

Research platforms that link "omics" to biobank data – opportunities in Ontario

Speaker:

Tom Hudson Ontario Institute for Cancer Research



How big is "BIG"?

The Causal Complexity of Chronic Diseases

Diabetes Asthma Heart Disease Schizophrenia Cancer Multiple Sclerosis Obesity Arthritis



"webs of causation"



For common diseases, effects that we want to measure are small.

Most GWAS hits have Odds ratios in this range: 1.1 - 1.5

Disease	Gene	Polymorphism	Approximate frequency of the disease associated allele	Approximate odds ratio for disease associated allele	Ref
Thrombophilia	F5	Leiden Arg506Gln	0.03	4	12
Crohn's disease	CARD15	3 SNPs	0.06(composite)	4.6	67
Alzheimer's disease	APOE	ε2/3/4	0.15	3.3	13,68
Osteoporotic fractures	COL1A1	Sp1 restriction site	0.19	1.3	69,70
Type 2 diabetes	KCNJ11	Glu23Lys	0.36	1.23	71
Type 1 diabetes	CTLA4	Thr17Ala	0.36	1.27	72,73
Graves' Disease	CTLA4	Thr17Ala	0.36	1.6	74
Type 1 diabetes	INS	5' VNTR	0.67	1.2	75
Bladder Cancer	GSTM1	Null (gene deletion)	0.70	1.28	76
Type 2 diabetes	PPARG	Pro12Ala	0.85	1.23	11

Hattersley AT, McCarthy MI. Lancet 2005;366:1315-1323 Examples of some polymorphisms or haplotypes that have shown consistent association with complex disease

Genetic main effects





Odds Ratio (log scale)

Paul Burton





Odds Ratio (log scale)

Paul Burton

Number of cases required (log scale)

Detecting rare variants



Global Alliance for Genomics & Health

N ~ 10,000 for 90% power to detect variants in 1% of the population with the expected odds ratio of ~2

(assuming matched controls, equal sizes, etc)

Altshuler et al. Science (2008)

Adam Kiezun

Cancer genomes have a high background mutation rate





Mike Lawrence, Petar Stojanov, Paz Polak et al. Nature (2013)

Completing the catalogue of cancer genes will require 100,000's of

cancer genomes

Lawrence et al. Nature (2014)



For 90% power to detect 90% of genes at frequency ≥ 2%:

Global Alliance

for Genomics & Health

Need mean of ~2000 samples

50 tumor types x 2,000 = 100,000 tumors

Detecting Biomarkers that predict drug response



Example: Response to RAF/MEK inhibition in *BRAFV600E* melanoma



Chapman et al., NEJM (2011)

Levi Garraway

Detecting biomarkers that predict drug response



Assumptions: 50% of patient respond to a drug. We want to find a biomarker (out of 100 candidates) that predicts 80% response



Charles Sawyers

Detecting biomarkers that predict drug response





Charles Sawyers

Summary for "How big is "BIG"?"



We need to aggregate large datasets with genomic and clinical data to obtain sufficient power to:

- 1. Find germline risk alleles (10,000s / tumor type)
- Complete the catalog of cancer genes and pathways
 (>2% of patients) (1000s / tumor)
- 3. Detect biomarkers for response (100s to 1000s / tumor type / drug)

We must share **GENOMIC** and **CLINICAL DATA** from hundreds of thousands to **MILLIONS** of subjects!

We need to make harmonized data and results easily available to researchers/tool developers, clinicians and patients



Overview of the Ontario Health Study



A large innovative prospective cohort in Ontario that will serve as an integrated platform for investigating the complex interplay of environmental, lifestyle and genetic factors that increase individual and community risk of developing cancer, heart disease, diabetes, asthma, depression and other common adult diseases

The Study is one of five regional initiatives being conducted across Canada for the Canadian Partnership for Tomorrow Project

Ontario Health Study
Atlantic Partnership for Tomorrow's Health
Alberta Tomorrow Project
CartaGene Quebec
BC Generations project





Most patients participated by

filling in an online questionnaires

		Wel	come Jenr	nifer		
Home	Study	Reports	Science	News	Info	Media
Base Questionnaire	Personal Info	Consents Refer	ences Account	Preferences Activ	ities	
	0%	Moc	lified Base uestionnai	line re	Français	

To answer all of the questions, including optional questions, it would be helpful if you had:

- The Drug Identification Number (DIN) of any prescription medications you are taking at this time. The DIN is located on the bottle your medication is stored in;
- Your current height and weight;
- The circumference of your waist and hips. Instructions to measure your waist and hips will be provided later in the questionnaire.

Please enter a response to each question on the screen. If there are questions you do not feel comfortable answering, please select the "Prefer not to answer" option.

If you are not sure how to answer a question, please feel free to contact us:

Call our toll-free number in Canada: 1-866-606-0686

Email us at: info@ontariohealthstudy.ca

For answers to commonly asked questions, check our website at OntarioHealthStudy.ca/en/faq

Open

Cancel

About The Study News Privacy FAQ Contact Us © Ontario Health Study 2012

Data linkages at ICES are underway

Biospecimen Collection (currently 20,000)







OHS Toronto Assessment Centre

 Operating at 790 Bay Street from July 2012 through March 2014, the OHS Toronto Assessment Centre completed physical assessments and collected blood and urine samples from over 4,800 Study participants.

Blood Collection Program

 Through a Partnership with LifeLabs Medical Laboratory Services, nearly 7,000 participants have volunteered to provide a small blood sample at one of over 120 LifeLabs locations in Ontario. This program was launched in November 2012.

Local Study Centres

Beginning in 2014, the OHS will pilot and launch a series of Local Study

OHS Demographics

Ethnicity



Gender: 60.9% female

Age: mean: 46.5 years median: 47.2 years

	OHS Participants	2006 Census
Aboriginal	2.7%	1.9%
Black	2.0%	3.7%
Chinese	4.2%	4.5%
South Asian	3.7%	6.2%
White	76.5%	72.1%

OHS Demographics







Prevalence of Major Chronic Diseases in OHS

Particip	ants	Females	Males
	(n= 188,015)	(n= 112,927)	(n= 75,088)
Hypertension	20.1%	16.2%	26.0%
	(37,509)	(18,128)	(19,381)
Heart Disease	3.3%	1.8%	5.5%
	(5,460)	(1,1721)	(3,739)
Diabetes	6.1%	4.7%	8.1%
	(11,306)	(5,268)	(6,038)
Arthritis	19.4%	20.9%	17.1%
	(35,999)	(23,271)	(12,728)
Cancer	8.4%	8.2%	8.6%
	(15,565)	(9,159)	(6,406)
Major depression	10.3%	12.9%	6.3%
	(19,137)	(14,424)	(4,713)

Smoking and Alcohol Use



Smoking Status			
	All participants	Females	Males
	(n= 106,427)	(n= 62,511)	(n= 43,916)
Current Smoker	23.7%	24.9%	21.9%
	(25,178)	(15,554)	(9,624)
Former Smoker	48.9%	47.8%	50.6%
	(52,079)	(29,849)	(22,230)
Non-Smoker	27.4%	27.4%	27.5%
	(29,170)	(17,108)	(12,062)
	Alcohol Con	sumption	
12 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0			
	Frequency of Al	cohol Consumption	

Physical Activity



Physical Activity Level

	All Participants	Females	Males
	(n= 188,015)	(n= 112,927)	(n= 75,088)
Low	4.9%	4.7%	5.3%
	(9,296)	(5,289)	(4,007)
Medium	29.1%	30.0%	27.7%
	(54,643)	(33,818)	(20,825)
High	23.5%	22.2%	25.5%
	(44,209)	(25,034)	(19,175)
	42.5%	43.2%	41.4%
Unknown	(79,867)	(48,786)	(31,081)

Nutrition







Challenges in handling BIG data



GA4GH Data Working Group

Developing solutions for genome and health datasets for millions of research participants

Data Working Group Members



Name	Institution
Richard Durbin (Co-Chair)	Wellcome Trust Sanger Institute, Cambridgeshire, United Kingdom
David Haussler (Co-Chair)	University of California, Santa Cruz, United States
Ewan Birney	European Bioinformatics Institute, Cambridgeshire, United Kingdom
Gaddy Getz	Broad Institute and Massachusetts General Hospital, Boston, United States
Heng Li	Broad Institute, Boston, United States
Gil McVean	University of Oxford, Oxford, United Kingdom
Nicola Mulder	University of Cape Town, Cape Town, South Africa
David Patterson	University of California, Berkeley, Berkeley, United States
Anthony Philippakis	Genome Bridge LLC, Cambridge, United States
Lincoln Stein	Ontario Institute for Cancer Research, Toronto, Canada
Michael Baudis	Swiss Institute of Bioinformatics, Zurich, Switzerland

Big data problems to overcome



- Existing open source bioinformatics software is unprofessional, large medical centers are making the problem worse
- Major medical centers are separately hiring software engineers or using postdocs to build custom genomics pipelines
- Creates Balkanized, incompatible, inadequate systems
- Reinforces barriers to data sharing

Different Requirements for 1M Genomess for G

- Different types of data interactions:
 - Support both research and clinical practice
 - Compute within a provided cloud
 - Separately URIed, metadata-tagged parts of a single patient file supporting 3rd party mashups and tools
- New consents models, sample donor trusts the security provided
- APIs, not file formats.

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Benchmarking so all can use system to improve methods, e.g. SMaSH, somatic variant calling DREAM competition

Dave Patterson, www.eecs.berkeley.edu/Pubs/TechRpts/2012/EECS-2012-211.html

Possible Genome Commons Archit





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- Very large datasets are needed to answer clinically relevant questions related to common diseases and cancer
- New technologies are needed to store, share and analyze large amounts of data to enable learning rules and patterns
- International standards need to be developed for data to be shared responsibly with researchers, clinicians, and public health organizations to accelerate progress and provide benefits to patients. [Discussed by Peter Goodhand]