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A Bioinformatics Approach to
Synthetic Lethal Interactions in
Breast Cancer with Gene
Expression Data

S. Thomas Kelly

a thesis submitted for the degree of
Doctor of Philosophy
at the University of Otago, Dunedin,
New Zealand.

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Abstract

Background

Synthetic lethal genetic interactions are re-emerging in the post-genomics era due to their potential for precision medicine against cancers. Synthetic lethal drug design exploits functional redundancy with genes disrupted in cancers (including tumour suppressors) to develop specific treatments. E-cadherin, encoded by *CDH1*, is a tumour suppressor gene with loss of function in breast and stomach cancers. Experimental screens have identified candidate synthetic lethal interactions for drug target triage which can be further supported with bioinformatics analysis. Furthermore, gene expression data is amenable to investigation of the pathway composition and structure of synthetic lethal candidates.

Approach

A computational methodology, the Synthetic Lethal Prediction Tool (SLIPT) was developed to detect synthetic lethal interactions in gene expression data. This methodology was demonstrated on interactions with *CDH1* in breast and stomach cancer data from The Cancer Genome Atlas (TCGA) project. Synthetic lethal genes and pathways were further investigated with unsupervised clustering, gene set over-representation analysis, metagenes, and permutation resampling. In particular, analyses focused on comparing SLIPT gene candidates to an experimental siRNA screen Telford *et al.* (2015). Graph theory methods were also applied to the most supported pathways to test for pathway structure among between synthetic lethal candidates. Simulation and modelling was used to assess the statistical performance of SLIPT, including simulated data with correlation structures derived from graph structures.

Findings

Many candidate synthetic lethal partners of *CDH1* were detected in both TCGA breast cancer. These genes clustered into several distinct groups, with distinct biological functions and elevated expression in different clinical subtypes. While the number of genes detected by both approaches was not significant, these contained significantly enriched pathways. In particular $G_{\alpha i}$ signalling, cytoplasmic microfibres, and extracellular fibrin clotting were robustly supported by both approaches which is consistent with the known cytoskeletal and cell signalling roles of E-cadherin and validation of GPCRs performed by Telford *et al.* (2015). Many of these pathways were replicated in stomach cancer. The pathways supported only by SLIPT included regulation of immune signalling and translational elongation which were unlikely to be detected in an isogenic cell line model but are still candidates for further investigation.

Synthetic lethal candidates detected by SLIPT and siRNA were compared within graph structures of the candidate synthetic lethal pathways. These genes did not differ by network measures of importance or connectivity in the pathway. There was also little support for SLIPT gene candidates being upstream or downstream of siRNA gene candidates within a pathway, consistently across pathways.

A model of synthetic lethality used to simulate gene expression data with synthetic lethal partners of a gene. The SLIPT methodology had high statistical performance detecting few synthetic lethal partners, although this diminishes with more synthetic lethal partners or lower sample size. The SLIPT methodology performs better than Pearson correlation or the χ^2 -test. In particular, it performs well with high specificity for datasets containing thousands of genes or genes positively correlated with the query gene (as expected in human expression data). It was also robust across correlation structures, including those derived from complex pathway structures and often distinguished synthetic lethal genes from those positively or negatively correlated with them. Therefore SLIPT is appropriate to identify synthetic lethal genes within pathways and use candidate synthetic lethal genes (and their correlates) to identify synthetic lethal pathways.

Summary

Thus my thesis has developed, evaluated and refined a bioinformatics approach to discovery of synthetic lethal genes solely from gene expression data. This approach has been demonstrated to detect biologically informative and clinically relevant candidate partners for *CDH1* in breast and stomach cancers. These investigations have also involved the development of network analysis and simulation procedures which may be more widely applicable.

Research Contributions During Candidature

Publications

Kelly, S. T. and Spencer, H. G. (2017) Population-Genetics Models of Sex-Limited Genomic Imprinting. *Theoretical Population Biology* **115**:35-44
doi:10.1016/j.tpb.2017.03.004

Manuscripts Submitted

Kelly, S. T., Single, A. B., Telford, B. J., Beetham, H. G., Godwin, T. D., Chen, A., Black, M., A., and Guilford, P. J. (2017) Towards HDGC chemoprevention: vulnerabilities in E-cadherin-negative cells identified by genomic interrogation of isogenic cell lines and whole tumors. Submitted to *Cancer Prevention Research*.

Kelly, S. T., Chen, A., Guilford, P. J., and Black, M. A. (2017) Synthetic lethal interaction prediction of target pathways in E-cadherin deficient breast cancers. Submitted to *BMC Genomics*.

Conference Presentations

Consortium of Biological Sciences 2017 (Kobe) December TBC

eResearch 2017 (Queenstown) February 20th-22nd

Research Bazaar 2016 (Dunedin) February 2nd-4th

eResearch 2016 (Queenstown) February 9th-11th

Genetics Otago Symposium 2016 (Dunedin) March 7th-8th

DunDead: Zombie Science and Culture Festival 2014 (Dunedin) August 16th-17th

eResearch 2014 (Hamilton) June 30th-July 2nd (Supported by Google)

Poster Presentations

Next Generation Sequencing Asia 2016 (Singapore) October 11th-12th (Supported by the University of Otago Division of Health Sciences; Maurice and Phyllis Paykel Trust)

Research Bazaar 2015 (Melbourne, Australia) February 16th-18th (Supported by the New Zealand eScience Infrastructure)

Otago School of Medical Sciences Postgraduate Symposium 2015 (Dunedin, New Zealand) April 28th-29th

QMB Cancer Drugs Satellite 2014 (Queenstown, New Zealand) August 24th-25th

Seminar Presentations

University of Otago Department of Biochemistry 2017 (Dunedin) November TBC

Tohoku University 2016 (Sendai) November 11th

Okinawa Institute of Science and Technology 2016 (Onna) November 1st

Sokendai Graduate University 2016 (Hayama) October 25th

Tokyo University Institute of Medical Science 2016 (Shirokanedai) October 24th

National Institute of Genetics 2016 (Mishima) October 21st

RIKEN Division of Genomic Technologies 2016 (Yokohama) October 20th

Software Packages

Software packages in the R language have been released. Please refer to the appropriate GitHub repository for more information (including documentation, vignettes, and installation instructions), on the following account: <https://github.com/TomKellyGenetics>

- `slipt` to accompany the synthetic lethal publication above and release SLIPT (Synthetic Lethal Interaction Prediction Tool)
- `vioplotx` to provide enhanced violin plots
- `heatmap.2x` to provide annotated heatmaps
- `igraph.extensions` metapackage for the packages for iGraph objects:
 - `plot.igraph` to provide plotting for directed graphs
 - `info.centraliity` to compute network analysis metrics
 - `pathway.structure.permutation` for resampling within pathways
 - `graphsim` to simulate expression (`mvtnorm`) from pathway structures

The `slipt-app` GitHub repository also hosts an application for Synthetic Lethal Interaction Prediction Tool (SLIPT) developed in the R `shiny` environment as part of a related project. There is also a digital copy of this thesis, including high resolution full-colour figures, hosted at:

<https://github.com/TomKellyGenetics/thesis/blob/master/thesis.pdf>

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- REANNZ, NZGL, and NeSI (eResearch 2016 conference, Queenstown)
- Otago Division of Health Sciences, Oxford Global, and Maurice and Phyllis Paykel Trust (NGS Asia 2016, Singapore)
- RIKEN Division of Genomics Technologies and the Okinawa Institute of Science and Technology (funding seminar visits in Japan)

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どうもありがとう由ちゃん。また来月。頑張った！行きます！

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Glossary

synthetic lethal Genetic interactions where inactivation of multiple genes is inviable (or deleterious) which are viable if inactivated separately.

Acronyms

ANOVA	Analysis of Variance.
GPCR	G protein coupled receptor.
mtSLIPT	Synthetic Lethal Interaction Prediction Tool (with respect to mutation).
siRNA	Short interfering ribonucleic acid.
SLIPT	Synthetic lethal interaction prediction tool.
TCGA	The Cancer Genome Atlas (genomics project).

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