Dynamic Graph Machine Learning for Early Detection of Antimicrobial Resistant Outbreaks

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Imperial College London

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Introduction

– Explain disease propagation using graphs

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- Predict spread using machine learning

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- Predict spread using machine learning
- Determine intervention strategies

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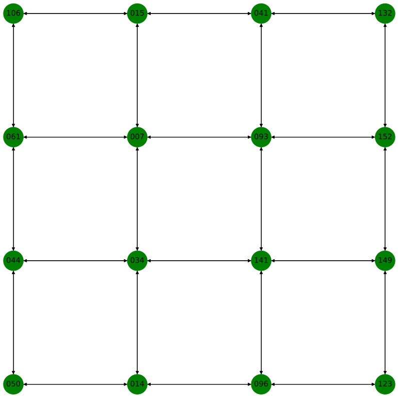

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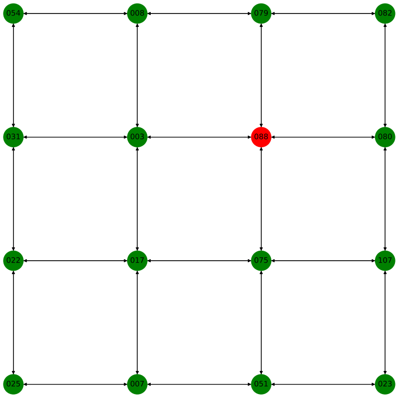

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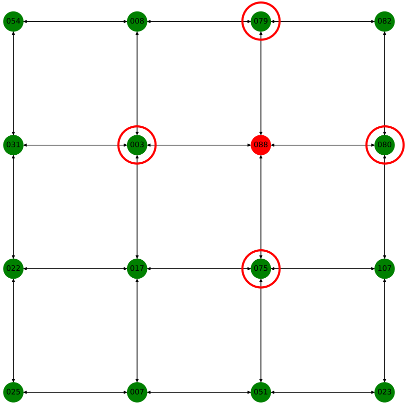

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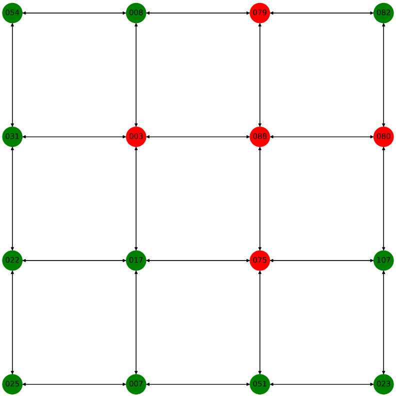

Data and Graphs

Column Name	**Data Type**
patient id	`str`
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discharge time	`datetime`
bed number	`int`
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- Each node $v_i \in \mathcal{V}$ contains a set of features h_i

Dynamic Graphs

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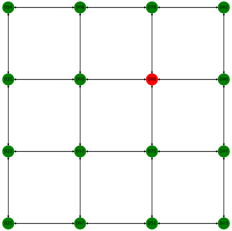
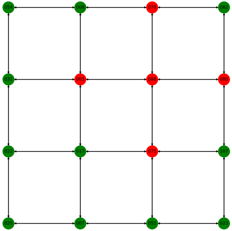
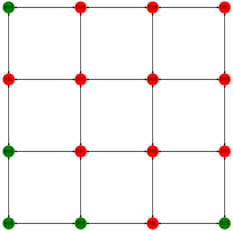


$t = 0$ $(\mathcal{G}^0)$



$t = 1$ $(\mathcal{G}^1)$



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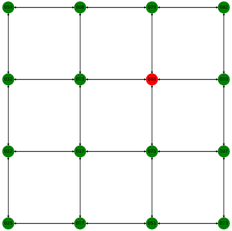

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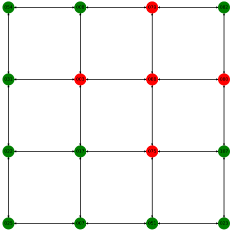

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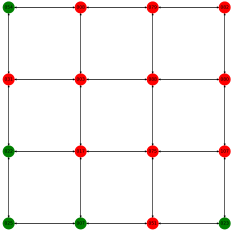

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– Given $\mathcal{G}^0, \mathcal{G}^1, \mathcal{G}^2$ predict $\mathcal{G}^3$

Dynamic Graphs

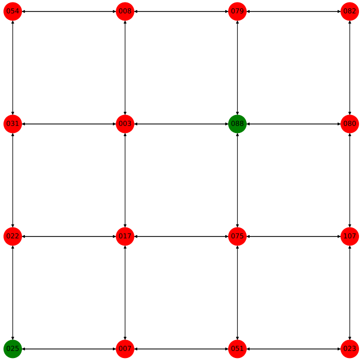

Figure: $\mathcal{G}^3$

Machine Learning

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  - → Incorporate features of neighbouring nodes and gain information about position in the graph
- Multiply by (learnable) weight matrix and apply activation function to predict node labels

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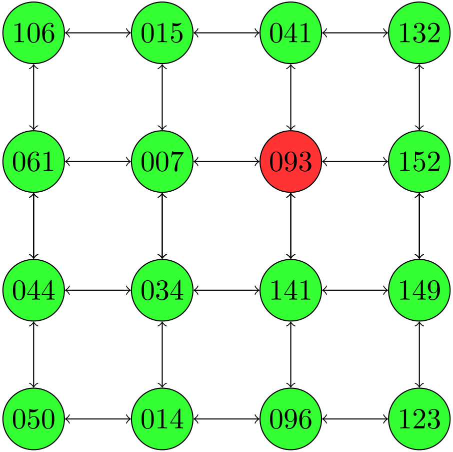

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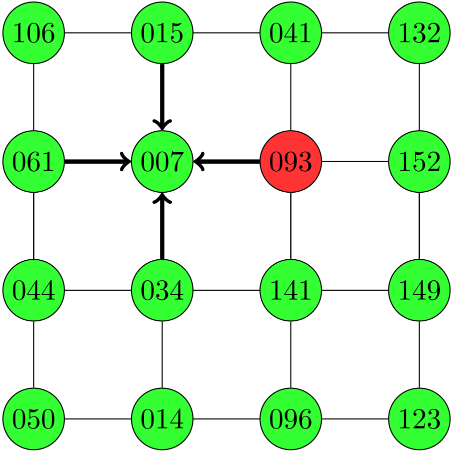

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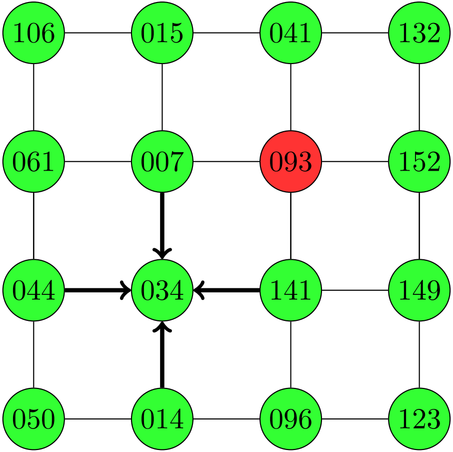

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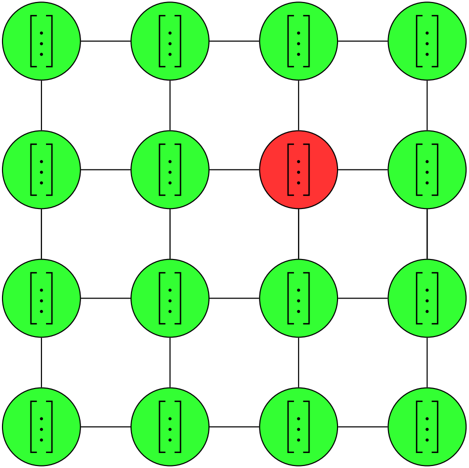

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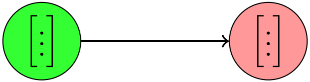
$$h_i^{(l+1)} = \sigma\left(\sum_{j \in \mathcal{N}(i)} \frac{1}{c_{ji}} h_j^{(l)} W^{(l)}\right)$$



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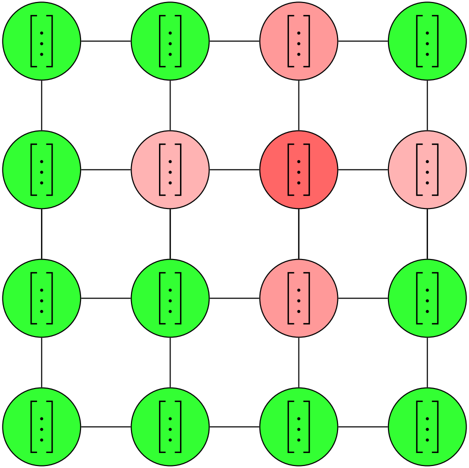

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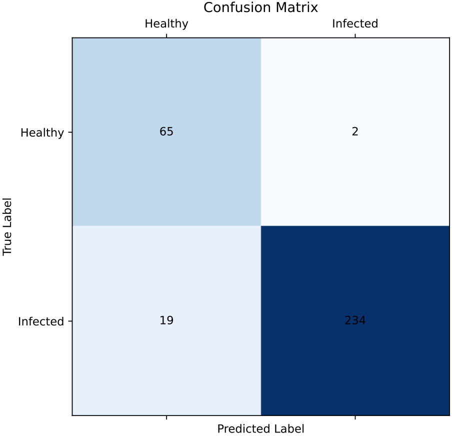
- Validate on test set

Results



Accuracy: ~ 0.95

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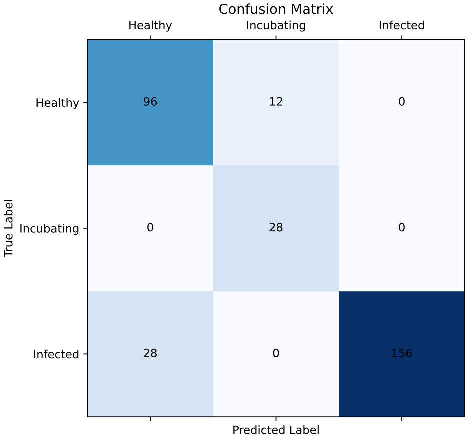

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- (Roughly) captures incubation time

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- Extend beyond a single ward

Further Thoughts

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- Modelled without in-depth understanding of how wards are run

Questions?

– Any questions?