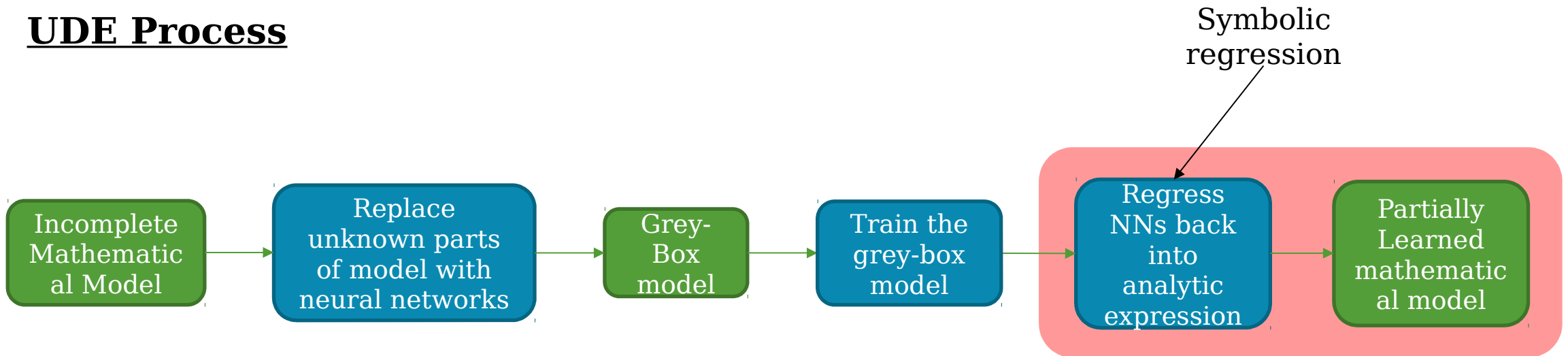
When and How to Use Grey-Box Models

- Complex mathematical models can be incomplete due to difficulties in calculating certain parameter values and/or gaps in existing knowledge.
- For incomplete models, it is possible to **replace the unknown parts of the mathematical model with neural networks**. This is a grey-box model.
- Most of the structure of the dynamics (equations) are still known, so the grey-box model doesn't require as much data as the black-box neural network → data efficient.
- This is a powerful tool for long term prediction when the mathematical model is incomplete.

Universal Differential Equations:

1. Replace unknown terms in a system of ODEs with neural networks.
2. Regress trained neural networks back into mechanistic form.

UDE Process



Experiment: Lorenz Equations

Original Model

$$\begin{aligned} \frac{dx}{dt} &= 10(y - x) \\ \frac{dy}{dt} &= x(28 - z) - y \\ \frac{dz}{dt} &= xy - \frac{8}{3}z \end{aligned}$$

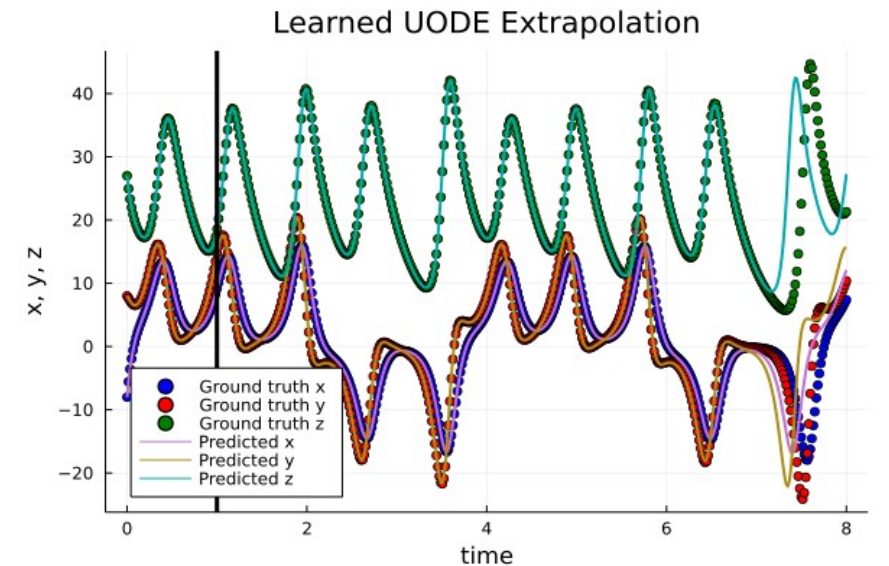
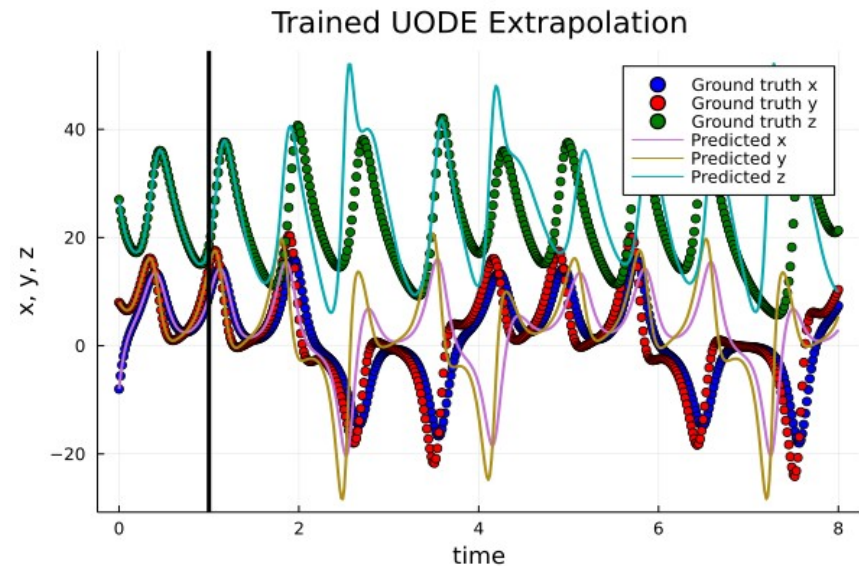
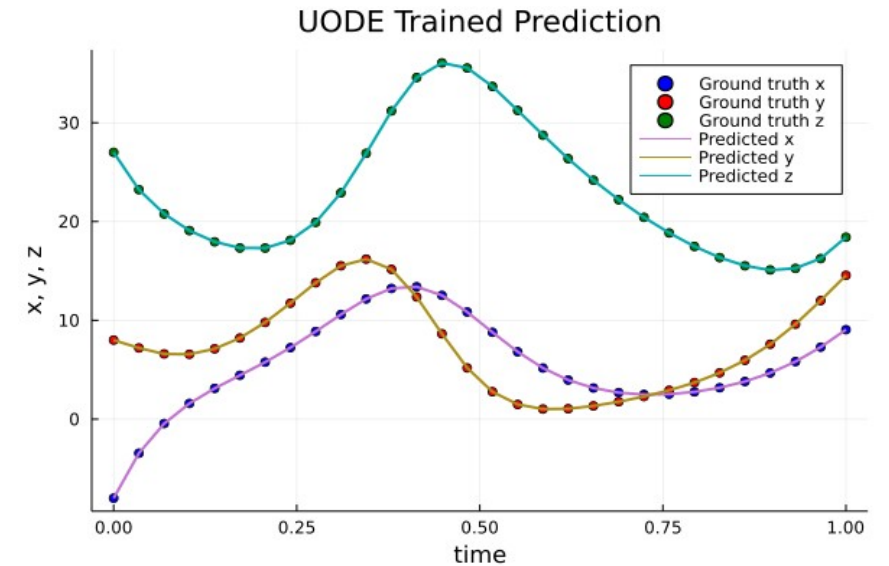
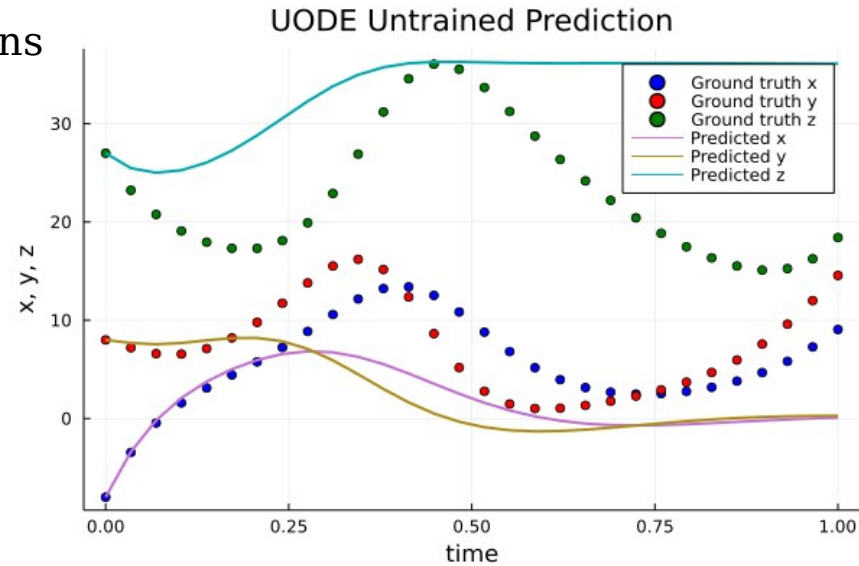
Grey-Box Model

$$\begin{aligned} \frac{dx}{dt} &= 10(y - x) \\ \frac{dy}{dt} &= x(28 - z) + NN_1 \\ \frac{dz}{dt} &= xy + NN_2 \end{aligned}$$

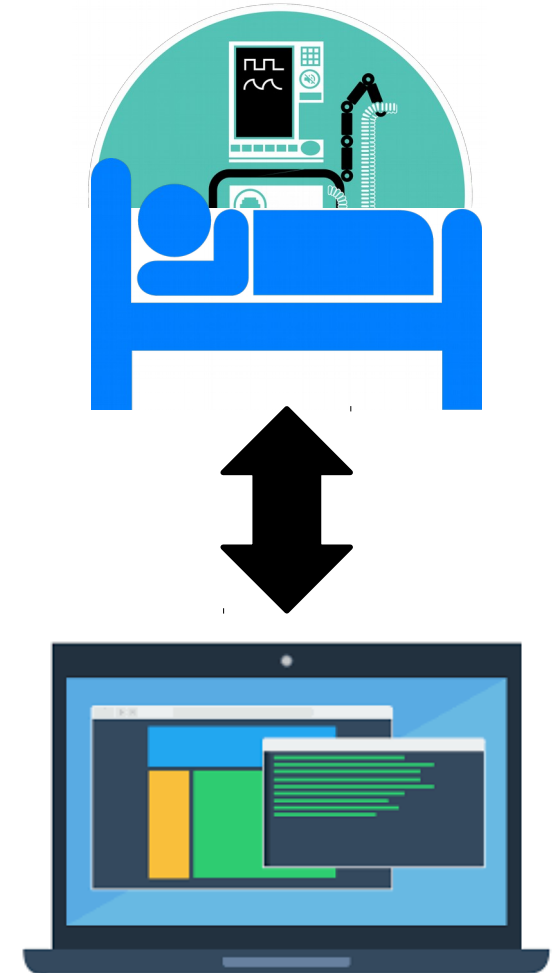
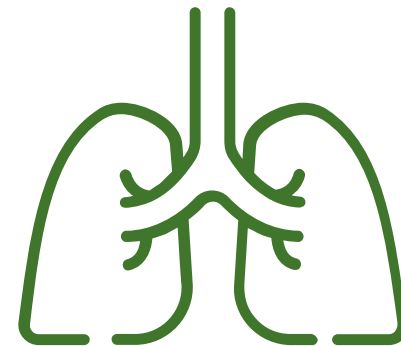
Learned Terms

$$NN_1 \rightarrow -0.9990727y$$

$$NN_2 \rightarrow -2.6667087z$$



- **WP1 and WP2:** Employing emulators and history matching to speed up performance of parameter fitting.
- **WP2 and WP3:** Using the grey box approach to determine suitable biomechanical twin model components that mimic given patient data.
- **WP1 and WP3:** Predictive tools using complexity measures.



Directors

Prof Becky Shipley (Mech Eng, UCL)
Prof Christina Pagel (CORU, UCL)

WP1

Dr Alex Diaz (CORU, UCL)
Dr Victoria Volodina (CORU, UCL)
Hugh Kinnear (CORU, UCL)
Prof Jim Smith (Warwick)

WP2

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Prof Nicholas Ovenden (Maths, UCL)
Dr Sina Saffaran (Mech Eng, UCL)
Abi Smith (Maths, UCL)
Manuel Teixeira Cabeleira (Mech Eng, UCL)

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Dr Sandip George (Comp Sci, UCL)
Gevik Grigorian (Comp Sci, UCL)

Clinicians

Dr Claire Black (UCLH)
Dr Steve Harris (UCLH)
Prof Mark Peters (GOSH)
Dr Samiran Ray (GOSH)

		Year 1	Year 2	Year 3	Year 4
<i>Work Packages</i>					
WP1	Statistical Learning from Clinical Data (A Diaz)				
WP1.1	Missing data				
WP1.2	Sequential parameter estimation				
WP1.3	Hierarchical modelling				
WP2	Testing and Improving Biomechanical Models through an Iterative Learning Loop (Ovenden/ V Diaz)				
WP2.1	Initial assessment of biomechanical models				
WP2.2	Validation and selection via tracking observations				
WP2.3	Classify patient risk through machine learning				
WP3	Learning Biophysical Model Structure and Parameters with Neural Networks (Arridge)				
WP3.1	Framework for learned coupled non-linear differential equations				
WP3.2	Learned network model for electro-mechanical cardiac dynamics				
WP3.3	Learned network model incorporating other organs				
WP4	Multidisciplinary Workshops, Clinical and Industry Engagement (Shipley/ Pagel/ Aviles/ Cade/ Ray/ Peters/ Harris)				
WP4.1	Distribution of partnership resource				
	Co-production of selection process for allocation of partnership resource				
	Project panels for allocation of PDRA and PhD resource				
	Project panels for allocation of seedcorn funding				
WP4.2	Multidisciplinary workshop programme engaging new clinical, academic and industry partners (including ATI DSG in year 3)				
WP4.3	Funding bids by investigator team, project partners to grow the CHIMERA base and support long-term vision				
WP5	Data Curation, Infrastructure, Open Source Data and Model Platforms (Shipley/ Arridge/ Ray/ Peters/ Harris)				
WP5.1	Data curation and infrastructure development				
WP5.2	Open source data libraries, synthetic data and model platform development				
WP6	Patient and Public Engagement, Dissemination (Pagel/ Shipley/ Cade/ Aviles)				
WP6.1	Patient and public involvement (PPI) - workshops (year 3/4), researcher training, hosting blogs, Twitter live chats				
WP6.2	Dissemination of hub outputs - publications, conferences website, newsletter series, social media, seminar/ webinar series				