

Challenges in genomic privacy

Sriram Sankararaman

Department of Computer Science
Department of Human Genetics
UCLA

Genomic data

Consumer genomics

GWAS



Biobanks



Outline

Consumer genomics

GWAS

Clinical genomics and biobanks

Consumer genomics

AncestryDNA, 23andMe

~ 1million genotyped customers

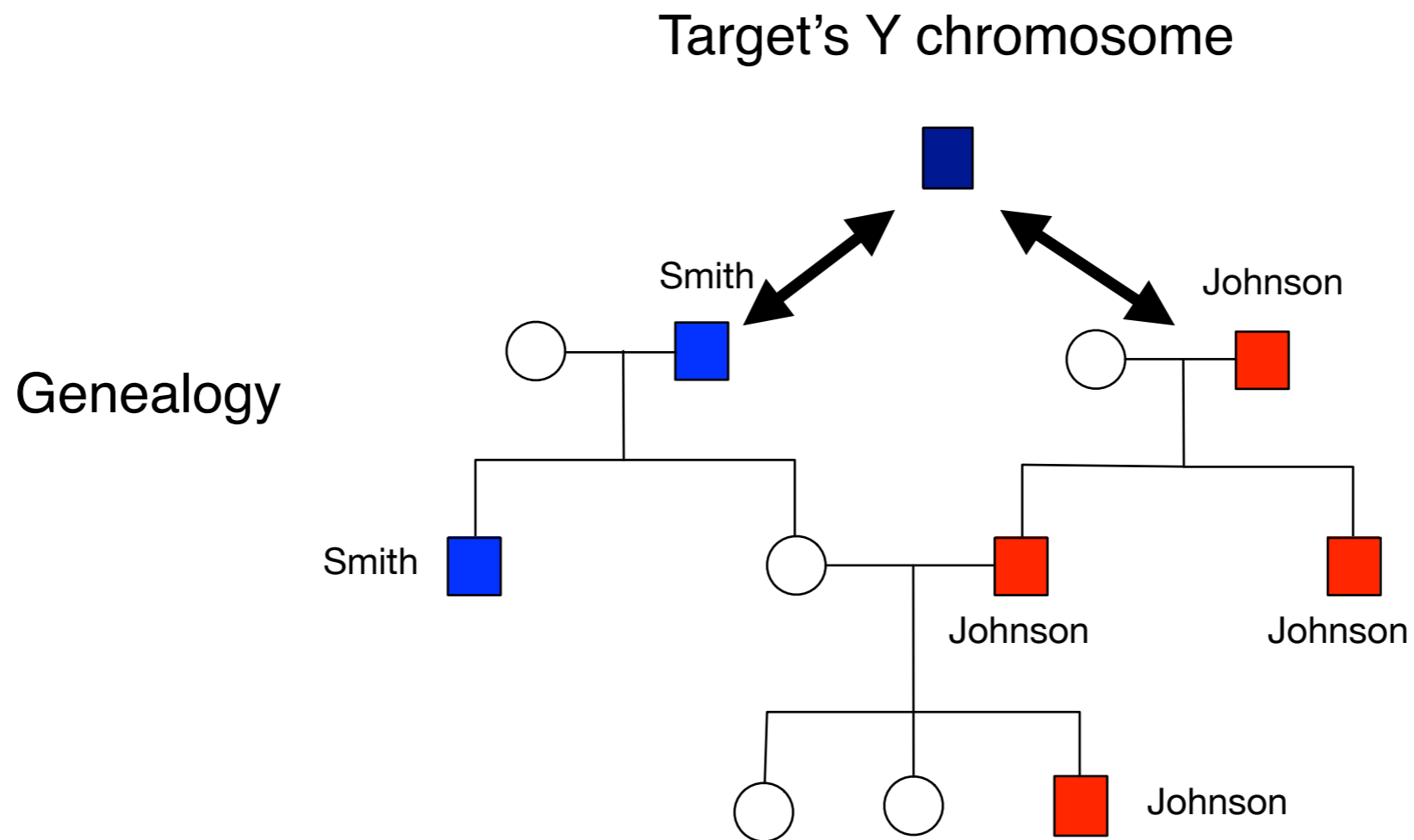
FamilyTreeDNA

~100K individuals

Identity tracing

Genealogical triangulation

De-identified genome to surname

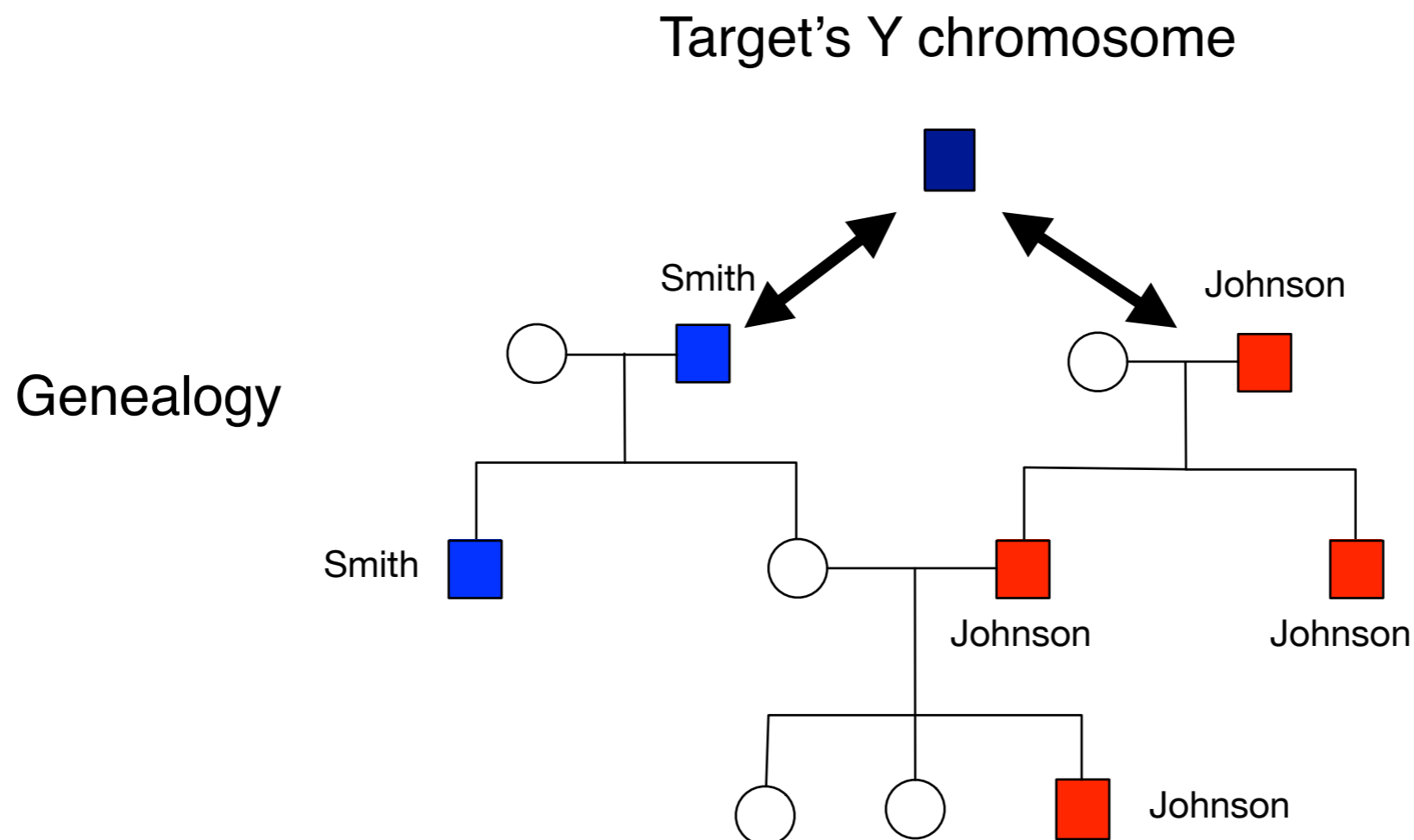


Identity tracing

Genealogical triangulation

Given query and potential match i , compute

$$t_i = \operatorname{argmax}_t \Pr(\text{Mismatches}_i | \text{Generations} = t, \theta)$$



Identity tracing

Genealogical triangulation

Genealogical databases (~135K records, 39,000 unique records)

~12% of males can be correctly identified (83% unknown, 5% false positive rate)

Many surnames shared by less than <400,000 individuals (as informative as zip code)

Combine with year of birth and state of residency, gives median list of 12 individuals.

Questions

What happens with whole genome sequence vs Y chromosomes ?

Designing private queries

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Genome-wide Association Studies (GWAS)

	SNPs										Phenotype	
Individual	A	C	G	A	A	C	G	G	T	A	A	1
	C	C	G	G	T	C	G	G	T	C	T	1
	C	C	T	A	T	G	A	A	A	A	A	0
	A	T	G	A	A	G	G	G	T	A	T	0

GWAS pipeline



Data cleaning

Remove outlier SNPs and individuals

Impute missing data

Identify confounders

Observed (Gender, Age)

Unobserved (Ancestry): Needs to be inferred

Compute association statistics for a phenotype with each SNP j

$$Y \sim X_j + O + U$$

Compute model diagnostics

Replicate

GWAS have low power

Most SNP effects are weak

Strongest association for type-2 diabetes increase risk by ~20%

Large number of hypothesis tested (p-value < $5e-8$ for statistical significance)

The missing heritability problem

For type-2 diabetes, current associations only explain ~12% of risk.

Sample size is key

Data sharing and meta-analyses

Opens up the possibility of re-identification attacks

Sample size is key

A two-tier access system for many repositories

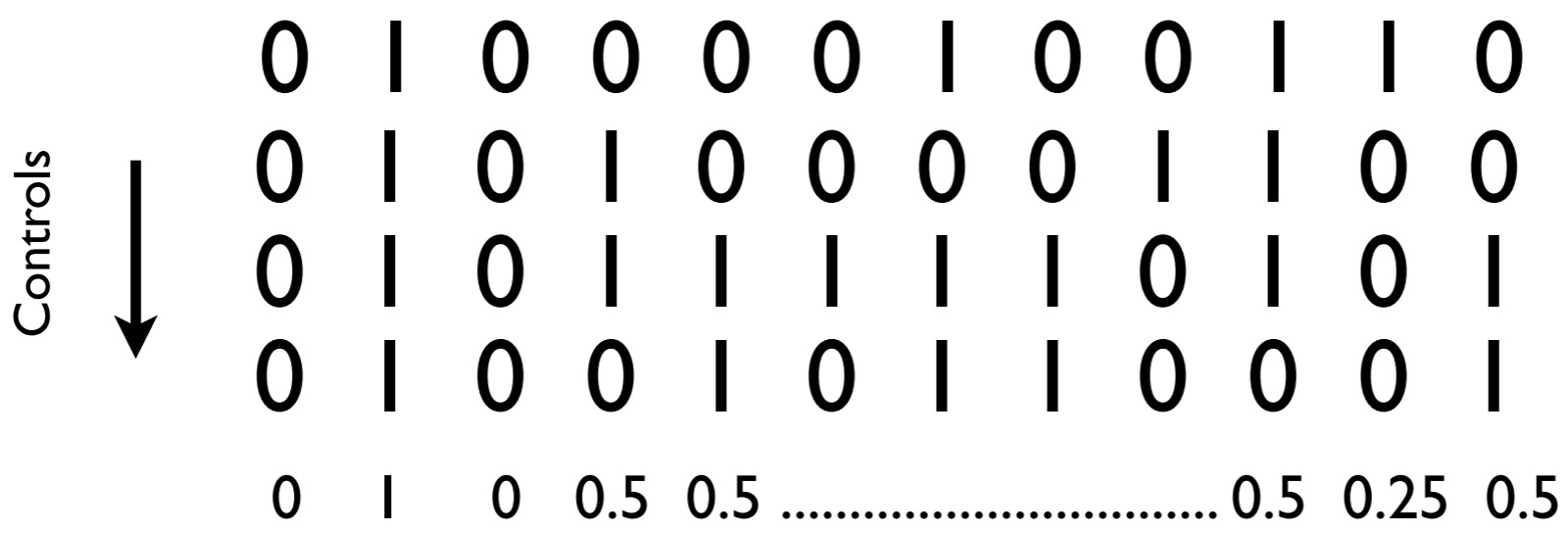
Restricted access to individual-level genotype and phenotype data

Public access for summary statistics

Identification from summary statistics



0 1 1 1 0 0 0 0 1 0 1 0 : Is this in the case ?



Identification also possible with other summary statistics

Marginal regression coefficients (Im et al. 2012)
and their standard errors

Questions

Marginal regression coefficients

What is the lower bound in this setting if the summary statistics are distorted ?

What if the goal is to accurately predict the phenotype (and not the membership)?

Questions

DP in High-dimensional setting

How do we perform meta-analysis on DP estimates?

Two goals of GWAS : prediction vs discovering new associations (hypothesis testing)

Is one easier than the other ?

How do we build DP GWAS pipelines ?

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Federated genomic datasets

Resides across multiple centers

Global Alliance for Genomics and Health
(GA4GH)

~300 institutions with software interface that connects across these institutions

The Beacon project

Web service that allows multiple datasets that are registered in the GA4GH to be queried

Query: Do you have any genomes with an A at position 104,444 on chromosome 1 ?

Answer :Yes or No

Allows researchers to explore datasets for alleles of interest before they decide to apply for access

The Beacon project

Tracing attack on the beacons (Shringarpure et al. 2015)

Analogous to Homer et al. 2008

Questions

Potential for application of DP given the relatively small number of queries (compared to the larger number of SNPs released in GWAS)

Local versus global models of DP (each entity wants to participate without being open to breaches)

Other *-omics data

Gene expression

Schadt et al. 2012

Microbiome data

Franzosa et al. 2015

Electronic medical records

Loukides et al. 2010

