EINN: Epidemic Prediction using ML

Mert Saruhan, B.Sc.

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HOCHSCHULE MITTWEIDA
University of Applied Sciences

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1. What is EINN?
2. Background
3. EINN Schema
4. Results

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Introduction

- EINN is a (**Neural Network**) machine learning model to predict epidemic dynamics [1]
- EINN combines the knowledge of PINN, RNN, and ODE [1]

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SIR epidemic models

- Statical way to predict epidemic dynamics
- Uses ODE to predict
- Have many models: SIR, SEIR, SEIRM etc.
- Susceptible (S): $\frac{dS_t}{dt} = -\beta_t \frac{S_t I_t}{N}$
- Exposed (E): $\frac{dE_t}{dt} = \beta_t \frac{S_t I_t}{N} - \alpha_t E_t$
- Infected (I): $\frac{dI_t}{dt} = \alpha_t E_t - \gamma_t I_t - \mu_t I_t$
- Recovered (R): $\frac{dR_t}{dt} = \gamma_t I_t$
- Mortality (M): $\frac{dM_t}{dt} = \mu_t I_t$

Note: $\Omega_t = \{\alpha_t, \beta_t, \gamma_t, \mu_t\}$ are parameters, N is the population number, and t is time.

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RNN

- RNN is a neural network model
- Uses the previous state as an input to predict the next state
- Used in object detection and NLP

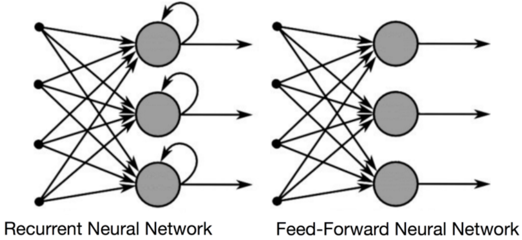

Figure: Example structure of RNN and NN [2]

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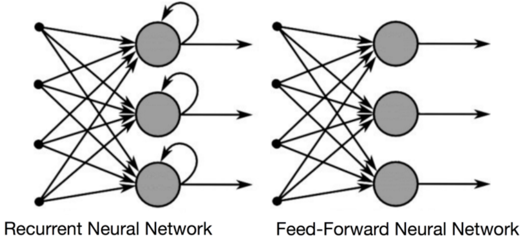

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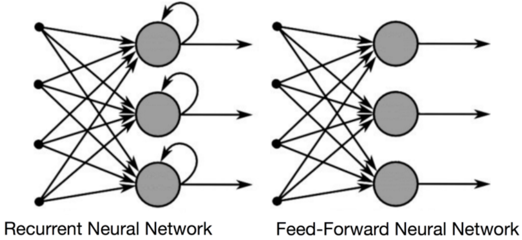

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Background

PINN

- Uses physics laws to predict the next state
- Uses PDE (partial differential equation) and ODE (ordinary differential equation) as a loss estimator
- L_{data}: loss from data fitting
- $L_{physics}$: loss from physics laws

  e.g. $\vec{a} = -\mu \|\vec{v}\| \vec{v} - \vec{g}, \vec{v} = \frac{df}{dt}, \vec{a} = \frac{d^2 f}{dt^2}$

  $L_{physics} = \frac{1}{N} \sum_{i=0}^{N-1} (-\mu \| \frac{df_i}{dt_i} \| \frac{df_i}{dt_i} - \vec{g} - \frac{d^2 f_i}{dt_i^2})^2$
- $L_{total} = L_{data} + L_{physics}$

Note: $\vec{a}$ is acceleration, $\vec{v}$ is velocity, $\vec{g}$ is gravity, μ is friction, f is position, t is time, and N is the number of data points.

Background

PINN for Systems Biology

- Recent works with PINN for Systems Biology [3, 4] enables ODE for PINN
- Uses time t as input for Neural Network $N(t)$ and rate of change in ODE systems $f_{\text{ODE}}(t)$
- Uses $(\frac{dN(t)}{dt} - f_{\text{ODE}}(t))$ as a loss

EINN Schema

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Model summary

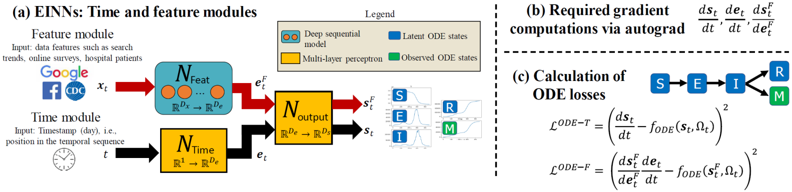

Figure: EINN Schema. (a) The training model. (b) Needed gradients to train the model using autograd. (c) ODE losses of feature module and time module. Taken from: [1]

EINN Schema

Source model (Time module)

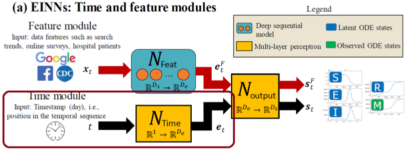

Figure: Cropped model summary showing the training summary. Cropped from: [1]

- Source model is a PINN model
- Input: time
- Output: embedding of the epidemic ODE states (D_e is the lenght of e_t)
- Uses PINN for Systems Biology loss
- Uses autograd to compute loss

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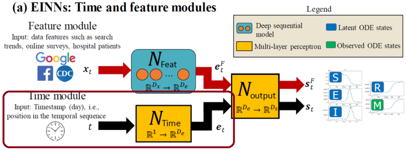

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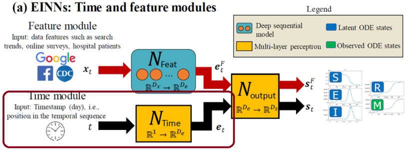

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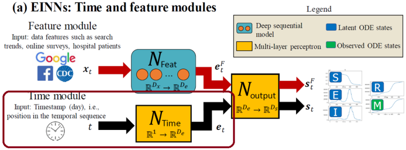

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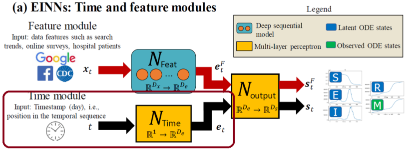

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Results

Bibliography I

[1] A. Rodríguez, J. Cui, N. Ramakrishnan, B. Adhikari, and B. A. Prakash, *Einns: Epidemiologically-informed neural networks*, 2023. DOI: 10.48550/arXiv.2202.10446. arXiv: 2202.10446 [cs.LG].

[2] *A guide to recurrent neural networks: Understanding rnn and lstm networks*, https://builtin.com/data-science/recurrent-neural-networks-and-lstm, Accessed: 2023-11-26.

[3] A. Yazdani and et al., *Systems biology informed deep learning for inferring parameters and hidden dynamics*. PLOS Comp. Bio., 2020.

[4] G. Karniadakis and et al., *Physics-informed machine learning*, 2021.

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University of Applied Sciences

Thank You

Mert Saruhan, B.Sc.

msaruhan@hs-mittweida.de

Mathematics for Network and Data Science (MA20w1-M)

Hochschule Mittweida
University of Applied Sciences
Technikumplatz 17 | 09648 Mittweida

hs-mittweida.de