

HERIOT-WATT UNIVERSITY

MASTERS THESIS

---

# Thesis Title

---

*Author:*

John SMITH

*Supervisor:*

Dr. James SMITH

*A thesis submitted in fulfilment of the requirements  
for the degree of MSc.*

*in the*

School of Mathematical and Computer Sciences

January 2023



# Declaration of Authorship

I, John SMITH, declare that this thesis titled, 'Thesis Title' and the work presented in it is my own. I confirm that this work submitted for assessment is my own and is expressed in my own words. Any uses made within it of the works of other authors in any form (e.g., ideas, equations, figures, text, tables, programs) are properly acknowledged at any point of their use. A list of the references employed is included.

Signed:

---

Date:

---

*“Thanks to my solid academic training, today I can write hundreds of words on virtually any topic without possessing a shred of information, which is how I got a good job in journalism.”*

Dave Barry

# *Abstract*

The Thesis Abstract is written here (and usually kept to just this page).

# *Acknowledgements*

The acknowledgements and the people to thank go here, don't forget to include your project advisor :)

# Contents

<b>Declaration of Authorship</b>	<b>i</b>
<b>Abstract</b>	<b>iii</b>
<b>Acknowledgements</b>	<b>iv</b>
<b>Contents</b>	<b>v</b>
<b>List of Figures</b>	<b>vii</b>
<b>List of Tables</b>	<b>viii</b>
<b>Abbreviations</b>	<b>ix</b>
<b>Symbols</b>	<b>x</b>
<b>1 Introduction</b>	<b>1</b>
1.1 Welcome and Thank You . . . . .	1
<b>2 Outline and Fundamentals</b>	<b>2</b>
2.1 Graph Signal Processing . . . . .	2
2.1.1 A broad overview of the field . . . . .	2
2.1.2 The graph Laplacian . . . . .	2
2.1.3 Graph filters . . . . .	2
2.2 Regression and Reconstruction . . . . .	2
2.2.1 Graph Signal Reconstruction . . . . .	2
2.2.2 Kernel Graph Regression . . . . .	2
2.2.3 Regression with Network Cohesion . . . . .	2
2.3 Thesis overview . . . . .	2
<b>3 Kernel Generalized Least Squares Regression for Network Data</b>	<b>3</b>
3.1 Kernel Graph Regression with Missing Values . . . . .	3
3.2 GLS Kernel Graph Regression . . . . .	3
3.2.1 A Gauss-Markov estimator . . . . .	3
3.2.2 AR(1) processes . . . . .	3

3.2.3	Experiments . . . . .	3
<b>4</b>	<b>Regression and Reconstruction on Cartesian Product Graphs</b>	<b>4</b>
4.1	Introduction . . . . .	4
4.2	Graph Signal Reconstruction on Cartesian Product Graphs . . . . .	4
4.2.1	A stationary iterative method . . . . .	4
4.2.2	A conjugate gradient method . . . . .	4
4.2.3	Convergence properties . . . . .	4
4.2.4	Image processing experiments . . . . .	5
4.3	Kernel Graph Regression with Unrestricted Missing Data Patterns . . . . .	5
4.3.1	Cartesian product graphs and KGR . . . . .	5
4.3.2	Convergence properties . . . . .	5
4.4	Regression with Network Cohesion . . . . .	5
4.4.1	Regression with node-level covariates . . . . .	5
4.4.2	Convergence properties . . . . .	5
4.5	Multi-Dimensional Cartesian Product Graphs . . . . .	5
4.5.1	Fast computation with $d$ -dimensional Kronecker products . . . . .	6
4.5.2	Signal reconstruction . . . . .	6
4.5.3	Kernel Graph Regression . . . . .	6
4.5.4	Regression with Network Cohesion . . . . .	6
<b>5</b>	<b>Signal Uncertainty: Estimation and Sampling</b>	<b>7</b>
5.1	Introduction . . . . .	7
5.2	Posterior Estimation . . . . .	7
5.2.1	Log-variance prediction . . . . .	7
5.2.2	Estimation models . . . . .	7
5.2.3	Query strategies . . . . .	7
5.2.4	Comparison and analysis . . . . .	7
5.3	Posterior Sampling . . . . .	7
5.3.1	Perturbation optimization . . . . .	7
5.4	Estimation vs Sampling . . . . .	7
5.4.1	Experiments . . . . .	7
<b>6</b>	<b>Working with Binary-Valued Graph Signals</b>	<b>8</b>
6.1	Logistic Graph Signal Reconstruction . . . . .	8
6.2	Logistic Kernel Graph Regression . . . . .	8
6.3	Logistic Regression with Network Cohesion . . . . .	8
6.4	Approximate Sampling via the Laplace Approximation . . . . .	8
<b>7</b>	<b>Conclusions</b>	<b>9</b>
7.1	Main Section 1 . . . . .	9
<b>A</b>	<b>Appendix Title Here</b>	<b>10</b>

# List of Figures



# List of Tables

# Abbreviations

**LAH** List Abbreviations **Here**

# Symbols

Unless otherwise specified, the following naming conventions apply.

## Scalar constants

$N$	The number of nodes in a graph
$T$	The number of time points considered
$M$	The number of explanatory variables
$Q$	The number of queries

## Scalar variables

$\alpha$	An autocorrelation regularisation parameter
$\beta$	A hyperparameter characterising a graph filter
$\gamma$	A precision parameter
$\lambda$	An eigenvalue <i>or</i> ridge regression penalty parameter
$\mu$	The mean of a random variable
$\theta$	AR(1) autocorrelation parameter
$\sigma^2$	The variance of a random variable

## Matrices

<b>A</b>	The graph adjacency matrix
<b>D</b>	A diagonal matrix
<b>E</b>	The prediction residuals
<b>F</b>	A predicted graph signal
<b>G</b>	A graph filter
<b>H</b>	A Hessian matrix
<b>I</b>	The identity matrix

<b>K</b>	A kernel (Gram) matrix
<b>L</b>	The graph Laplacian
<b>S</b>	A binary selection matrix
<b>U</b>	Laplacian eigenvector matrix
<b>V</b>	Kernel eigenvector matrix
<b>X</b>	Data matrix of explanatory variables
<b>Y</b>	(Partially) observed graph signal
<b><math>\Lambda</math></b>	A diagonal eigenvalue matrix
<b><math>\Sigma</math></b>	A covariance matrix
<b><math>\Phi</math></b>	Auxiliary eigenvector matrix
<b><math>\Psi</math></b>	Auxiliary eigenvector matrix
<b><math>\Omega</math></b>	Log marginal variance matrix

### Vectors/tensors

<b>e</b>	The prediction residuals
<b>f</b>	The predicted graph signal
<b>s</b>	A binary selection vector/tensor
<b>x</b>	A vector of explanatory variables
<b>y</b>	The observed graph signal
<b><math>\alpha</math></b>	A flexible intercept vector/tensor
<b><math>\beta</math></b>	A graph filter parameter vector <i>or</i> vector of regression coefficients
<b><math>\theta</math></b>	A aggregated coefficient vector $[\alpha^\top, \beta^\top]^\top$

### Functions

<b><math>g(\cdot)</math></b>	A graph filter function
<b><math>p(\text{statement})</math></b>	The probability that a statement is true
<b><math>\pi(\cdot)</math></b>	A probability density function
<b><math>\xi(\cdot)</math></b>	Optimisation target function
<b><math>\kappa(\cdot, \cdot)</math></b>	A kernel function

### Operations

<b><math>(\cdot)^\top</math></b>	Transpose of a matrix/vector
<b><math>\ \cdot\ _F</math></b>	The Frobenius norm

---

$\text{vec}(\cdot)$	Convert a matrix to a vector in column-major order
$\text{vec}_{\text{RM}}(\cdot)$	Convert a matrix to a vector in row-major order
$\text{mat}(\cdot)$	Convert a vector to a matrix in column-major order
$\text{mat}_{\text{RM}}(\cdot)$	Convert a vector to a matrix in row-major order
$\text{diag}(\cdot)$	Convert a vector to a diagonal matrix
$\text{diag}^{-1}(\cdot)$	Convert the diagonal of a matrix into a vector
$\otimes$	The Kronecker product
$\oplus$	The Kronecker sum
$\circ$	The Hadamard product

### Miscellaneous

$\hat{(\cdot)}$	The estimator of a matrix/vector/tensor
$O(\cdot)$	The runtime complexity
$x_i$	A vector element
$\mathbf{X}_i$	A matrix column
$\mathbf{X}_{ij}$	A vector element

*For/Dedicated to/To my...*

# Chapter 1

## Introduction

### 1.1 Welcome and Thank You

[\[Arnold et al., 1998\]](#)

## Chapter 2

# Outline and Fundamentals

### 2.1 Graph Signal Processing

#### 2.1.1 A broad overview of the field

#### 2.1.2 The graph Laplacian

#### 2.1.3 Graph filters

### 2.2 Regression and Reconstruction

#### 2.2.1 Graph Signal Reconstruction

#### 2.2.2 Kernel Graph Regression

#### 2.2.3 Regression with Network Cohesion

### 2.3 Thesis overview



## Chapter 3

# Kernel Generalized Least Squares Regression for Network Data

### 3.1 Kernel Graph Regression with Missing Values

### 3.2 GLS Kernel Graph Regression

#### 3.2.1 A Gauss-Markov estimator

#### 3.2.2 AR(1) processes

#### 3.2.3 Experiments

## Chapter 4

# Regression and Reconstruction on Cartesian Product Graphs

### 4.1 Introduction

Hello

### 4.2 Graph Signal Reconstruction on Cartesian Product Graphs

Hello

#### 4.2.1 A stationary iterative method

Hello

#### 4.2.2 A conjugate gradient method

Hello

#### 4.2.3 Convergence properties

Hello

#### **4.2.4 Image processing experiments**

Hello

### **4.3 Kernel Graph Regression with Unrestricted Missing Data Patterns**

Hello

#### **4.3.1 Cartesian product graphs and KGR**

Hello

#### **4.3.2 Convergence properties**

Hello

### **4.4 Regression with Network Cohesion**

Hello

#### **4.4.1 Regression with node-level covariates**

Hello

#### **4.4.2 Convergence properties**

Hello

### **4.5 Multi-Dimensional Cartesian Product Graphs**

Hello

#### 4.5.1 Fast computation with $d$ -dimensional Kronecker products

Hello

#### 4.5.2 Signal reconstruction

Hello

#### 4.5.3 Kernel Graph Regression

Hello

#### 4.5.4 Regression with Network Cohesion

## Chapter 5

# Signal Uncertainty: Estimation and Sampling

### 5.1 Introduction

### 5.2 Posterior Estimation

#### 5.2.1 Log-variance prediction

#### 5.2.2 Estimation models

#### 5.2.3 Query strategies

#### 5.2.4 Comparison and analysis

### 5.3 Posterior Sampling

#### 5.3.1 Perturbation optimization

### 5.4 Estimation vs Sampling

#### 5.4.1 Experiments

## Chapter 6

# Working with Binary-Valued Graph Signals

6.1 Logistic Graph Signal Reconstruction

6.2 Logistic Kernel Graph Regression

6.3 Logistic Regression with Network Cohesion

6.4 Approximate Sampling via the Laplace Approximation

## Chapter 7

# Conclusions

### 7.1 Main Section 1

## Appendix A

# Appendix Title Here

Write your Appendix content here.



# Bibliography

Arnold, A. S., Wilson, J. S., and Boshier, M. G. (1998). A simple extended-cavity diode laser. *Review of Scientific Instruments*, 69(3):1236–1239.