Protecting Patient Privacy in Genomic Analysis

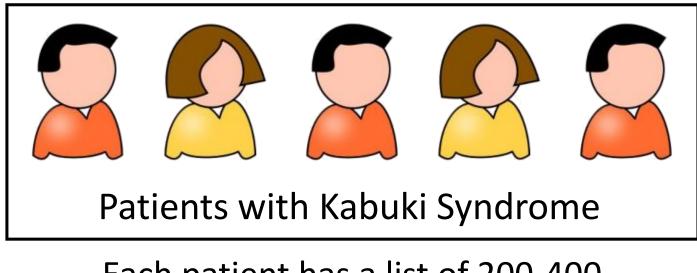
David Wu Stanford University

based on joint works with:

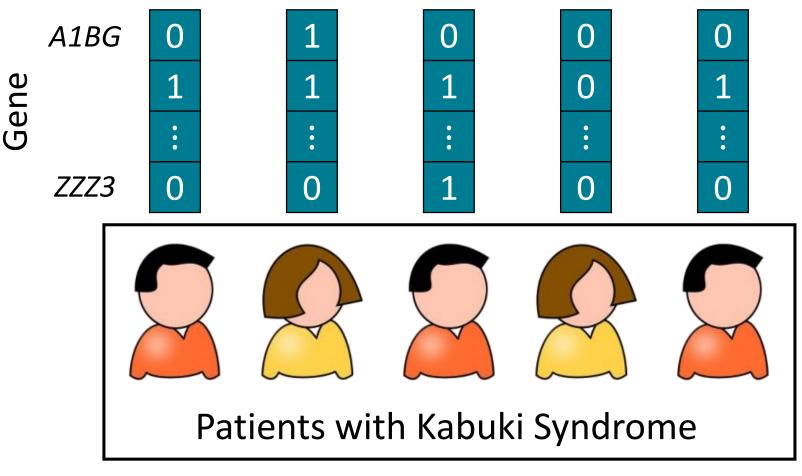
Gill Bejerano, Bonnie Berger, Johannes A. Birgmeier, Dan Boneh, Hyunghoon Cho, and Karthik A. Jagadeesh

Jagadeesh-W-Birgmeier-Boneh-Bejerano [Science 2017]

What gene causes a specific (rare) disease?



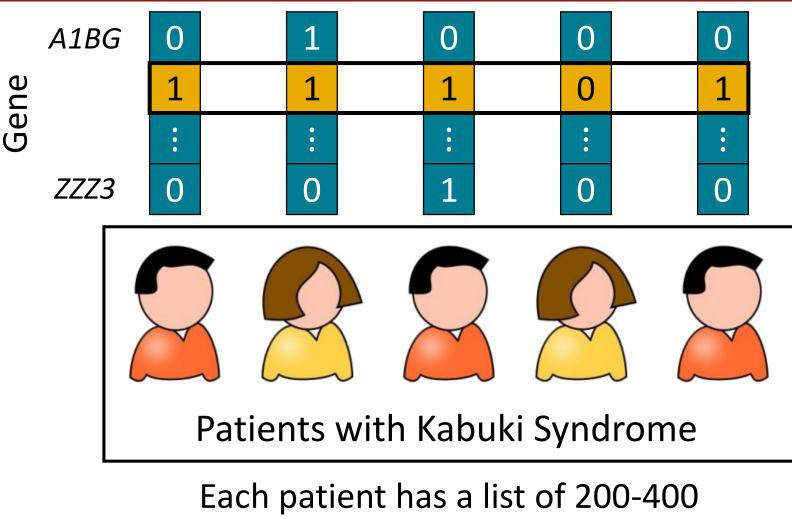
Jagadeesh-W-Birgmeier-Boneh-Bejerano [Science 2017]



Each patient has a vector vwhere $v_i = 1$ if patient has a rare variant in gene i

Goal: Identify gene with most variants across all patients

Jagadeesh-W-Birgmeier-Boneh-Bejerano [Science 2017]



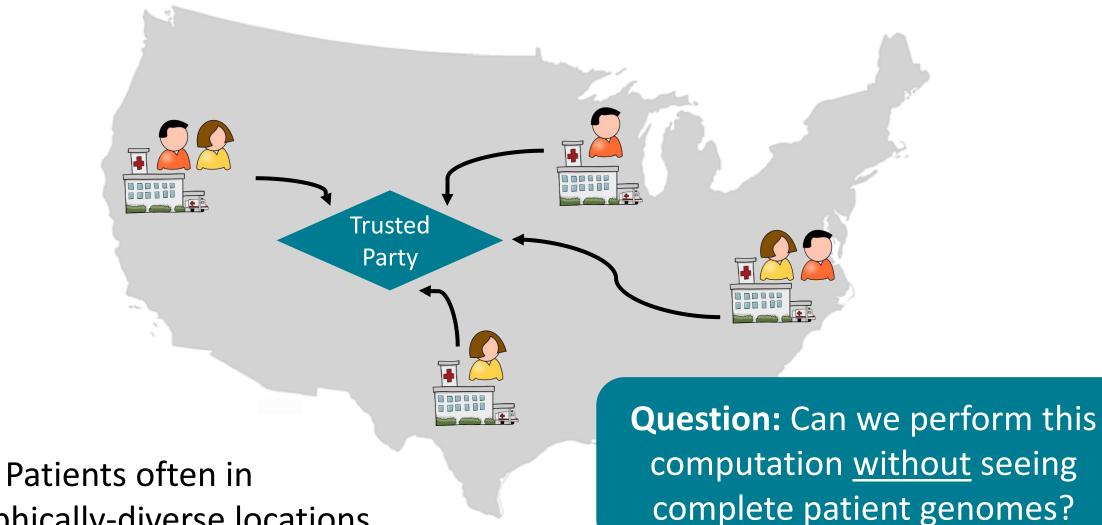
rare variants over ≈20,000 genes

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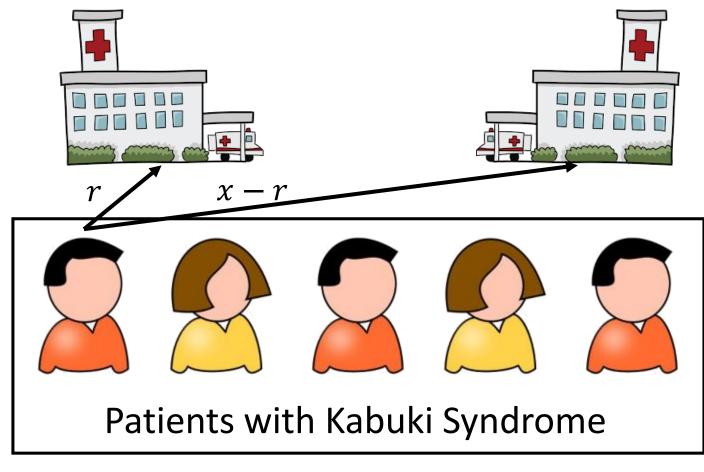
Works well for <u>Mendelian</u> (monogenic) diseases (estimated to affect ≈10% of individuals)

Jagadeesh-W-Birgmeier-Boneh-Bejerano [Science 2017]



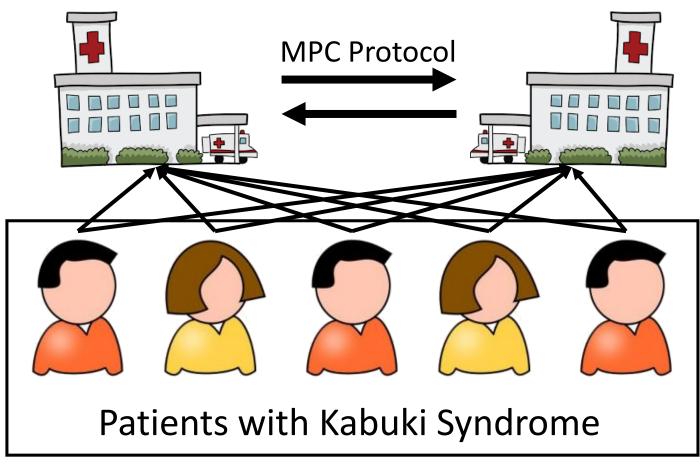
geographically-diverse locations

Jagadeesh-W-Birgmeier-Boneh-Bejerano [Science 2017]



Patients "secret share" their data with two non-colluding hospitals

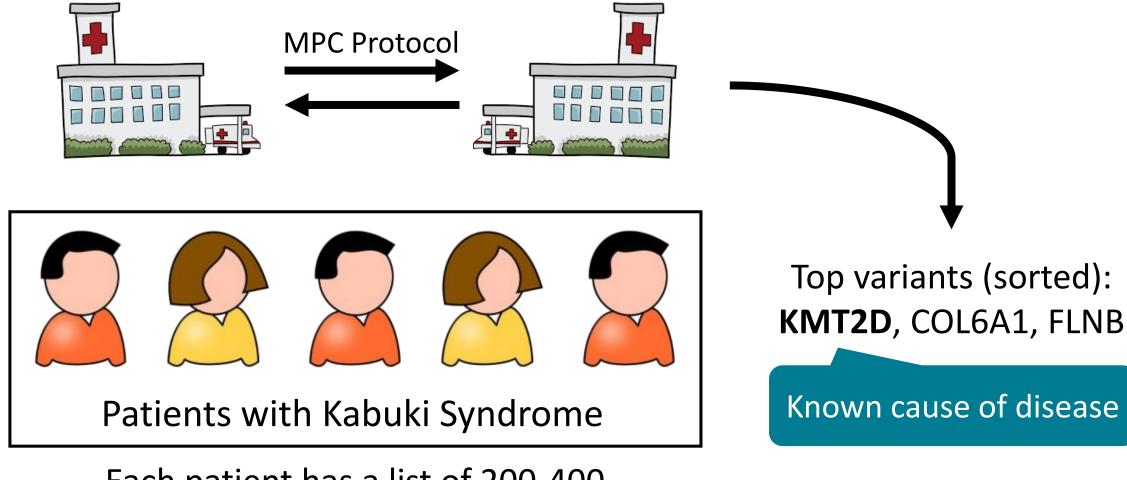
Jagadeesh-W-Birgmeier-Boneh-Bejerano [Science 2017]



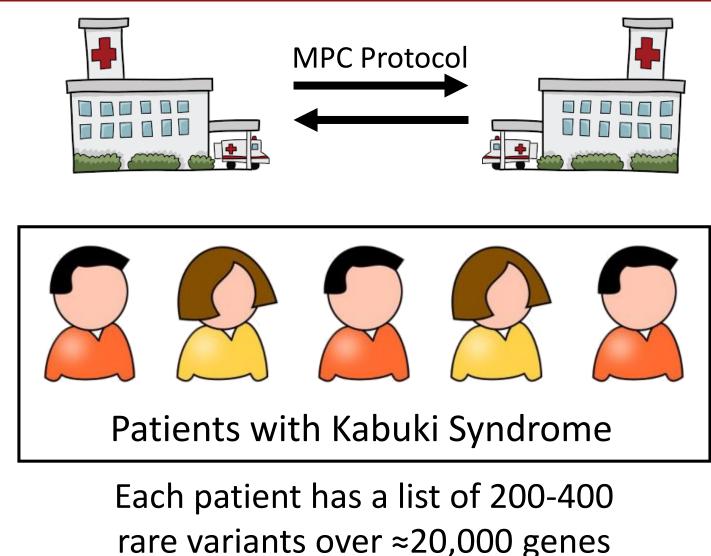
Hospitals run a multiparty computation (MPC) protocol on pooled inputs

Patients "secret share" their data with two non-colluding hospitals

Jagadeesh-W-Birgmeier-Boneh-Bejerano [Science 2017]



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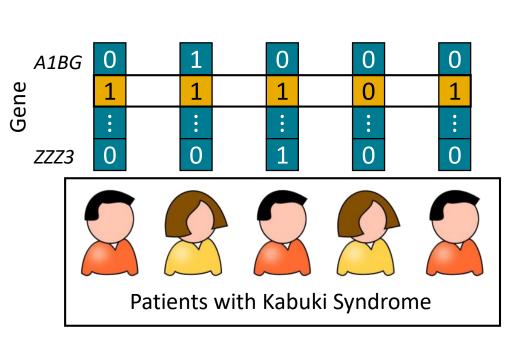


Top variants (sorted): **KMT2D**, COL6A1, FLNB

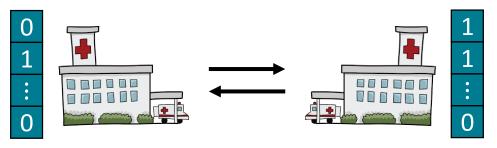
Other variants that the patients possess are kept <u>hidden</u>

Jagadeesh-W-Birgmeier-Boneh-Bejerano [Science 2017]

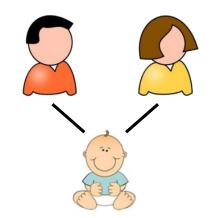
General techniques apply to many different scenarios for diagnosing Mendelian diseases



Identify causal gene for a rare disease given a small patient cohort



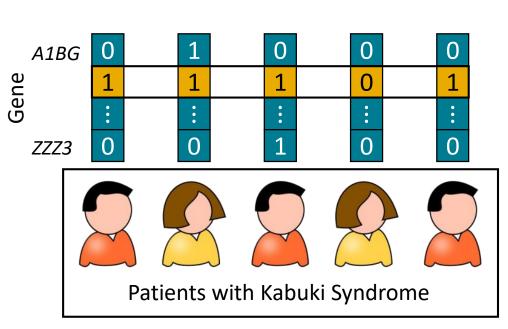
Identify patients with the same rare functional mutation at two different hospitals



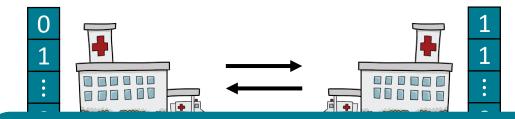
Identify rare functional variants that are present in the child but in neither of the parents

Jagadeesh-W-Birgmeier-Boneh-Bejerano [Science 2017]

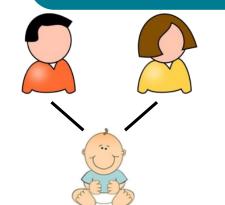
General techniques apply to many different scenarios for diagnosing Mendelian diseases



Identify causal gene for a rare disease given a small patient cohort



Simple frequency-based algorithms, but techniques enabled us to <u>discover</u> a <u>previously unidentified</u> pathogenic variant

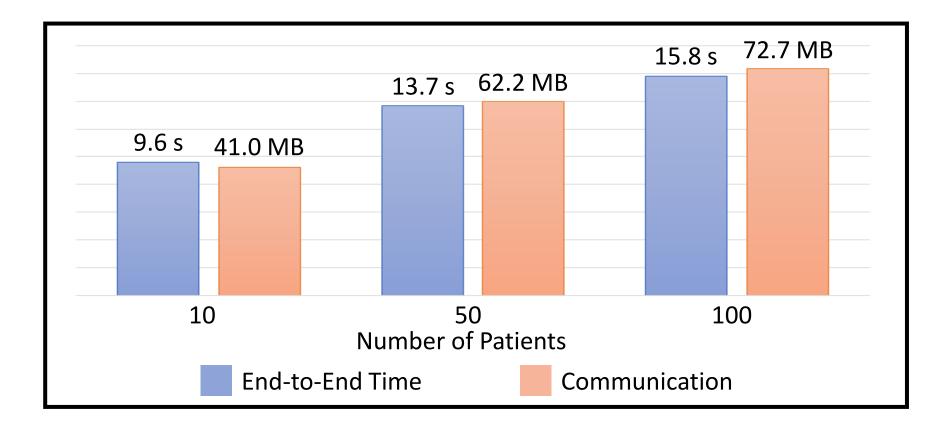


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Experimental benchmarks for identifying causal gene in small disease cohort

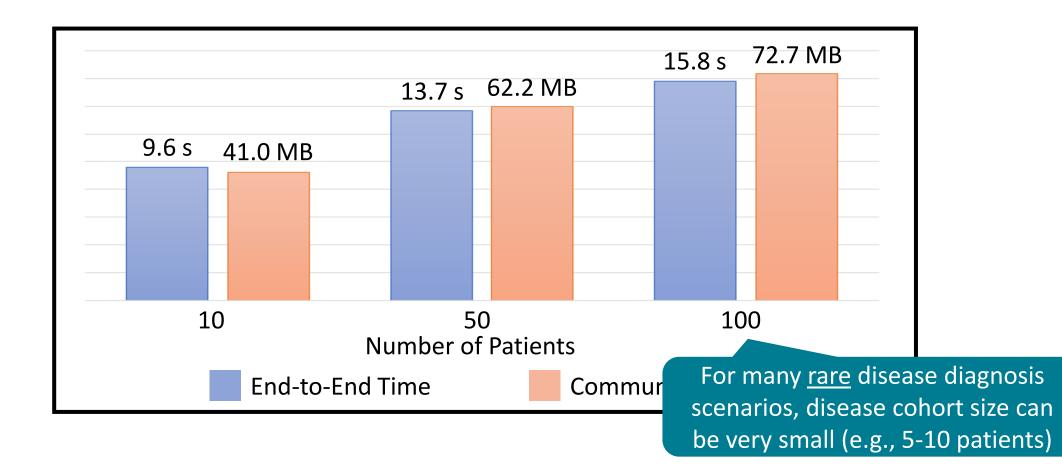
• Simulated two non-colluding entities with 1 server on East Coast and 1 on West Coast



Jagadeesh-W-Birgmeier-Boneh-Bejerano [Science 2017]

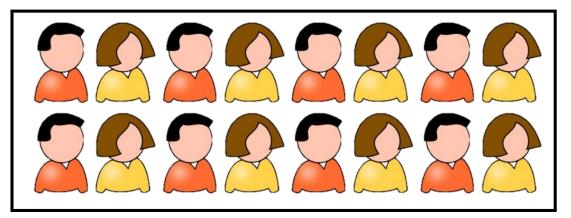
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What About More Complex Diseases?

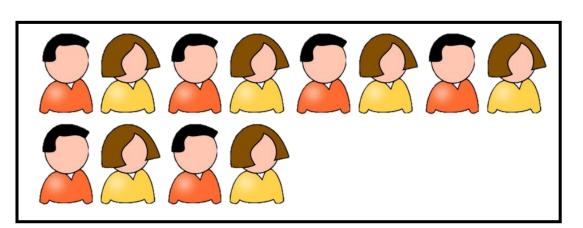
Cho-W-Berger [Nature Biotechnology 2018]



Control group (healthy)

Genome-wide association studies (GWAS):

- Identify genetic variants most correlated with a particular disease (or particular phenotype)
- Oftentimes, focused on identifying complex interactions between many variants



Challenges:

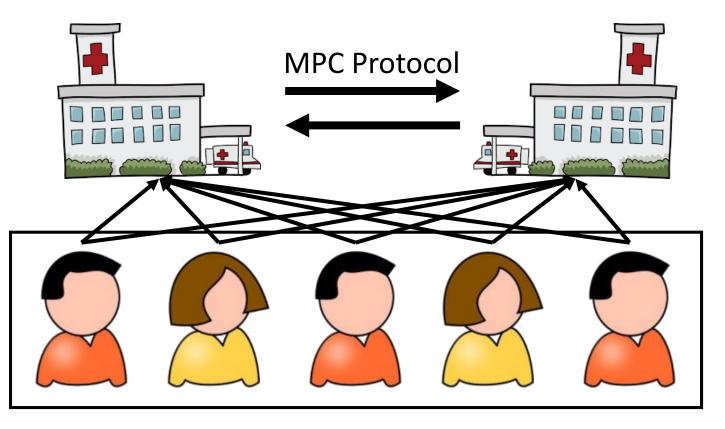
- Need <u>large</u> case/control groups to identify weak genetic signals (e.g., 10K-1M individuals)
- Oftentimes need to correct for populationlevel effects

Case group (affected)

What About More Complex Diseases?

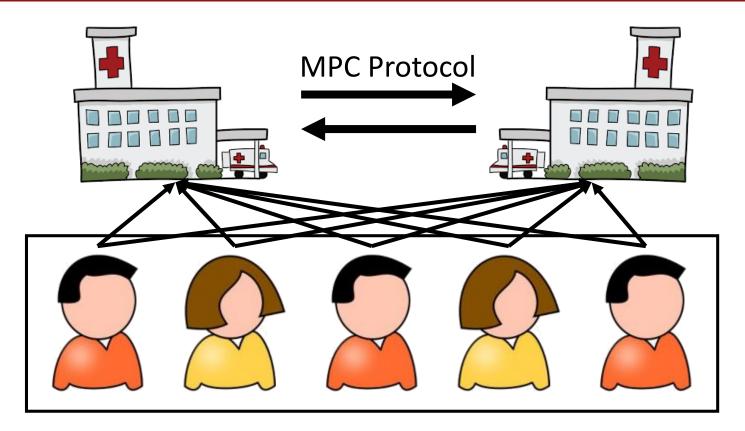
Cho-W-Berger [Nature Biotechnology 2018]

Similar model for genome outsourcing:

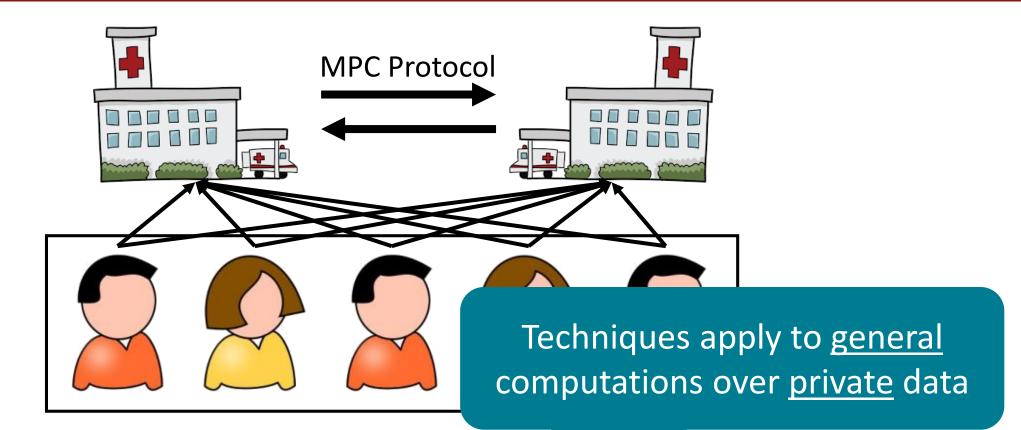


This work: first <u>end-to-end</u> GWAS protocol (with population correction)

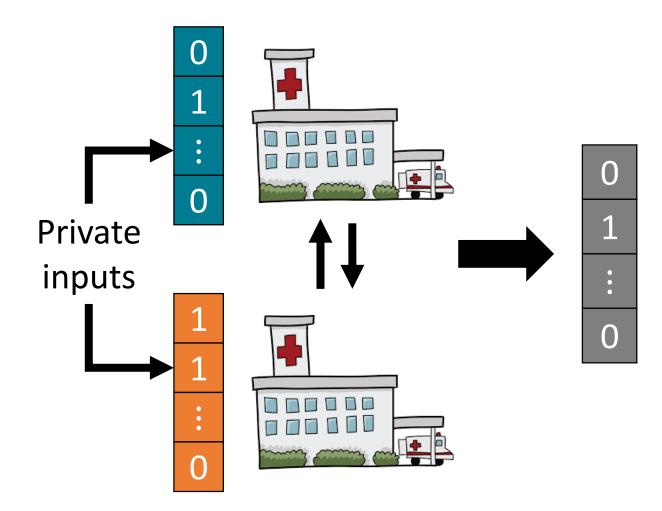
 For 25K individuals, computation completes in about 3 days: <u>feasible</u> for performing large-scale scientific studies



Modern cryptographic tools enable useful computations while protecting the privacy of individual genomes

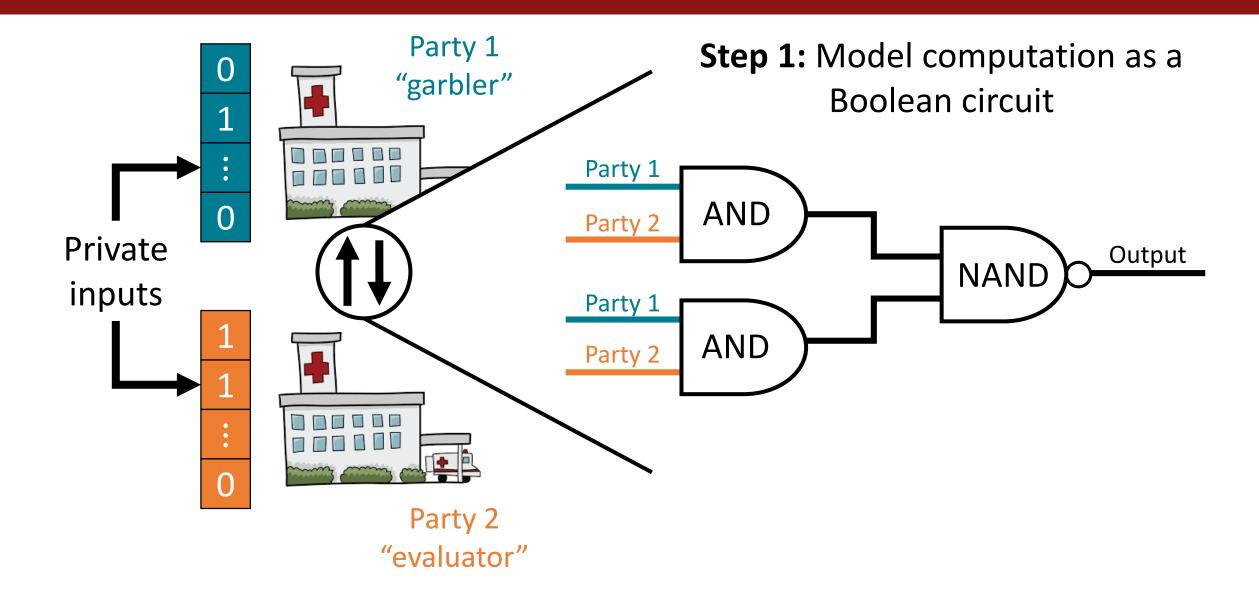


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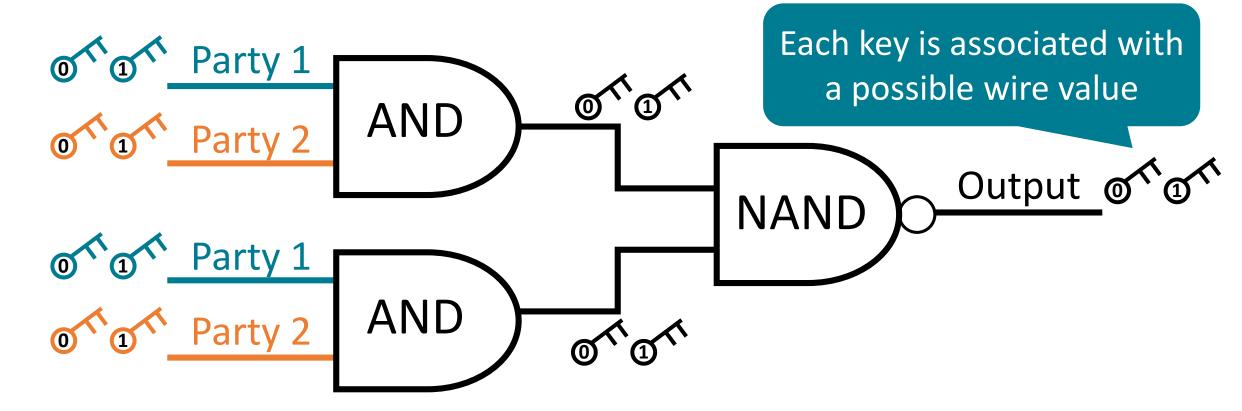


Security guarantee: everything the parties learn can be inferred from the output and their individual inputs

Classic protocol for two-party computation

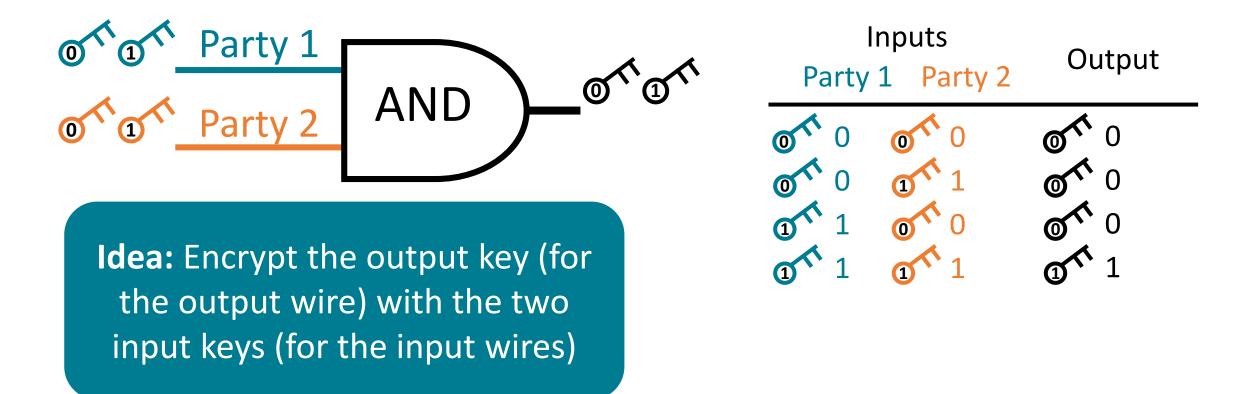


Step 2: Garbler "encrypts" the circuit (i.e., "garbles" the circuit)

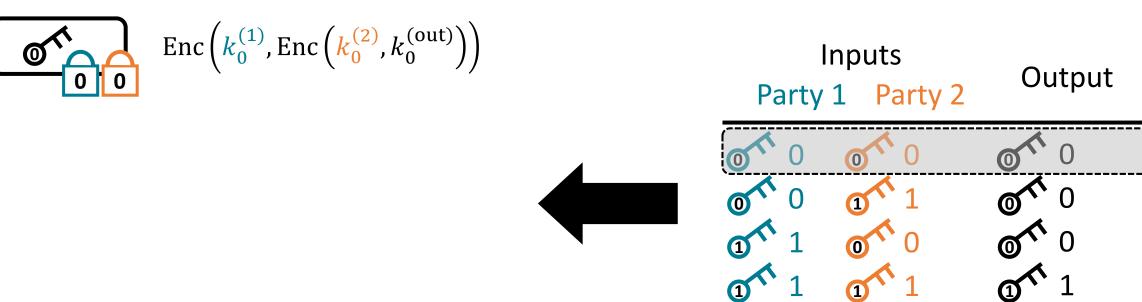


Garbler chooses two different encryption keys for every wire in the circuit

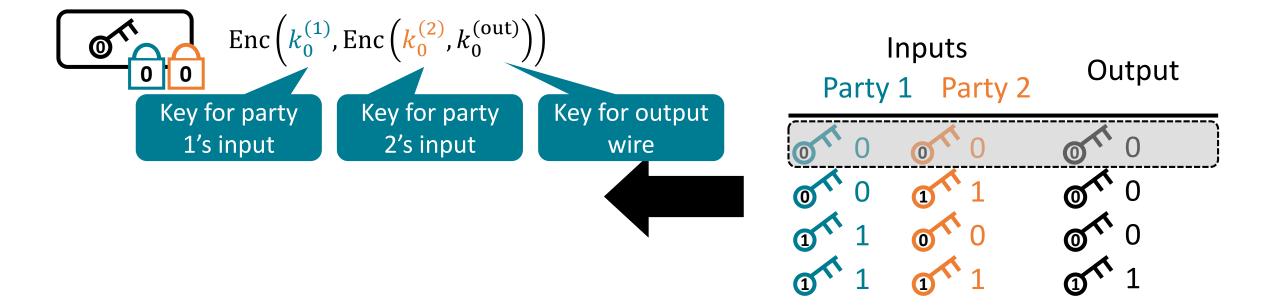
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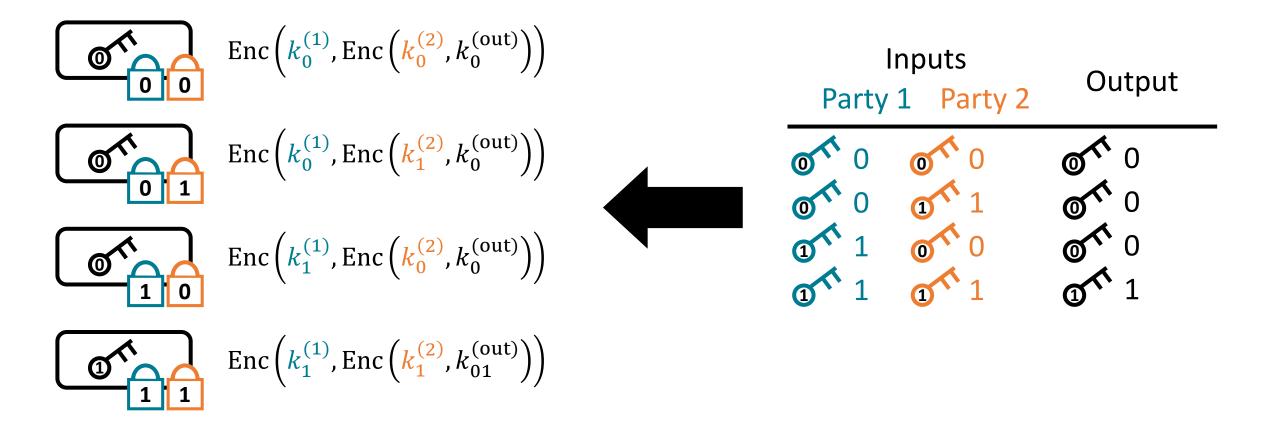
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Enc
$$\left(k_{0}^{(1)}, \operatorname{Enc}\left(k_{1}^{(2)}, k_{0}^{(\operatorname{out})}\right)\right)$$

 $\operatorname{Enc}\left(k_{0}^{(1)}, \operatorname{Enc}\left(k_{0}^{(2)}, k_{0}^{(\operatorname{out})}\right)\right)$

Garbled truth table randomly permuted



$$\operatorname{Enc}\left(k_{1}^{(1)},\operatorname{Enc}\left(k_{0}^{(2)},k_{0}^{(\operatorname{out})}\right)\right)$$

 $\left[\begin{array}{c} \textcircled{1} \\ \textcircled{1} \\ \textcircled{1} \\ \end{array} \right] = \operatorname{Enc}\left(k_{1}^{(1)}, \operatorname{Enc}\left(k_{1}^{(2)}, k_{01}^{(\text{out})}\right)\right)$

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Garbled truth table randomly permuted

Invariant: Given just a single key for each input wire, evaluator can learn a <u>single</u> key for the output wire

1
$$k_1^{(1)}$$
 1 $k_0^{(2)}$

Step 2: Garbler "encrypts" the circuit (i.e., "garbles" the circuit)

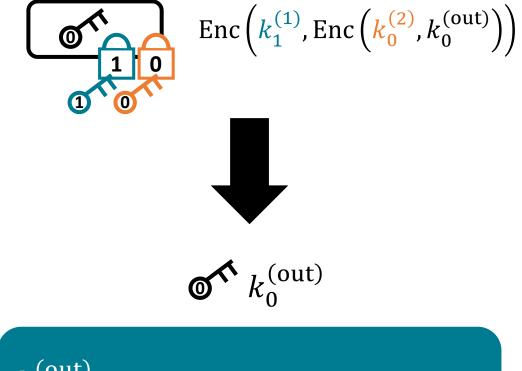
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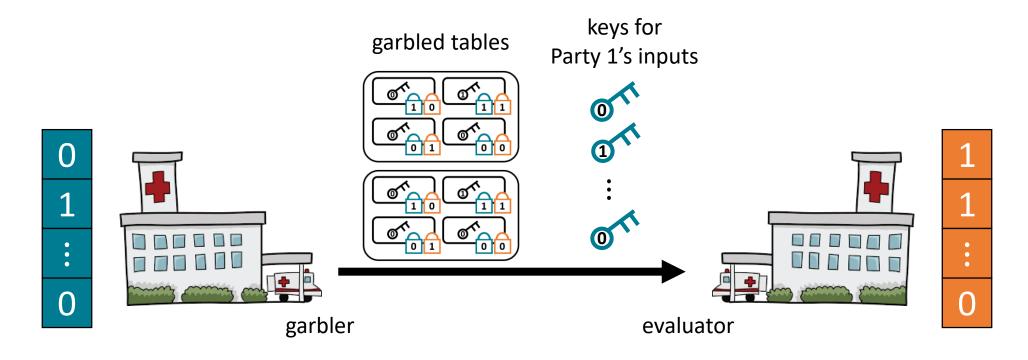


 $k_0^{(out)}$ is just a symmetric key – does <u>not</u> reveal what the output bit is Garbled truth table randomly permuted

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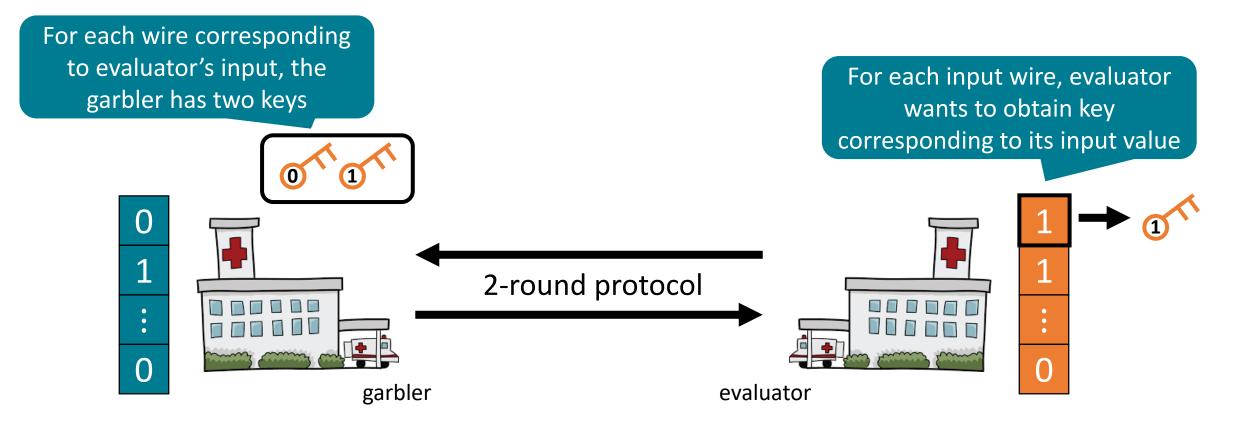
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Question: how does evaluator obtain keys for its input?

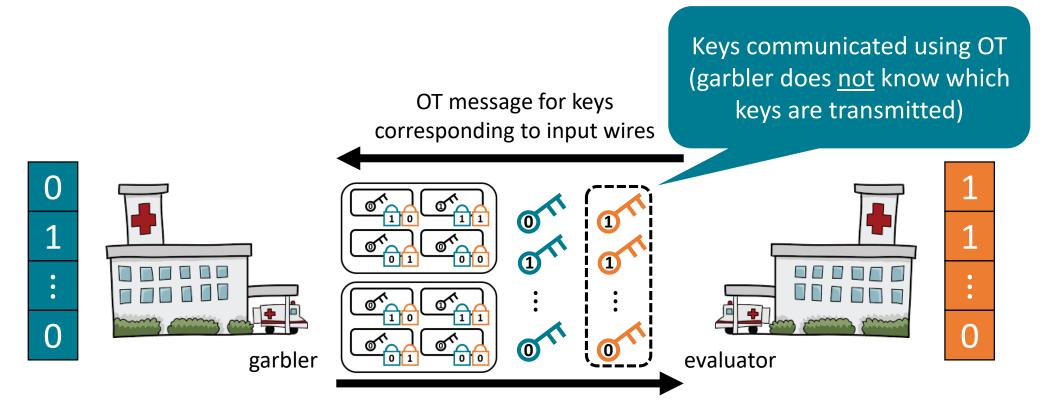
Garbler can send garbled truth tables and keys for its inputs

Step 3: Evaluator uses "oblivious transfer" to obtain keys for its input



At the end of the oblivious transfer protocol, garbler learns <u>nothing</u> about which key evaluator obtains, and evaluator learns <u>exactly one</u> of the two keys

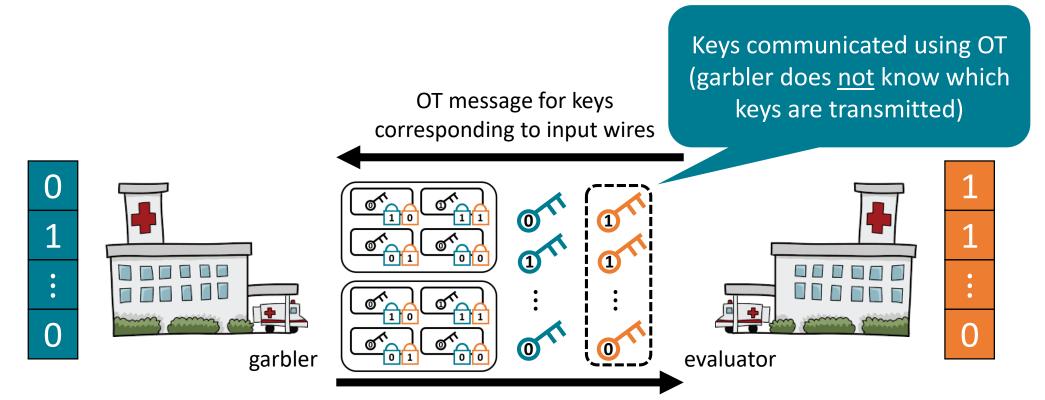
Two-round protocol for secure two-party communication



Many improvements are possible to achieve better performance

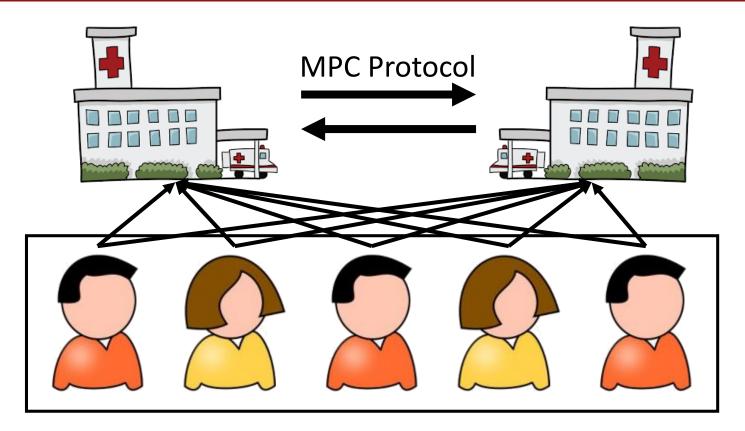
Evaluator uses keys to evaluate circuit gate-by-gate

Two-round protocol for secure two-party communication

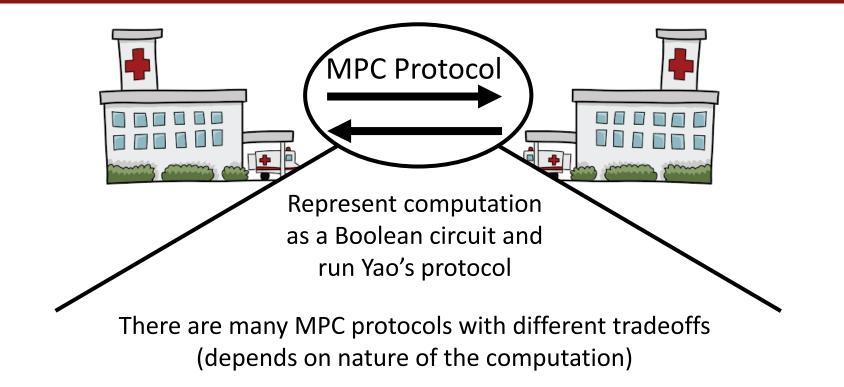


Many improvements are possible to achieve better performance

Protocol is very efficient; <u>communication</u> is the bottleneck

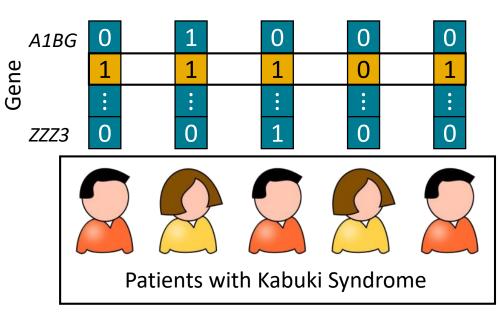


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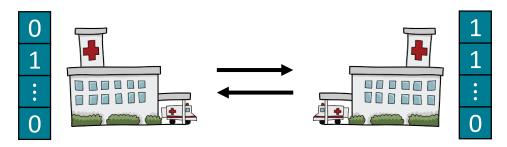


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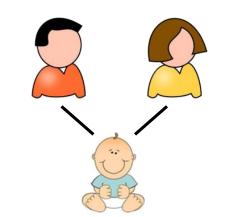
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Paper:

http://science.sciencemag.org/content/357/6352/692

Sample Implementation:

https://github.com/dwu4/genome-privacy

Nature Biotechnology paper on privacy-preserving GWAS forthcoming!

Thank you!