## Private Computation with Genomic Data for Genome-Wide Association and Linkage Studies

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## Motivation

- GWAS play a crucial role in medicine and the pharmaceutical industry
- We treat the problem of securing computation associated with GWAS and GWLS
$\checkmark$ Hardy-Weinberg equilibrium (HWE)
$\checkmark$ linkage disequilibrium (LD)
$\checkmark$ Cochran-Armitage test for trend (CATT)
$\checkmark$ Fisher test
- There is a desire to protect highly sensitive DNA data of users participating in these tests
- We choose a flexible framework for privately computing with genomic data
$\checkmark$ secure joint computation by multiple entities
$\checkmark$ secure computation outsourcing to a number of computational servers


## Statistical Tests

- HWE
$\checkmark$ is used to estimate the frequency of alleles in a population
$\checkmark$ is typically performed using chi-squared test

$$
\chi^{2}=\sum_{i \in\{A A, A a, a a\}} \frac{\left(N_{i}-E_{i}\right)^{2}}{E_{i}}
$$

$\star E_{i}$ 's represent expected values of the genotypes, defined as $E_{A A}=\left(N_{A}\right)^{2} /(4 N), E_{A a}=\left(N_{A} N_{a}\right) /(2 N)$, and $E_{a a}=\left(N_{a}\right)^{2} /(4 N)$

## Statistical Tests

- LD
$\checkmark$ occurs when genotypes at two different loci are not independent of each other
$\checkmark$ is computed by chi-squared for the hypothesis of no disequilibrium

$$
\chi_{A, B}^{2}=\frac{2 N\left(D_{A B}\right)^{2}}{p_{A}\left(1-p_{A}\right) p_{B}\left(1-p_{B}\right)}=\frac{2 N\left(D_{A B}\right)^{2}}{p_{A} p_{a} p_{B} p_{b}}
$$

* $D_{A B}$ is called the coefficient of LD and can be computed as $D_{A B}=p_{A B}-p_{A} p_{B}$


## Statistical Tests

- CATT
$\checkmark$ is used to assess the presence of association between a variable with two different categories (cases and controls) and a variable with 3 different categories in application to GWAS

|  | Group 0 | Group 1 | Group 2 | Total |
| :---: | :---: | :---: | :---: | :---: |
| Controls | $N_{00}$ | $N_{01}$ | $N_{02}$ | $R_{0}$ |
| Cases | $N_{10}$ | $N_{11}$ | $N_{12}$ | $R_{1}$ |
| Total | $C_{0}$ | $C_{1}$ | $C_{2}$ | $N$ |

$\checkmark$ represents a modification of chi-squared test

$$
\chi^{2}=\frac{\left(\sum_{i=0}^{2} w_{i}\left(N_{0 i} R_{1}-N_{1 i} R_{0}\right)\right)^{2}}{\frac{R_{0} R_{1}}{N}\left(\sum_{i=0}^{2} w_{i}^{2} C_{i}\left(N-C_{i}\right)-2 \sum_{i=0}^{1} \sum_{j=i+1}^{2} w_{i} w_{j} C_{i} C_{j}\right)}
$$

$\star w=\left(w_{0}, w_{1}, w_{2}\right)$ corresponds to predetermined weights

## Statistical Tests

- Fisher test
$\checkmark$ is used in the analysis of contingency tables similar to CATT to assess the presence of association between two categories of cases and controls and two groups of $A$ and $B$ alleles in application to GWAS and pharmaceutical drug tests

|  | $A$ | $B$ | Total |
| :--- | :---: | :---: | :---: |
| Controls | $N_{0 A}$ | $N_{0 B}$ | $R_{0}$ |
| Cases | $N_{1 A}$ | $N_{1 B}$ | $R_{1}$ |
| Total | $C_{A}$ | $C_{B}$ | $N$ |

$\checkmark$ is more accurate than chi-squared tests when sample sizes are small

$$
p=\frac{R_{0}!\cdot R_{1}!\cdot C_{A}!\cdot C_{B}!}{N!\cdot N_{0 A}!\cdot N_{0 B}!\cdot N_{1 A}!\cdot N_{1 B}!}
$$

* controls correspond to category 0 and cases to category 1


## Security Model

- We frame secure computation in a general setting where there are a number of input providers, a number of computational parties, and a number of output recipients
- These three sets of participants can be formed in an arbitrary way
- The focus of this work is on the semi-honest model. The techniques that we employ, however, can be extended to support the stronger malicious model as well using well-known results


## Underlying Techniques

- We build solutions based on secret sharing
- $(n, t)$ linear secret sharing:
$\checkmark$ A secret $s$ is divided into $n$ pieces.
$\checkmark$ No information will be learned regarding $s$ from $t$ or fewer shares.
$\checkmark$ With $t+1$ or more shares, $s$ can be reconstructed.
- We measure performance of secure computation in our framework in terms of interactive operations and rounds since local computation is very fast


## Secure Hardy-Weinberg Equilibrium Computation

- We expand the HWE formula and $\chi^{2}$ is being compared to the threshold $\tau$
- Because the division operation is significantly more expensive that integer multiplication in our framework, we can re-write the formula to replace divisions with multiplications

$$
\begin{aligned}
& \left(4 N \cdot\left[N_{A A}\right]-\left[N_{A}\right]^{2}\right)^{2}\left[N_{a}\right]^{2}+2\left(2 N \cdot\left[N_{A a}\right]-\left[N_{A}\right] \cdot\left[N_{a}\right]\right)^{2}\left[N_{A}\right] \cdot\left[N_{a}\right] \\
& +\left(4 N \cdot\left[N_{a a}\right]-\left[N_{a}\right]^{2}\right)^{2}\left[N_{A}\right]^{2} \leq 4 N \cdot \tau \cdot\left[N_{A}\right]^{2} \cdot\left[N_{a}\right]^{2}
\end{aligned}
$$

- This can be accomplished in $4 \ell+8$ interactive operations in 6 rounds, where $\ell$ is the bitlength of the values being compared in previous equation which is proportional to $\log (N)$


## Secure Linkage Disequilibrium Computation

- We expand the LD formula and $\chi_{A, B}^{2}$ is being compared to the threshold $\tau$
- We re-structure the computation to avoid the division operation

$$
2 N \cdot\left(N \cdot\left[N_{A B}\right]-\left[N_{A}\right] \cdot\left[N_{B}\right]\right)^{2} \leq \tau \cdot\left[N_{A}\right] \cdot\left[N_{a}\right] \cdot\left[N_{B}\right] \cdot\left[N_{b}\right]
$$

- This can be accomplished in $4 \ell+2$ interactive operations in 5 rounds


## Secure Cochran-Armitage Test for Trend Computation

- We expand the CATT formula and $\chi^{2}$ is being compared to the threshold $\tau$
- We re-structure the computation to avoid the division operation

$$
\begin{aligned}
& N \cdot\left(\left[w_{1}\right] \cdot\left(\left[N_{01}\right] \cdot R_{1}-\left[N_{11}\right] \cdot R_{0}\right)+\left[w_{2}\right] \cdot\left(\left[N_{02}\right] \cdot R_{1}\right.\right. \\
& \left.\left.-\left[N_{12}\right] \cdot R_{0}\right)\right)^{2} \leq R_{0} R_{1} \tau \cdot\left(\left[w_{1}\right]^{2} \cdot\left[C_{1}\right] \cdot\left(N-\left[C_{1}\right]\right)\right. \\
& \left.+\left[w_{2}\right]^{2} \cdot\left[C_{2}\right] \cdot\left(N-\left[C_{2}\right]\right)-2\left[w_{1}\right] \cdot\left[w_{2}\right] \cdot\left[C_{1}\right] \cdot\left[C_{2}\right]\right)
\end{aligned}
$$

- This can be accomplished in $4 \ell+6$ interactive operations in 5 rounds
- When the weights $w_{1}$ and $w_{2}$ are public and non-zero, evaluation of previous equation costs $4 \ell+2$ interactive operations in 4 rounds


## Secure Fisher Test Computation

- We proceed with computing the logarithm of the p-value instead of directly implementing Fisher test equation
$\checkmark$ to avoid working with values of excessive bitlength
$\checkmark$ to replace the division operation with a very fast subtraction operation

$$
\begin{array}{r}
\log (p)=\log \left(R_{0}!\right)+\log \left(R_{1}!\right)+\log \left(C_{A}!\right)+\log \left(C_{B}!\right)-\log (N!) \\
-\log \left(N_{0 A}!\right)-\log \left(N_{0 B}!\right)-\log \left(N_{1 A}!\right)-\log \left(N_{1 B}!\right)
\end{array}
$$

## Secure Fisher Test Computation

- We can simultaneously compute $\log \left(\left[N_{0 A}\right]!\right)$ and $\log \left(\left[N_{0 B}\right]\right.$ ! $)$ using one set of $R_{0}$ comparisons. Therefore, oblivious computations of $\log \left(v_{A}!\right)$ and $\log \left(v_{b}!\right)$ for some private $v_{A}$ and $v_{B}$

$$
\begin{aligned}
& {\left[v_{A}\right]=\left[v_{B}\right]=0 ;} \\
& \text { for } i=2, \ldots, R_{0}-1 \\
& \quad\left[c_{i}\right]=\operatorname{LTE}(i,[v]) ; \\
& \quad\left[v_{A}\right]=\left[v_{A}\right]+\left[c_{i}\right] \cdot \log (i) ; \\
& \quad\left[v_{B}\right]=\left[v_{B}\right]+\left(1-\left[c_{i}\right]\right) \cdot \log \left(R_{0}+1-i\right) ;
\end{aligned}
$$

- Our implementation of securely evaluating $\log (v!)$ for some private $v$ proceeds similar to the computation of a table lookup with a private index
- Our solution has $O(N \log N)$ complexity and $O(\log N)$ round complexity


## Performance Results

| Test | $N$ | Modulus |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | Number $M$ of alleles |  |  |  |  |
|  |  | 10 | 100 | 1,000 | 10,000 |  |
| HWE | 200 | 98 | 0.042 | 0.321 | 3.21 | 32.5 |
|  | 400 | 104 | 0.046 | 0.355 | 3.39 | 33.9 |
|  | 800 | 110 | 0.047 | 0.361 | 3.64 | 36.3 |
|  | 1600 | 116 | 0.051 | 0.374 | 3.87 | 38.9 |
| LD | 200 | 89 | 0.037 | 0.298 | 2.99 | 30.6 |
|  | 400 | 94 | 0.040 | 0.313 | 3.08 | 31.9 |
|  | 800 | 99 | 0.042 | 0.337 | 3.18 | 32.1 |
|  | 1600 | 104 | 0.043 | 0.345 | 3.37 | 33.7 |

## Performance Results

| Test | $N$ | Modulus size | Number $M$ of alleles |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  | 10 | 100 | 1,000 | 10,000 |
| CATT with private weights | 200 | 86 | 0.036 | 0.297 | 2.92 | 29.5 |
|  | 400 | 91 | 0.039 | 0.295 | 2.98 | 30.7 |
|  | 800 | 96 | 0.040 | 0.319 | 3.02 | 31.3 |
|  | 1600 | 101 | 0.045 | 0.348 | 3.23 | 32.6 |
| CATT with public weights | 200 | 86 | 0.035 | 0.291 | 2.86 | 29.1 |
|  | 400 | 91 | 0.039 | 0.298 | 2.99 | 30.7 |
|  | 800 | 96 | 0.039 | 0.308 | 3.07 | 31.5 |
|  | 1600 | 101 | 0.041 | 0.340 | 3.27 | 32.7 |
| Fisher | 100 | 67 | 0.108 | 0.979 | 9.78 | 98.1 |
|  | 200 | 68 | 0.217 | 2.09 | 20.9 | N/A |
|  | 400 | 69 | 0.453 | 4.47 | 44.6 | N/A |



