

Contents

1	Introduction	1
1.1	Cancer Research in the Post-Genomic Era	1
1.1.1	Cancer as a Global Health Concern	2
1.1.1.1	The Genetics and Molecular Biology of Cancers	3
1.1.2	The Human Genome Revolution	6
1.1.2.1	The First Human Genome Sequence	6
1.1.2.2	Impact of Genomics	7
1.1.3	Technologies to Enable Genetics Research	7
1.1.3.1	DNA Sequencing and Genotyping Technologies	7
1.1.3.2	Microarrays and Quantitative Technologies	8
1.1.3.3	Massively Parallel “Next Generation” Sequencing	9
1.1.3.3.1	Molecular Profiling with Genomics Technology	11
1.1.3.3.2	Sequencing Technologies	11
1.1.3.4	Bioinformatics as Interdisciplinary Genomic Analysis	12
1.1.4	Follow-up Large-Scale Genomics Projects	13
1.1.5	Cancer Genomes	14
1.1.5.1	The Cancer Genome Atlas Project	15
1.1.5.1.1	Findings from Cancer Genomes	15
1.1.5.1.2	Genomic Comparisons Across Cancer Tissues	17
1.1.5.1.3	Cancer Genomic Data Resources	18
1.1.6	Genomic Cancer Medicine	18
1.1.6.1	Cancer Genes and Driver Mutations	18
1.1.6.2	Personalised or Precision Cancer Medicine	19
1.1.6.2.1	Molecular Diagnostics and Pan-Cancer Medicine	20
1.1.6.3	Targeted Therapeutics and Pharmacogenomics	21
1.1.6.3.1	Targeting Oncogenic Driver Mutations	21
1.1.6.4	Systems and Network Biology	22
1.1.6.4.1	Network Medicine, and Polypharmacology	24
1.2	A Synthetic Lethal Approach to Cancer Medicine	25
1.2.1	Synthetic Lethal Genetic Interactions	26
1.2.2	Synthetic Lethal Concepts in Genetics	26
1.2.3	Studies of Synthetic Lethality	27
1.2.3.1	Synthetic Lethal Pathways and Networks	28
1.2.3.1.1	Evolution of Synthetic Lethality	29
1.2.4	Synthetic Lethal Concepts in Cancer	29

1.2.5	Clinical Impact of Synthetic Lethality in Cancer	31
1.2.6	High-throughput Screening for Synthetic Lethality	33
1.2.6.1	Synthetic Lethal Screens	34
1.2.7	Computational Prediction of Synthetic Lethality	37
1.2.7.1	Bioinformatics Approaches to Genetic Interactions	37
1.2.7.2	Comparative Genomics	38
1.2.7.3	Analysis and Modelling of Protein Data	41
1.2.7.4	Differential Gene Expression	43
1.2.7.5	Data Mining and Machine Learning	44
1.2.7.6	Bimodality	47
1.2.7.7	Rationale for Further Development	48
1.3	E-cadherin as a Synthetic Lethal Target	48
1.3.1	The <i>CDH1</i> gene and it's Biological Functions	48
1.3.1.1	Cytoskeleton	49
1.3.1.2	Extracellular and Tumour Micro-Environment	49
1.3.1.3	Cell-Cell Adhesion and Signalling	49
1.3.2	<i>CDH1</i> as a Tumour (and Invasion) Suppressor	50
1.3.2.1	Breast Cancers and Invasion	50
1.3.3	Hereditary Diffuse Gastric Cancer and Lobular Breast Cancer	50
1.3.4	Somatic Mutations	52
1.3.4.1	Mutation Rate	52
1.3.4.2	Co-occurring Mutations	52
1.3.5	Models of <i>CDH1</i> loss in cell lines	53
1.4	Summary and Research Direction of Thesis	54
2	Methods and Resources	58
2.1	Bioinformatics Resources for Genomics Research	58
2.1.1	Public Data and Software Packages	58
2.1.1.1	Cancer Genome Atlas Data	59
2.1.1.2	Reactome and Annotation Data	60
2.2	Data Handling	61
2.2.1	Normalisation	61
2.2.2	Sample Triage	61
2.2.3	Metagenes and the Singular Value Decomposition	63
2.2.3.1	Candidate Triage and Integration with Screen Data	63
2.3	Techniques	64
2.3.1	Statistical Procedures and Tests	64
2.3.2	Gene Set Over-representation Analysis	65
2.3.3	Clustering	66
2.3.4	Heatmap	66
2.3.5	Modeling and Simulations	66
2.3.5.1	Receiver Operating Characteristic (Performance)	67
2.3.6	Resampling Analysis	68
2.4	Pathway Structure Methods	69
2.4.1	Network and Graph Analysis	69
2.4.2	Sourcing Graph Structure Data	70

2.4.3	Constructing Pathway Subgraphs	70
2.4.4	Network Analysis Metrics	70
2.5	Implementation	71
2.5.1	Computational Resources and Linux Utilities	71
2.5.2	R Language and Packages	73
2.5.3	High Performance and Parallel Computing	75
3	Methods Developed During Thesis	77
3.1	A Synthetic Lethal Detection Methodology	77
3.2	Synthetic Lethal Simulation and Modelling	80
3.2.1	A Model of Synthetic Lethality in Expression Data	80
3.2.2	Simulation Procedure	84
3.3	Detecting Simulated Synthetic Lethal Partners	87
3.3.1	Binomial Simulation of Synthetic lethality	87
3.3.2	Multivariate Normal Simulation of Synthetic lethality	89
3.3.2.1	Multivariate Normal Simulation with Correlated Genes	92
3.3.2.2	Specificity with Query-Correlated Pathways	99
3.3.2.3	Importance of Directional Testing	99
3.4	Graph Structure Methods	101
3.4.1	Upstream and Downstream Gene Detection	101
3.4.1.1	Permutation Analysis for Statistical Significance	102
3.4.1.2	Hierarchy Based on Biological Context	103
3.4.2	Simulating Gene Expression from Graph Structures	104
3.5	Customised Functions and Packages Developed	108
3.5.1	Synthetic Lethal Interaction Prediction Tool	108
3.5.2	Data Visualisation	109
3.5.3	Extensions to the iGraph Package	112
3.5.3.1	Sampling Simulated Data from Graph Structures	112
3.5.3.2	Plotting Directed Graph Structures	112
3.5.3.3	Computing Information Centrality	113
3.5.3.4	Testing Pathway Structure with Permutation Testing	113
3.5.3.5	Metapackage to Install iGraph Functions	114
4	Synthetic Lethal Analysis of Gene Expression Data	115
4.1	Synthetic Lethal Genes in Breast Cancer	116
4.1.1	Synthetic Lethal Pathways in Breast Cancer	118
4.1.2	Expression Profiles of Synthetic Lethal Partners	119
4.1.2.1	Subgroup Pathway Analysis	122
4.2	Comparing Synthetic Lethal Gene Candidates	125
4.2.1	Primary siRNA Screen Candidates	125
4.2.2	Comparison with Correlation	126
4.2.3	Comparison with Primary Screen Viability	128
4.2.4	Comparison with Secondary siRNA Screen Validation	129
4.2.5	Comparison to Primary Screen at Pathway Level	131
4.2.5.1	Resampling Genes for Pathway Enrichment	133
4.2.6	Integrating Synthetic Lethal Pathways and Screens	136

4.3	Metagene Analysis	138
4.3.1	Pathway Expression	139
4.3.2	Somatic Mutation	141
4.3.3	Synthetic Lethal Pathway Metagenes	145
4.3.4	Synthetic Lethality in Breast Cancer	146
4.4	Replication in Stomach Cancer	147
4.4.1	Synthetic Lethal Genes and Pathways	147
4.4.2	Synthetic Lethal Expression Profiles	149
4.4.3	Comparison to Primary Screen	151
4.4.3.1	Resampling Analysis	152
4.4.4	Metagene Analysis	153
4.5	Global Synthetic Lethality	153
4.5.1	Hub Genes	155
4.5.2	Hub Pathways	156
4.6	Replication in the Cancer Cell Line Encyclopaedia	157
4.7	Discussion	160
4.7.1	Strengths of the SLIPT Methodology	160
4.7.2	Synthetic Lethal Pathways for E-cadherin	161
4.7.3	Replication and Validation	163
4.7.3.1	Integration with siRNA Screening	163
4.7.3.2	Replication across Tissues and Cell lines	163
4.8	Summary	164
5	Synthetic Lethal Pathway Structure	164
5.1	Synthetic Lethal Genes in Reactome Pathways	164
5.1.1	The PI3K/AKT Pathway	165
5.1.2	The Extracellular Matrix	167
5.1.3	G Protein Coupled Receptors	170
5.1.4	Gene Regulation and Translation	170
5.2	Network Analysis of Synthetic Lethal Genes	171
5.2.1	Gene Connectivity and Vertex Degree	172
5.2.2	Gene Importance and Centrality	173
5.2.2.1	Information Centrality	173
5.2.2.2	PageRank Centrality	175
5.3	Relationships between Synthetic Lethal Genes	177
5.3.1	Hierarchical Pathway Structure	177
5.3.1.1	Contextual Hierarchy of PI3K	177
5.3.1.2	Testing Contextual Hierarchy of Synthetic Lethal Genes	177
5.3.2	Upstream or Downstream Synthetic Lethality	181
5.3.2.1	Measuring Structure of Candidates within PI3K	181
5.3.2.2	Resampling for Synthetic Lethal Pathway Structure	183
5.4	Discussion	185
5.5	Summary	187

6	Simulation and Modeling of Synthetic Lethal Pathways	190
6.1	Comparing methods	191
6.1.1	Performance of SLIPT and χ^2 across Quantiles	192
6.1.1.1	Correlated Query Genes affects Specificity	195
6.1.2	Alternative Synthetic Lethal Detection Strategies	197
6.1.2.1	Correlation for Synthetic Lethal Detection	197
6.1.2.2	Testing for Bimodality with BiSEp	199
6.2	Simulations with Graph Structures	201
6.2.1	Performance over a Graph Structure	202
6.2.1.1	Simple Graph Structures	202
6.2.1.2	Constructed Graph Structures	204
6.2.2	Performance with Inhibitions	208
6.2.3	Synthetic Lethality across Graph Structures	214
6.2.4	Performance within a Simulated Human Genome	218
6.3	Simulations over pathway-based graphs	224
6.3.1	Pathway Structures in a Simulated Human Genome	226
6.4	Discussion	229
6.4.1	Simulation Procedure	229
6.4.2	Design and Performance of SLIPT	230
6.4.3	Simulations from Graph Structures	232
6.5	Summary	233
7	Discussion	236
7.1	Synthetic Lethality and <i>CDH1</i> Biology	236
7.1.1	Established Functions of <i>CDH1</i>	237
7.1.2	The Molecular Role of <i>CDH1</i> in Cancer	237
7.2	Significance	238
7.2.1	Synthetic Lethality in the Genomic Era	238
7.2.2	Clinical Interventions based on Synthetic Lethality	240
7.3	Evaluating the Synthetic Lethality Prediction Tool	241
7.3.1	Strength of the Synthetic Lethality Prediction Tool	241
7.3.2	Limitations of the Synthetic Lethality Prediction Tool	241
7.3.3	Comparisons to Alternative Methods	241
7.3.3.1	Combined with Experimental Screening	241
7.3.3.2	Differences to Computational Methods	241
7.4	Future Directions	241
7.4.1	Refinements Synthetic Lethality Prediction Methods	243
7.4.1.1	Wider Use of Synthetic Lethality Prediction	243
7.4.2	Validation of Synthetic Lethal Genes and Pathways	243
7.4.2.1	Pre-clinical and Clinical Testing	243
7.4.3	Application to Further Genes and Pathways	243
8	Conclusion	244
	References	248

A	Sample Quality	269
A.1	Sample Correlation	269
A.2	Replicate Samples in TCGA Breast	272
B	Software Used for Thesis	276
C	Mutation Analysis in Breast Cancer	285
C.1	Synthetic Lethal Genes and Pathways	285
C.2	Synthetic Lethal Expression Profiles	288
C.3	Comparison to Primary Screen	291
C.3.1	Resampling Analysis	293
C.4	Compare SLIPT genes	295
C.5	Metagene Analysis	297
C.6	Expression of Somatic Mutations	298
C.7	Metagene Expression Profiles	301
D	Intrinsic Subtyping	304
E	Stomach Expression Analysis	306
E.1	Synthetic Lethal Genes and Pathways	306
E.2	Comparison to Primary Screen	309
E.2.1	Resampling Analysis	311
E.3	Metagene Analysis	313
F	Stomach Mutation Analysis	314
F.1	Synthetic Lethal Genes and Pathways	314
F.2	Synthetic Lethal Expression Profiles	317
F.3	Comparison to Primary Screen	320
F.3.1	Resampling Analysis	322
F.4	Metagene Analysis	324
G	Global Synthetic Lethality in Stomach Cancer	325
G.1	Hub Genes	327
G.2	Hub Pathways	328
H	Replication in cell line encyclopaedia	329
J	Synthetic Lethal Genes in Pathways	338
K	Pathway Connectivity for Mutation SLIPT	346
L	Information Centrality for Gene Essentiality	350
M	Pathway Structure for Mutation SLIPT	353
N	Performance of SLIPT and χ^2	356
N.0.1	Correlated Query Genes affects Specificity	362

O	Graph Structures	368
O.1	Simulations from Graph Structures	374
O.2	Simulations from Inhibiting Graph Structures	379
O.3	Simulation across Graph Structures	389
O.4	Graph Structure Simulations with 20K genes	393
O.4.1	Inhibiting Graph Structure Simulations with 20K genes	400
O.5	Simations from Pathway Graph Structures	412

List of Figures

1.1	Synthetic genetic interactions	27
1.2	Synthetic lethality in cancer	30
2.1	Read count density	62
2.2	Read count sample mean	62
3.1	Framework for synthetic lethal prediction	78
3.2	Synthetic lethal prediction adapted for mutation	79
3.3	A model of synthetic lethal gene expression	81
3.4	Modeling synthetic lethal gene expression	82
3.5	Synthetic lethality with multiple genes	83
3.6	Simulating gene function	85
3.7	Simulating synthetic lethal gene function	85
3.8	Simulating synthetic lethal gene expression	86
3.9	Performance of binomial simulations	88
3.10	Comparison of statistical performance	88
3.11	Performance of multivariate normal simulations	90
3.12	Simulating expression with correlated gene blocks	93
3.13	Simulating expression with correlated gene blocks	94
3.14	Synthetic lethal prediction across simulations	95
3.15	Performance with correlations	96
3.16	Comparison of statistical performance with correlation structure	97
3.17	Performance with query correlations	98
3.18	Statistical evaluation of directional criteria	99
3.19	Performance of directional criteria	100
3.20	Simulated graph structures	104
3.21	Simulating expression from a graph structure	106
3.22	Simulating expression from graph structure with inhibitions	107
3.23	Demonstration of violin plots with custom features	110
3.24	Demonstration of annotated heatmap	110
3.25	Simulating graph structures	113
4.1	Synthetic lethal expression profiles of analysed samples	121
4.2	Comparison of SLIPT to siRNA	125
4.3	Compare SLIPT and siRNA genes with correlation	126
4.4	Compare SLIPT and siRNA genes with correlation	127
4.5	Compare SLIPT and siRNA genes with viability	128

4.6	Compare SLIPT genes with siRNA viability	129
4.7	Resampled intersection of SLIPT and siRNA candidates	133
4.8	Pathway metagene expression profiles	140
4.9	Expression profiles for constituent genes of PI3K	142
4.10	Expression profiles for estrogen receptor related genes	143
4.11	Somatic mutation against the PI3K metagene	144
4.12	Synthetic lethal expression profiles of stomach samples	150
4.13	Synthetic lethal partners across query genes	154
5.1	Synthetic Lethality in the PI3K Cascade	166
5.2	Synthetic Lethality in the Elastic Fibre Formation Pathway	168
5.3	Synthetic Lethality in the Fibrin Clot Formation	169
5.4	Synthetic Lethality and Vertex Degree	172
5.5	Synthetic Lethality and Centrality	175
5.6	Synthetic Lethality and PageRank	176
5.7	Hierarchical Structure of PI3K	178
5.8	Hierarchy Score in PI3K against Synthetic Lethality in PI3K	179
5.9	Structure of Synthetic Lethality in PI3K	181
5.10	Structure of Synthetic Lethality Resampling in PI3K	182
6.1	Performance of χ^2 and SLIPT across quantiles	193
6.2	Performance of χ^2 and SLIPT across quantiles with more genes	194
6.3	Performance of χ^2 and SLIPT across quantiles with query correlation	195
6.4	Performance of χ^2 and SLIPT across quantiles with query correlation and more genes	196
6.5	Performance of negative correlation and SLIPT	198
6.6	Performance of simulations on a simple graph	203
6.7	Performance of simulations is similar in simple graphs	204
6.8	Performance of simulations on a constructed graph	205
6.9	Performance of simulations on a large graph	207
6.10	Performance of simulations on a simple graph with inhibition	209
6.11	Performance is higher on a simple inhibiting graph	210
6.12	Performance of simulations on a constructed graph with inhibition	212
6.13	Performance is affected by inhibition in graphs	213
6.14	Detection of Synthetic Lethality within a Graph Structure	215
6.15	Detection of Synthetic Lethality within a Graph Structure with Inhibitions	217
6.16	Performance of simulations including a simple graph	219
6.17	Performance on a simple graph improves with more genes	220
6.18	Performance on an inhibiting graph with more genes	221
6.19	Performance on an inhibiting graph improves with more genes	223
6.20	Performance of simulations on the PI3K cascade	225
6.21	Performance of simulations including the PI3K cascade	227
6.22	Performance on pathways improves with more genes	228
A.1	Correlation profiles of removed samples	270
A.2	Correlation analysis and sample removal	271

A.3	Replicate excluded samples	272
A.4	Replicate samples with all remaining	273
A.5	Replicate samples with some excluded	274
C.1	Synthetic lethal expression profiles of analysed samples	289
C.2	Comparison of mtSLIPT to siRNA	291
C.3	Compare mtSLIPT and siRNA genes with correlation	295
C.4	Compare mtSLIPT and siRNA genes with correlation	295
C.5	Compare mtSLIPT and siRNA genes with siRNA viability	296
C.6	Somatic mutation against PIK3CA metagene	298
C.7	Somatic mutation against PI3K protein	299
C.8	Somatic mutation against AKT protein	300
C.9	Pathway metagene expression profiles	301
C.10	Expression profiles for p53 related genes	302
C.11	Expression profiles for BRCA related genes	303
E.1	Comparison of SLIPT in stomach to siRNA	309
F.1	Synthetic lethal expression profiles of stomach samples	318
F.2	Comparison of mtSLIPT in stomach to siRNA	320
G.1	Synthetic lethal partners across query genes	326
J.1	Synthetic Lethality in the PI3K/AKT Pathway	338
J.2	Synthetic Lethality in the PI3K/AKT Pathway in Cancer	339
J.3	Synthetic Lethality in the Extracellular Matrix	340
J.4	Synthetic Lethality in the GPCRs	341
J.5	Synthetic Lethality in the GPCR Downstream	342
J.6	Synthetic Lethality in the Translation Elongation	343
J.7	Synthetic Lethality in the Nonsense-mediated Decay	344
J.8	Synthetic Lethality in the 3' UTR	345
K.1	Synthetic Lethality and Vertex Degree	346
K.2	Synthetic Lethality and Centrality	347
K.3	Synthetic Lethality and PageRank	348
L.1	Information centrality distribution	352
M.1	Synthetic Lethality and Heirarchy Score in PI3K	353
M.2	Heirarchy Score in PI3K against Synthetic Lethality in PI3K	354
M.3	Structure of Synthetic Lethality in PI3K	354
M.4	Structure of Synthetic Lethality Resampling	355
N.1	Performance of χ^2 and SLIPT across quantiles	356
N.2	Performance of χ^2 and SLIPT across quantiles	358
N.3	Performance of χ^2 and SLIPT across quantiles with more genes	360
N.4	Performance of χ^2 and SLIPT across quantiles with query correlation	362
N.5	Performance of χ^2 and SLIPT across quantiles with query correlation	364

N.6	Performance of χ^2 and SLIPT across quantiles with query correlation and more genes	366
O.1	Simple graph structures	368
O.2	Simple graph structure	369
O.3	Constructed graph structure	369
O.4	Large constructed graph structure.	370
O.5	Branching constructed graph structure	370
O.6	Complex constructed graph structure	372
O.7	Performance of simulations on a simple graph	375
O.8	Performance of simulations on a constructed graph	376
O.9	Performance of simulations on a branching graph	377
O.10	Performance of simulations on a complex graph	378
O.11	Performance of simulations on a simple graph with inhibition	380
O.12	Performance of simulations on a simple graph with inhibition	381
O.13	Performance of simulations on a constructed graph with inhibition	382
O.14	Performance of simulations on a large constructed graph with inhibition	383
O.15	Performance of simulations on a large constructed graph with inhibition	384
O.16	Performance of simulations on a branching graph with inhibition	385
O.17	Performance of simulations on a branching graph with inhibition	386
O.18	Performance of simulations on a complex graph with inhibition	387
O.19	Performance of simulations on a complex graph with inhibition	388
O.20	Detection of Synthetic Lethality within a Graph Structure	389
O.21	Detection of Synthetic Lethality within an Inhibiting Graph Structure	391
O.22	Detection of Synthetic Lethality within an Inhibiting Graph Structure	392
O.23	Performance of simulations on a simple graph with more genes	394
O.24	Performance of simulations including a simple graph	395
O.25	Performance of simulations including a constructed graph	396
O.26	Performance of simulations including a large graph	397
O.27	Performance of simulations including a branching graph	398
O.28	Performance of simulations including a complex graph	399
O.29	Performance of simulations including a simple graph with inhibition	401
O.30	Performance of simulations including a simple graph with inhibition	402
O.31	Performance of simulations including a simple graph with inhibition	403
O.32	Performance of simulations including a constructed graph with inhibition	404
O.33	Performance of simulations including a constructed graph with inhibition	405
O.34	Performance of simulations including a large graph with inhibition	406
O.35	Performance of simulations including a large graph with inhibition	407
O.36	Performance of simulations including a branching graph with inhibition	408
O.37	Performance of simulations including a branching graph with inhibition	409
O.38	Performance of simulations including a complex graph with inhibition	410
O.39	Performance of simulations including a complex graph with inhibition	411
O.40	Performance of simulations on the $G_{\alpha i}$ signalling pathway	412
O.41	Performance of simulations including the $G_{\alpha i}$ signalling pathway	413

List of Tables

1.1	Methods for Predicting Genetic Interactions	38
1.2	Methods for Predicting Synthetic Lethality in Cancer	39
1.3	Methods used by Wu <i>et al.</i> (2014)	40
2.1	Excluded Samples by Batch and Clinical Characteristics.	63
2.2	Computers used during Thesis	72
2.3	Linux Utilities and Applications used during Thesis	72
2.4	R Installations used during Thesis	73
2.5	R Packages used during Thesis	73
2.6	R Packages Developed during Thesis	75
4.1	Candidate synthetic lethal gene partners of <i>CDH1</i> from SLIPT	117
4.2	Pathways for <i>CDH1</i> partners from SLIPT	119
4.3	Pathway composition for clusters of <i>CDH1</i> partners from SLIPT	123
4.4	Analysis of variance (ANOVA) for Synthetic Lethality and Correlation with <i>CDH1</i>	127
4.5	Comparing SLIPT genes against secondary siRNA screen in breast cancer	130
4.6	Pathway composition for <i>CDH1</i> partners from SLIPT and siRNA screen- ing	132
4.7	Pathways for <i>CDH1</i> partners from SLIPT	135
4.8	Pathways for <i>CDH1</i> partners from SLIPT and siRNA primary screen .	137
4.9	Candidate synthetic lethal metagenes against <i>CDH1</i> from SLIPT	146
4.10	Pathways for <i>CDH1</i> partners from SLIPT in stomach cancer	149
4.11	Query synthetic lethal genes with the most SLIPT partners	155
4.12	Pathways for genes with the most SLIPT partners	157
4.13	Pathways for <i>CDH1</i> partners from SLIPT in CCLE	158
4.14	Pathways for <i>CDH1</i> partners from SLIPT in breast CCLE	159
5.1	ANOVA for Synthetic Lethality and Vertex Degree	173
5.2	ANOVA for Synthetic Lethality and Information Centrality	175
5.3	ANOVA for Synthetic Lethality and PageRank Centrality	177
5.4	ANOVA for Synthetic Lethality and PI3K Hierarchy	180
5.5	Resampling for pathway structure of synthetic lethal detection methods	184
B.1	R Packages used during Thesis	276
C.1	Candidate synthetic lethal gene partners of <i>CDH1</i> from mtSLIPT	286
C.2	Pathways for <i>CDH1</i> partners from mtSLIPT	287

C.3	Pathway composition for clusters of <i>CDH1</i> partners from mtSLIPT . .	290
C.4	Pathway composition for <i>CDH1</i> partners from mtSLIPT and siRNA . .	292
C.5	Pathways for <i>CDH1</i> partners from mtSLIPT	293
C.6	Pathways for <i>CDH1</i> partners from mtSLIPT and siRNA primary screen	294
C.7	Candidate synthetic lethal metagenes against <i>CDH1</i> from mtSLIPT . .	297
D.1	Comparison of Intrinsic Subtypes	304
E.1	Synthetic lethal gene partners of <i>CDH1</i> from SLIPT in stomach cancer	307
E.2	Pathway composition for clusters of <i>CDH1</i> partners in stomach SLIPT	308
E.3	Pathway composition for <i>CDH1</i> partners from SLIPT and siRNA screen- ing	310
E.4	Pathways for <i>CDH1</i> partners from SLIPT in stomach cancer	311
E.5	Pathways for <i>CDH1</i> partners from SLIPT in stomach and siRNA screen	312
E.6	Candidate synthetic lethal metagenes against <i>CDH1</i> from SLIPT in stomach cancer	313
F.1	Synthetic lethal gene partners of <i>CDH1</i> from mtSLIPT in stomach cancer	315
F.2	Pathways for <i>CDH1</i> partners from mtSLIPT in stomach cancer	316
F.3	Pathway composition for clusters of <i>CDH1</i> partners in stomach mtSLIPT	319
F.4	Pathway composition for <i>CDH1</i> partners from mtSLIPT and siRNA . .	321
F.5	Pathways for <i>CDH1</i> partners from mtSLIPT in stomach cancer	322
F.6	Pathways for <i>CDH1</i> partners from mtSLIPT in stomach and siRNA screen	323
F.7	Candidate synthetic lethal metagenes against <i>CDH1</i> from mtSLIPT in stomach cancer	324
G.1	Query synthetic lethal genes with the most SLIPT partners	327
G.2	Pathways for genes with the most SLIPT partners	328
H.1	Candidate synthetic lethal gene partners of <i>CDH1</i> from SLIPT in CCLE	330
H.2	Candidate synthetic lethal gene partners of <i>CDH1</i> from SLIPT in breast CCLE	331
H.3	Candidate synthetic lethal gene partners of <i>CDH1</i> from SLIPT in stom- ach CCLE	332
H.4	Pathways for <i>CDH1</i> partners from SLIPT in stomach CCLE	333
H.5	Pathways for <i>CDH1</i> partners from SLIPT in breast and stomach CCLE	333
K.1	ANOVA for Synthetic Lethality and Vertex Degree	349
K.2	ANOVA for Synthetic Lethality and Information Centrality	349
K.3	ANOVA for Synthetic Lethality and PageRank Centrality	349
L.1	Information centrality for genes and molecules in the Reactome network	351
M.1	ANOVA for Synthetic Lethality and PI3K Hierarchy	353
M.2	Resampling for pathway structure of synthetic lethal detection methods	355

Chapter 7

Discussion

This thesis combines analysis of gene expression data from The Cancer Genome Atlas (TCGA) with experimental screening results (Telford *et al.*, 2015) to demonstrate synthetic lethal discovery for *CDH1* in expression data generated by genomics technologies with comparisons to existing experimental candidates. Together these findings further elucidate the functions for *CDH1* in the cell, functional redundancy in breast cancer, and potential targets against cancers with loss of *CDH1* function. These candidate synthetic lethal genes were further investigated for relationships within synthetic lethal pathways, developing a network-based approach to comparing genes identified in genomics experiments and analyses in the process.

The synthetic lethal detection methodology, Synthetic Lethal Interaction Prediction Tool (SLIPT), that was applied to gene expression data throughout this thesis was evaluated with simulated data. A simulation procedure was developed to stringently generate gene expression data from known synthetic lethal partners in simulated data, including simple and complex correlation structures and modelling synthetic lethal genes within pathways. Together, these results demonstrate SLIPT as a robust widely applicable gene expression analysis procedure (for which an R package has been released) for discovery of synthetic lethal partner genes. Performance of SLIPT on simulated data also highlights the strengths of the procedure and future directions to improve upon it.

7.1 Synthetic Lethality and *CDH1* Biology

The *CDH1* gene was selected to identify synthetic lethal partners to demonstrate the novel SLIPT methodology as an important tumour suppressor gene in cancers. These include sporadic breast and stomach cancers and the familial syndromes such as hered-

itary diffuse gastric cancer (HDGC). The analysis of synthetic lethal partners of *CDH1* in breast and stomach cancers was also enabled by the availability of molecular data (Bass *et al.*, 2014; TCGA, 2012) and a synthetic lethal screen conducted in MCF10A breast cells (Chen *et al.*, 2014; Telford *et al.*, 2015).

Synthetic lethal interactions are generally regarded to arise due to functional redundancy (Boone *et al.*, 2007; Fece de la Cruz *et al.*, 2015; Kaelin, Jr, 2005) and as such the synthetic lethal partners of *CDH1* indicates the wide-ranging biological functions that E-cadherin is involved in. The diverse synthetic lethal pathways identified supports the known pleiotropic nature of the *CDH1* gene by detecting established functions of *CDH1*, replicating candidates from an experimental screen (Telford *et al.*, 2015), and identifying novel interactions with candidate genes and pathways for further investigation. The highly pleiotropic functions of E-cadherin as also consistent with *CDH1* being a tumour suppressor gene for which epithelial cells are significantly disrupted at the molecular level and prone to becoming cancerous.

7.1.1 Established Functions of *CDH1*

The *CDH1* has established functions in cell-cell communication and maintaining the cytoskeleton, specifically with cell-cell adhesion by forming tight junctions and the adherens complex. More recently, additional functions of *CDH1* in the extracellular matrix and fibrin clotting have also been identified. Synthetic lethal interactions within biological pathways (i.e., partners in the same pathway as the query gene) are expected according to previous synthetic lethal experiments and (Boone *et al.*, 2007; Kelley and Ideker, 2005). Synthetic lethal interactions identified in these pathways are consistent with these being functions of *CDH1*, in addition to potentially actionable targets against cancers.

7.1.2 The Molecular Role of *CDH1* in Cancer

The involvement of *CDH1* in the extracellular matrix is also important in cancers as it indicates a mechanism by which *CDH1* loss may affect the tumour microenvironment, contributing to it's role as a tumour and invasion suppressor. Furthermore, perturbations in the extracellular matrix and tumour microenvironment present an potential means by which to specifically inhibit (cancerous) *CDH1*-deficient cells in addition to those currently being considered. Few genes in extracellular pathways were detected in an experimental screen (Telford *et al.*, 2015) conducted in an isolated cell model (Chen *et al.*, 2014) but these are not expected to be detected in such as system. These

may be further supported in further investigations with 3D cell culture, “organoid”, or mouse xenograft cancer models.

In contrast, many of the pathways involved in cell signalling, including G protein coupled receptors, were identified by SLIPT in addition to the experimental screen (Telford *et al.*, 2015). These support the previous results in cell line models, that these pathways are essential to growth of *CDH1*-deficient cancers and present a potential vulnerability specific to these (cancerous) cells. Furthermore, the replication of synthetic lethality of *CDH1* with cell signalling pathways in TCGA data across cancer types and genetic backgrounds robustly supports these pathways being clinically applicable beyond the genetic background of the model system of *CDH1*^{-/-} MCF10A cells (Chen *et al.*, 2014). While the specific synthetic lethal genes were not as consistently detected between the SLIPT analyses and short interfering ribonucleic acid (siRNA) screen (Telford *et al.*, 2015), the was sufficient to identify synthetic lethal pathways for further experimental investigation which are more likely to be replicated between genetic backgrounds (Dixon *et al.*, 2008). Together these results demonstrate how SLIPT can be integrated with an experimental screen to triage potential therapeutic targets for further pre-clinical investigation.

The analysis of expression data with SLIPT is also indicative of additional biological mechanisms of synthetic lethal in pathways beyond those identified in screening experiments (Telford *et al.*, 2015). In particular, translation and regulatory pathways, involving 3′ untranslated regions (UTRs) and nonsense-mediated decay (NMD), were identified as candidate synthetic lethal pathways with *CDH1* by SLIPT. These present downstream target regulated by the putative synthetic lethal signalling pathways which cancer cells are dependent on for sustained protein expression (Gao and Roux, 2015) to proliferate and evade host defense processes such as apoptosis and immune responses.

7.2 Significance

7.2.1 Synthetic Lethality in the Genomic Era

Development of an effective synthetic lethal discovery tool for bioinformatics analysis has a wide range of applications in genetics research including functional genomics, medical and agricultural applications. The SLIPT approach demonstrated in this thesis is widely applicable to other genes and biological questions. In addition to further query of cancer genes, including other tissues, synthetic lethal gene functions are also of wider interest for their implications for genetic redundancy. Highly redundant genes and the

genetically robust systems they give rise to are of further relevance to evolutionary, developmental, and systems biology to understand how these change over time and play a role in fundamental development of cell types, in addition to cancers.

Developmental genes in particular, are highly evolutionary conserved and subject to high rates of redundancy. These are often difficult to study with conventional functional genetics since individual knockouts of redundant genes do not necessarily have a mutant phenotype. Identifying genes with a common function is therefore also important to the study of developmental genes with unknown functions. Synthetic lethal discovery methods such as SLIPT provide a genomic approach to further systematic characterisation of gene function including such highly redundant developmental genes.

Similarly, variants of unknown significance and modifier loci are a major concerns in human genetics, including “monogenic” and “rare” diseases. Many of these could potentially be difficult to characterise individually due to synthetic lethal interactions where additional loci contribute to the disease (or only compensate for some variants). As such systematic identification of synthetic lethal interactions also has applications in the study of such “oligogenic” diseases along with similar applications in the study of heritability for traits including agricultural genome-based selection.

Genetic redundancy is also a concern in pharmacology. Polypharmacology and network medicine are rationales to account for this by using drugs with multiple (known and specific) targets (Barabási *et al.*, 2011; Hopkins, 2008). Further characterisation of synthetic lethal genes will be valuable to the design of effective multi-target drugs or combination therapies in a range of therapeutic applications including molecular targeted therapies against cancer for which combination therapies are a popular solution for acquired resistance against individual targeted therapies. Characterisation of genetic interactions and combination therapies also has the potential to expand pharmacogenomics investigations to understanding the impact of genotypes at multiple loci leading to adverse effects in a subset of the population or accounting for why the rest of the population does not experience this adverse effects since their synthetic lethal partner genes do not share the same variants.

Furthermore, redundant functions and synthetic lethal interactions also present a means to expand upon the concept of the “minimal” genome by accounting for essential gene functions that are performed by redundant genes (or in combination with pleiotropic) genes rather than simply those that are perturbed by individual genes as an essential gene approach is likely an underestimate that does not account for synthetic lethal interactions.

Therefore synthetic lethal interactions are a fundamentally important part of genetics and further understanding of them in a genomics context, facilitated by methods such as SLIPT, shows great potential to contribute a deeper understanding of gene functions and their role in traits or diseases in the post-genomic era. Genes do not function in isolation and so understanding them in the context of the complexity of a cell and across genetic backgrounds (such as the data provided by TCGA) is essential to further characterise their functions and ensure that further applications are reproducible beyond experimental systems.

7.2.2 Clinical Interventions based on Synthetic Lethality

Synthetic lethal discovery with SLIPT is of particular interest in cancer research as a complementary approach to discovery of synthetic lethal drug targets. The cancer research community relies on cell line and mouse models for screening and validation experiments (Fece de la Cruz *et al.*, 2015) which would benefit from integration with gene expression analysis as demonstrated for *CDH1* and the screen conducted by Telford *et al.* (2015). The potential for synthetic lethal drug design against cancer mutations including gene loss or overexpression could lead to a revolution in cancer therapy and chemoprevention with personalised treatment of cancers and high risk individuals. Examples of the synthetic lethal strategy (Bryant *et al.*, 2005; Farmer *et al.*, 2005) for cancer treatment have been shown to be clinically effective with many large-scale RNAi screens recently conducted to aiming discover gene function and drug targets for similar application with other cancer genes, including cancers in other tissues.

While SLIPT analysis and RNA interference (RNAi) screens represent a significant step towards anti-cancer medicines, further validation is required to ensure that the synthetic lethal candidate genes and pathways identified for *CDH1* in breast and stomach cancer are applicable against *CDH1*-deficient cancers in the clinic. Validation with RNAi or pharmacological inhibitors is needed since both the SLIPT analysis and siRNA screen are susceptible to false positives. These candidates will need to be tested in pre-clinical models (cell lines and mouse xenografts) before proceeding to clinical trials. A therapeutic intervention will also require a targeted therapeutic against the synthetic lethal partner if one has not been developed against another disease (for which it can be re-purposed). Drug targets must be feasible to have effective anti-cancer interventions designed against them, which raises the need for targets with existing drugs in the clinic, trials, or feasible to development with structural analysis or screening. Druggable targets could be selected by gene functions known to be amend-

able to drugs, with a structure amenable with development, with conserved specific sites without homology to other genes, or with known approval or developing drugs which could be repurposed from other disease applications.

Targeted therapeutics designed based on synthetic lethal interactions have potential to vastly expand the applications of “precision medicine” against molecular targets, particularly in cancer where many have been cancer genes have been identified. Synthetic lethality expands the range of cancer genes which can be (indirectly) targeted to include tumour suppressor genes with loss of function (such as *CDH1*) and oncogenes with disrupted functions that are dysregulated or highly homologous to non-cancerous proto-oncogenes (such as *MYC*, *EGFR* or *KRAS*). Applications against tumour suppressor genes is a particularly important application as these cannot be approached by careful dosing. Synthetic lethal drug design also has the added benefit of being highly specific against a particular genotype (such as *CDH1*^{-/-}) with the potential for target therapies with a wide therapeutic index and few adverse effects, in contrast to many current anti-cancer drug regimens (Hopkins, 2008; Kaelin, Jr, 2009). These properties are highly desirable for chemoprevention applications such as treatment against *CDH1*-deficient early cancers in HDGC patients before they are detectable during screening.

7.3 Evaluating the Synthetic Lethality Prediction Tool

7.3.1 Strength of the Synthetic Lethality Prediction Tool

7.3.2 Limitations of the Synthetic Lethality Prediction Tool

7.3.3 Comparisons to Alternative Methods

7.3.3.1 Combined with Experimental Screening

7.3.3.2 Differences to Computational Methods

7.4 Future Directions

Such a bioinformatically-informed synthetic lethal screening and validation strategy could be integrated into existing and future screens for synthetic lethality in cancer.

Possible improvements to the SLIPT method include developing a Bayesian inference method or simulations and modelling to account for pathway structure among

synthetic lethal genes. Another extension would be to test for higher order synthetic lethal interactions, where 3 or more genes perform a redundant function.

The synthetic lethal discovery strategy could be adapted to any form of gene inactivation or disruption such as changes to gene expression, regulation, epigenetics, DNA sequence, or copy number which could plausibly induce cell death due to SL interactions. Further applications of synthetic lethal interactions such as analysis of gene networks, tissue specificity, evolutionary conservation, or drug target feasibility are possible with synthetic lethal candidates predicted with confidence on a large scale.

Further development of the synthetic lethal model and simulation is needed to explore the parameters, ensure relevance to empirical data analysis, and understanding the implications of findings so far. An example of more complex correlation structure is shown in supplementary Figures S1 and S2 with genes correlated to the Query genes (showing need for directional synthetic lethal condition) and correlated with other non-synthetic lethal genes (showing the predictions are robust to other correlation structure). The impact of these modifications on model performance in a large number of genes or simulation replicates is yet to be seen or whether such correlation structure reflects the correlation structure of empirical data (as shown in Figure 3 with the row dendrogram for correlation distance between genes), known biological pathways, or known synthetic lethal interactions. Correlation between synthetic lethal genes could also be considered.

Comparing the findings of modelling and simulation with public gene expression analysis and experimental screen targets is still needed to identify putative synthetic lethal interactions. This application will be tested with the example of CDH1 as a query gene in breast cancer for follow up to earlier results, relevance to ongoing research in the Cancer genetics Laboratory, and comparison to the experimental screen data of MCF10A cells by Telford et al. (2015). While this methodology is intended to be widely applicable, particularly to other cancer genes and will be made available to the research community (manuscript and code release in preparation).

There are several avenues for further research on synthetic lethality in breast cancer. The main alternative themes are network analysis with a focus on tissue specificity or drug feasibility with an emphasis on pharmacogenomics, biological pathways, and whether candidate targets could be inactivated by compounds with favourable pharmacokinetic properties. Either approach remains within the scope of the project, although each will require adoption of new computational tools, which is important

topic for consideration in the meeting and changes to the project direction later in the year.

7.4.1 Refinements Synthetic Lethality Prediction Methods

7.4.1.1 Wider Use of Synthetic Lethality Prediction

7.4.2 Validation of Synthetic Lethal Genes and Pathways

7.4.2.1 Pre-clinical and Clinical Testing

7.4.3 Application to Further Genes and Pathways

Chapter 8

Conclusion

Synthetic lethal interactions are important for understanding gene function and development of targeted anti-cancer treatments. Synthetic lethal discovery with experimental screening is error prone and limited by the model systems in which it is performed. A bioinformatics tool to predict synthetic lethal interactions from genomics data would greatly benefit the cancer research community (and wider genetics research community). Several such tools exist, including one we have developed, but they have conflicting design and results are often inconsistent with experimental screen data. Therefore, modelling and simulation of synthetic lethality in gene expression data is needed to ensure the statistical validity of predictions. We have developed a model with correlation structure based on a Multivariate Normal distribution for which simulations detect synthetic lethality with high performance in simple cases and which has the potential to be developed to model complex correlation structure, biological pathways, or patterns observed in empirical gene expression data. The modelling, public data analysis, and experimental screen data approaches will be combined to further examine the example of CDH1 in breast cancer. Analysis of gene networks, tissue specificity, biological pathways, or drug targets remain options to explore tool development and implications for synthetic lethal cancer research in the future.

Aims

- To develop a statistical approach to detect synthetic lethal gene pairs in cancer from expression data
- To apply this methodology to public cancer gene expression data against *CDH1* and analyse pathway structure with comparisons to experimental screen data
- To construct a statistical model of synthetic lethality in multivariate normal expression data
- To develop a simulation pipeline of expression with pathway structure on a high-performance computing cluster
- To examine the statistical performance of the methodology with simulated expression including pathways and compare it to other approaches
- To release the synthetic lethal detection methodology and pathway simulation procedure as R software packages

Summary

- We have developed a Synthetic Lethal detection method that generates a high number of synthetic lethal candidates
- Pathways in cell signalling, extracellular matrix, and cytoskeletal functions were supported with experimental candidates and the known functions of E-cadherin
- Several candidate pathways were supported by mutation analysis and replicated across breast and stomach cancer
- Translation and immune functions were uniquely detected by the computational approach which may be explained by differences between patient samples and cell line models
- There remains the need to identify actionable genes within these pathways, relationships with experimental candidates, and how these pathways may affect viability when lost
- Synthetic Lethal genes were explored within a graph structures for key pathways identified previously
- In some cases these graph structures appeared to have relationships between synthetic lethal genes
- However, no existing network metrics of importance and connectivity with the networks were elevated significantly for Synthetic Lethal genes
- Nor was there significant evidence of upstream and downstream relationships between SLIPT and siRNA Candidates in a shortest path permutation analysis
- We have designed a straight-forward rational query-based synthetic lethal detection method with the example of application to *CDH1* in cancer gene expression
- We have developed a simulation pipeline to generate continuous gene expression with pathway structure including a procedure to simulate synthetic lethality

- Our simulation procedure is robust across pathway structures and has desirable performance compared to other statistical techniques

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