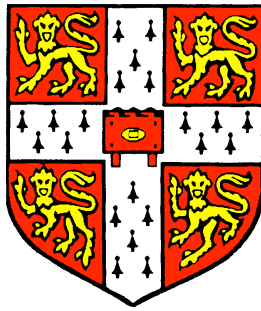


Development of computational methods  
for analysing proteomic data for  
genome annotation

University of Cambridge  
Darwin College



A thesis submitted for the degree of  
*Doctor of Philosophy*

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Dedicated to my family

# Declaration

This thesis describes work carried out between May 2006 and December 2009 under the supervision of Dr Jyoti Choudhary and Dr Tim Hubbard at the Wellcome Trust Sanger Institute, while member of Darwin College, University of Cambridge. This thesis is the result of my own work and includes nothing which is the outcome of work done in collaboration except where specifically indicated in the text.

This thesis does not exceed the specified length limit of 300 pages as defined by the Biology Degree Committee. This thesis has been typeset in 12pt font using L<sup>A</sup>T<sub>E</sub>X<sub>2</sub> $\epsilon$  according to the specifications defined by the Board of Graduate Studies and the Biology Degree Committee.

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December 2009.

# Summary

Current functional genomics relies on known and characterised genes, but despite significant efforts in the field of genome annotation, accurate identification and elucidation of protein coding gene structures remains challenging. Methods are limited to computational predictions and transcript-level experimental evidence, hence translation cannot be verified. Proteomic mass spectrometry is a method that enables sequencing of gene product fragments, enabling the validation and refinement of existing gene annotation as well as the detection of novel protein coding regions. However, the application of proteomics data to genome annotation is hindered by the lack of suitable tools and methods to achieve automatic data processing and genome mapping at high accuracy and throughput. The main objectives of this work are to address these issues and to demonstrate the applicability in a pilot study that validates and refines annotation of *Mus musculus*.

In the first part of this project I evaluate the scoring schemes of “Mascot”, which is a peptide identification software that is routinely used, for low and high mass accuracy data and show these to be not sufficiently accurate. I develop an alternative scoring method that provides more sensitive peptide identification specifically for high accuracy data, while allowing the user to fix the false discovery rate.

Building upon this, I utilise the machine learning algorithm “Percolator” to further extend my Mascot scoring scheme with a large set of orthogonal scoring features that assess the quality of a peptide-spectrum match. I demonstrate very good sensitivity with this approach and highlight the importance of reliable and robust peptide-spectrum match significance measures.

To close the gap between high throughput peptide identification and large scale genome annotation analysis I introduce a proteogenomics pipeline. A comprehensive database is the central element of this pipeline, enabling the efficient mapping of known and predicted peptides to their genomic loci, each of which is associated with supplemental annotation information such as gene and transcript identifiers. Software scripts allow the creation of automated genome annotation analysis reports.

In the last part of my project the pipeline is applied to a large mouse MS dataset. I show the value and the level of coverage that can be achieved for validating genes and gene structures, while also highlighting the limitations of this technique. Moreover, I show where peptide identifications facilitated the correction of existing annotation, such as re-defining the translated regions or splice boundaries. Moreover, I propose a set of novel genes that are identified by the MS analysis pipeline with high confidence, but largely lack transcriptional or conservational evidence.

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# Nomenclature

AMT	Adjusted Mascot Threshold
E-value	Expectation Value
FDR	False Discovery Rate
FP	False Positive
MATH	Mass Accuracy-Based THreshold
MHT	Mascot Homology Threshold
MIT	Mascot Identity Threshold
MMD	Maximum Mass Deviation
MS	Mass Spectrometry
MS/MS	Tandem Mass Spectrometry
PEP	Posterior Error Probability
PPM	Parts Per Million
PSM	Peptide Spectrum Match
ROC	Receiver Operating Characteristics
SQL	Structured Query Language
TP	True Positive