
Secure Multi-Party Computation of Probabilistic Threat Propagation

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Problem: Collaborative Cyber Defense



Companies should share cyber threat information with each other and USG to prevent attacks

- Global cyber situational awareness benefits all
- However, cybersecurity information is sensitive
 - Prior attacks may indicate weaknesses in defense
 - Business information could be used by competitors

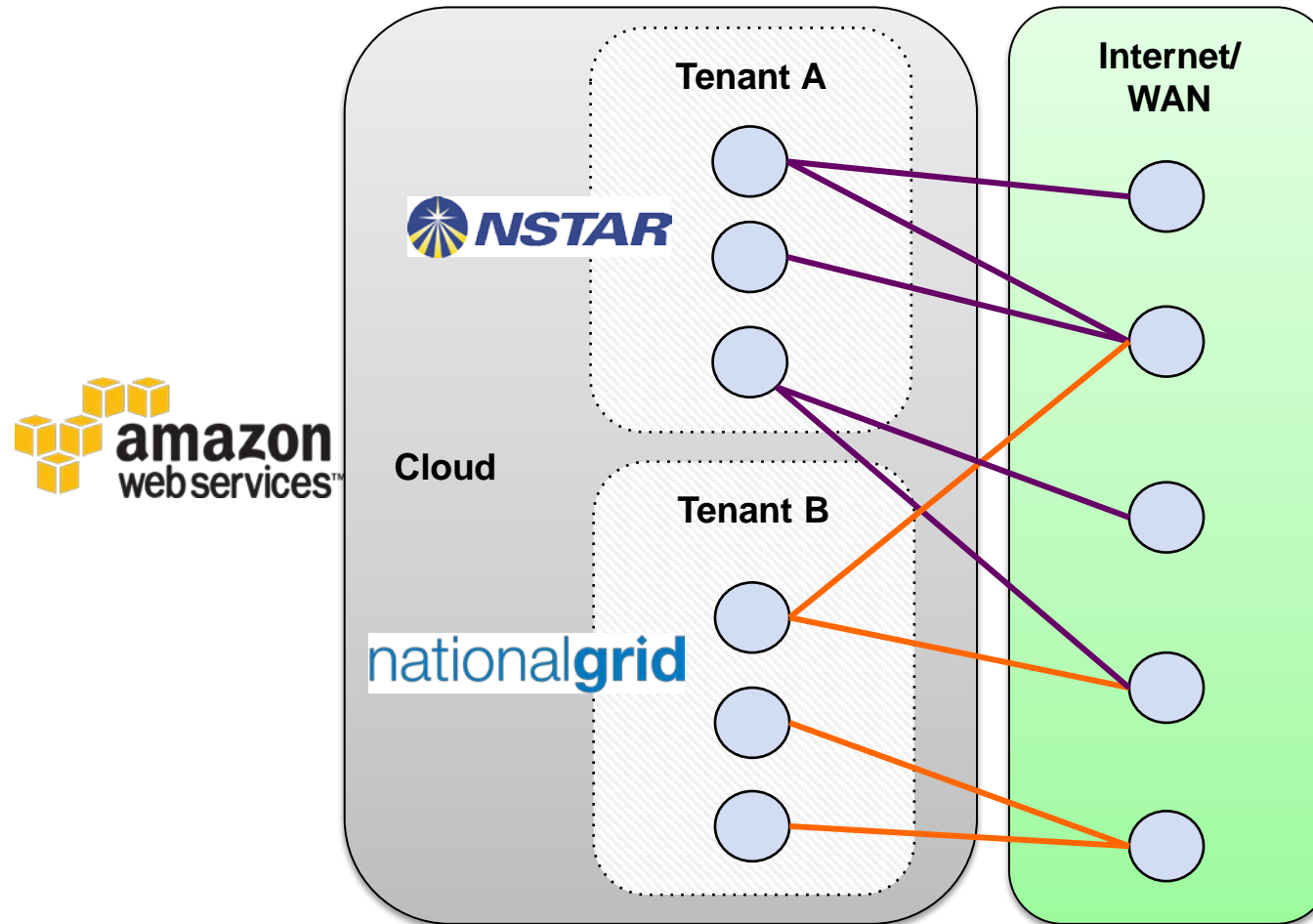
Sector-Specific Sharing Centers



Goal: Compute joint analytics without sharing sensitive cyber security information



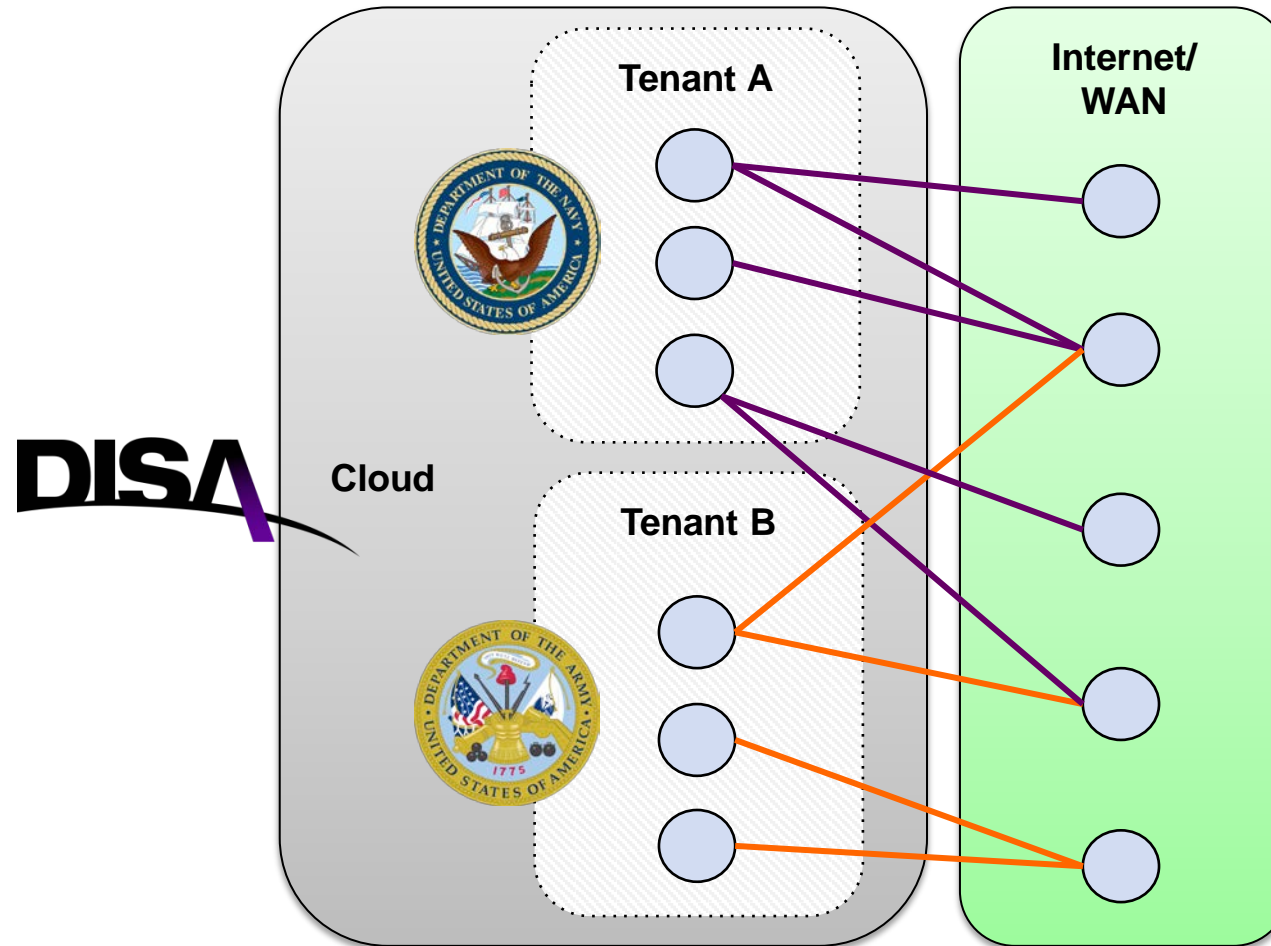
Cloud Threat Sharing



Cloud introduces provider and multiple tenants with varying trust



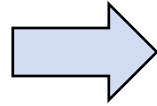
Cloud Threat Sharing



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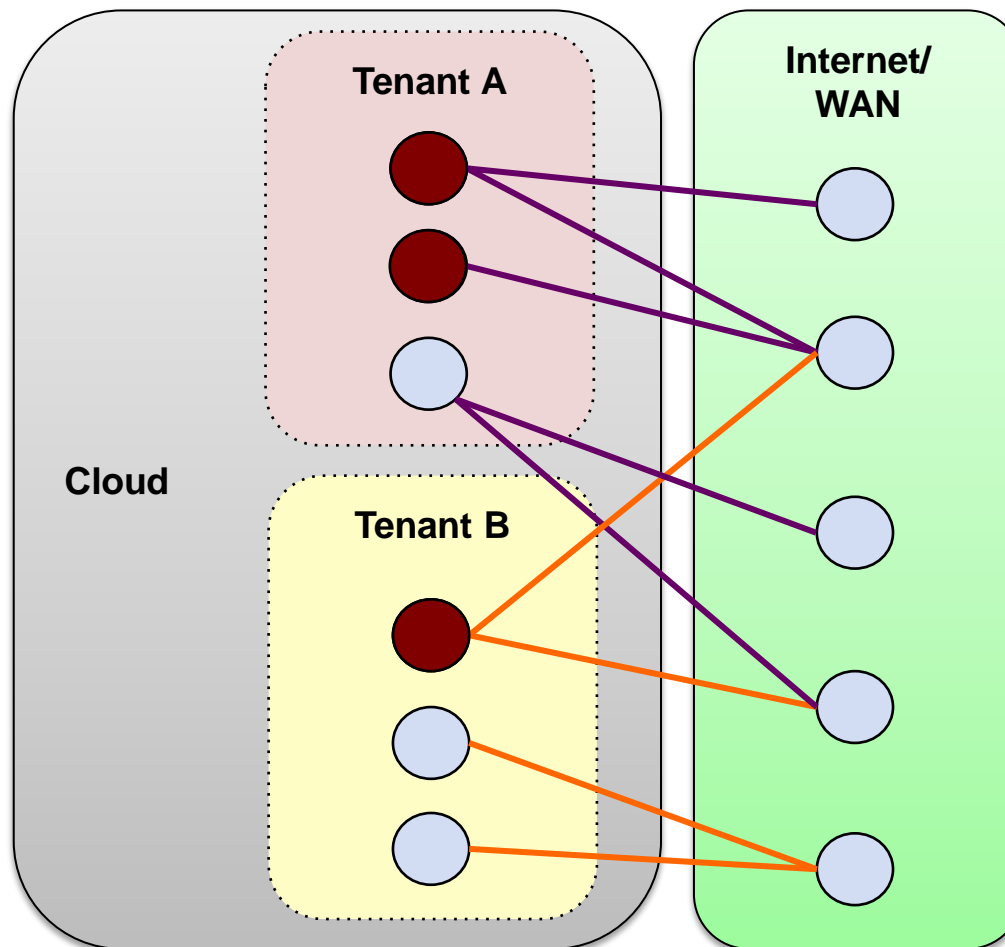
Outline



- **Motivation**
- **Probabilistic Threat Propagation (PTP)**
- **Secure Multi-Party Computation (MPC)**
- **Application of MPC to PTP**



Probabilistic Threat Propagation (PTP)



Require: $W, \{tips\}, \gamma, \alpha$
 $P \leftarrow \alpha^N, P(\{tips\}) \leftarrow \gamma$
 $C \leftarrow 0^{N \times N}$

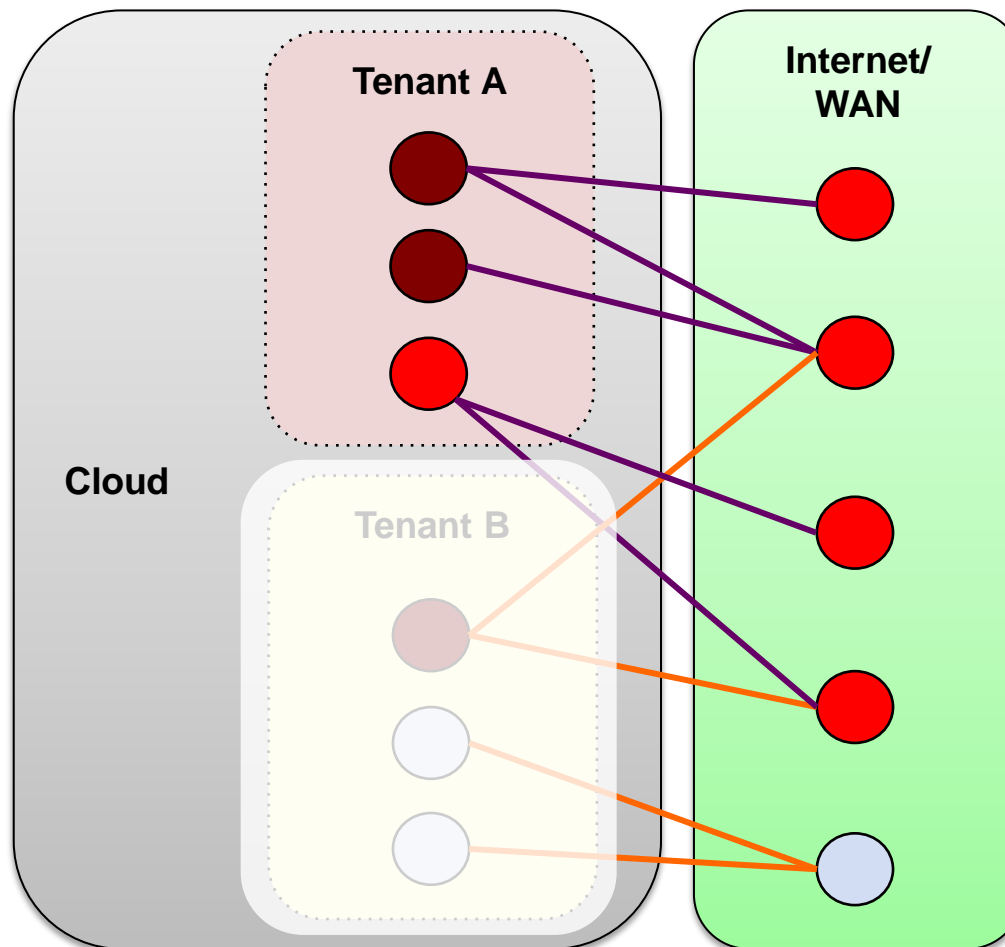
repeat
 $T \leftarrow W \otimes P^T$
 $C \leftarrow T - W \circ C^T$
 $P \leftarrow \langle C, \bar{1} \rangle$
 $C(\{tips\}, \cdot) \leftarrow 0$
 $P(\{tips\}) \leftarrow \gamma$

until P has converged
return P

Goal: Use connectivity graph and known bad hosts to predict other compromised hosts



Probabilistic Threat Propagation (PTP)



Require: $W, \{tips\}, \gamma, \alpha$
 $P \leftarrow \alpha^N, P(\{tips\}) \leftarrow \gamma$
 $C \leftarrow 0^{N \times N}$

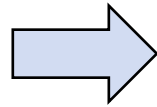
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until P has converged
return P

Tenants don't want to share compromised host info with each other or with provider



Outline

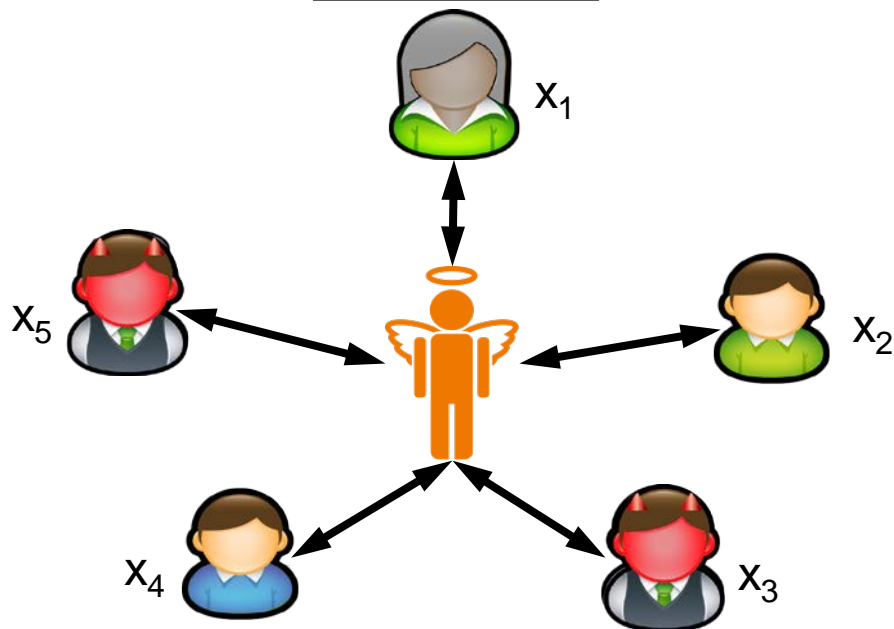


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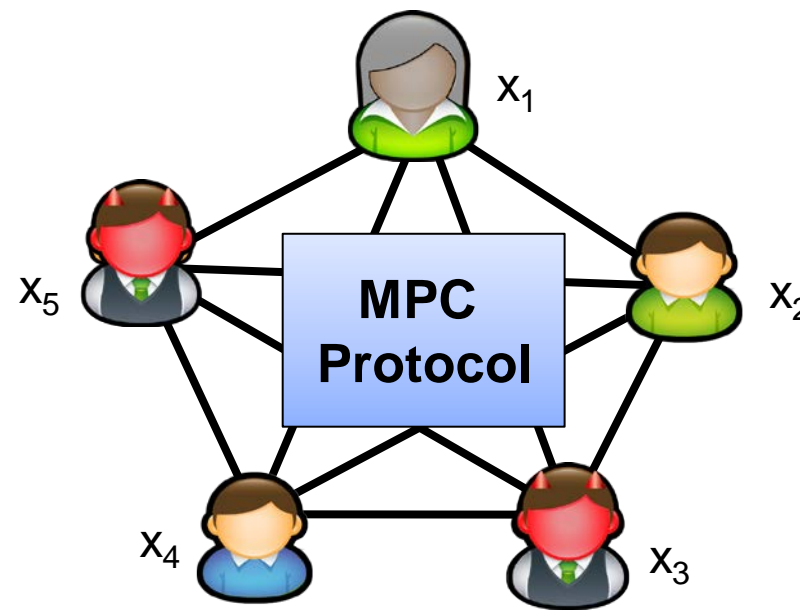
Secure Multi-Party Computation (MPC)

Ideal World



Output:
 $(y_1, \dots, y_n) = f(x_1, \dots, x_n)$

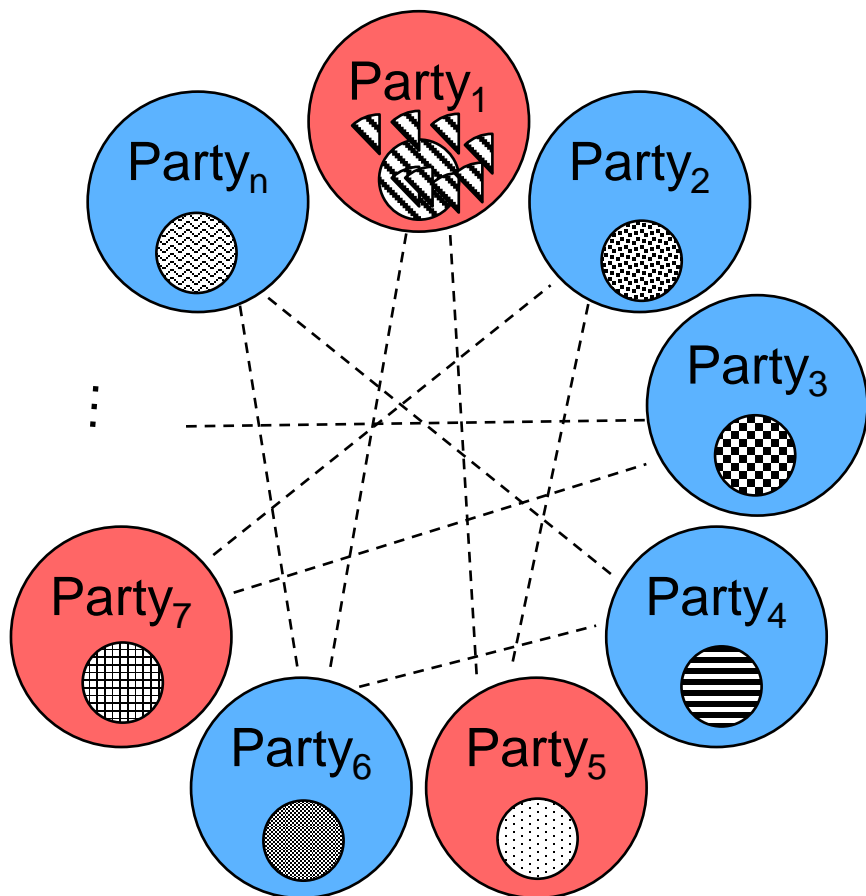
Real World



- MPC emulates a trusted party, assuming no more than a threshold number of adversarial parties, guaranteeing:
 - Correctness of computation
 - Confidentiality of inputs and outputs



Secret Sharing Overview

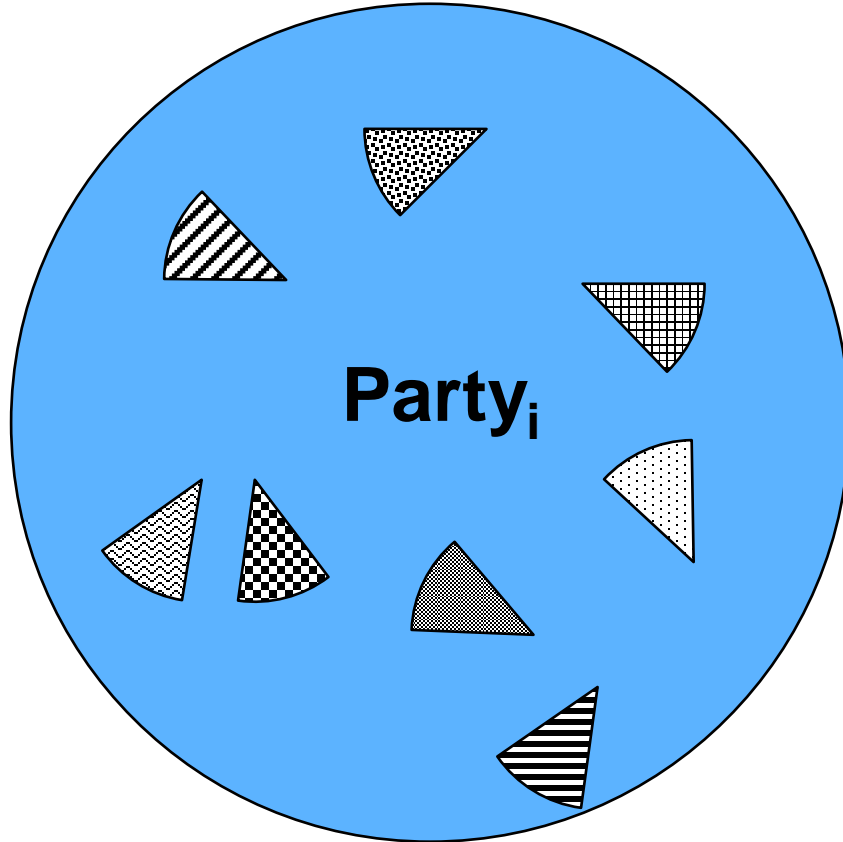


- Each secret value can be “split” into pieces (“shares”)
- If enough people combine shares, they can reconstruct the secret
- Otherwise, no one learns any info

Slide credit: Sasha Berkoff



MPC Based on Secret Sharing



To perform MPC, each party:

- Sends shares of its secret to each other party
- Computes on shares
 - Addition: local computation
 - Multiplication: requires interaction
- Interacts to combine manipulated shares to obtain final answer

Slide credit: Sasha Berkoff

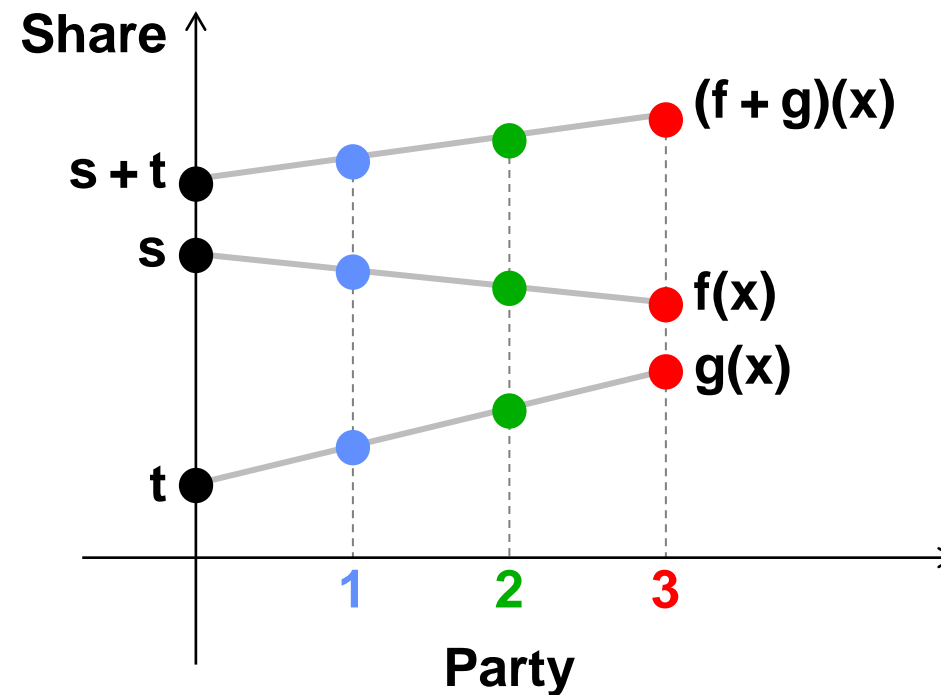


Secret Sharing Example

To secret share for a threshold k :

- Give each party a point on a random degree- k polynomial
- Reconstruction: interpolate any $>k$ points to recover degree- k polynomial
- Addition ($s + t$): $f(i) + g(i)$
- Multiplication ($s \times t$): $f(i) \times g(i)$, then interactive degree reduction

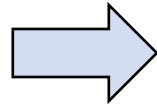
Example: threshold $k = 1$



Secret sharing can be used to compute any arithmetic function securely



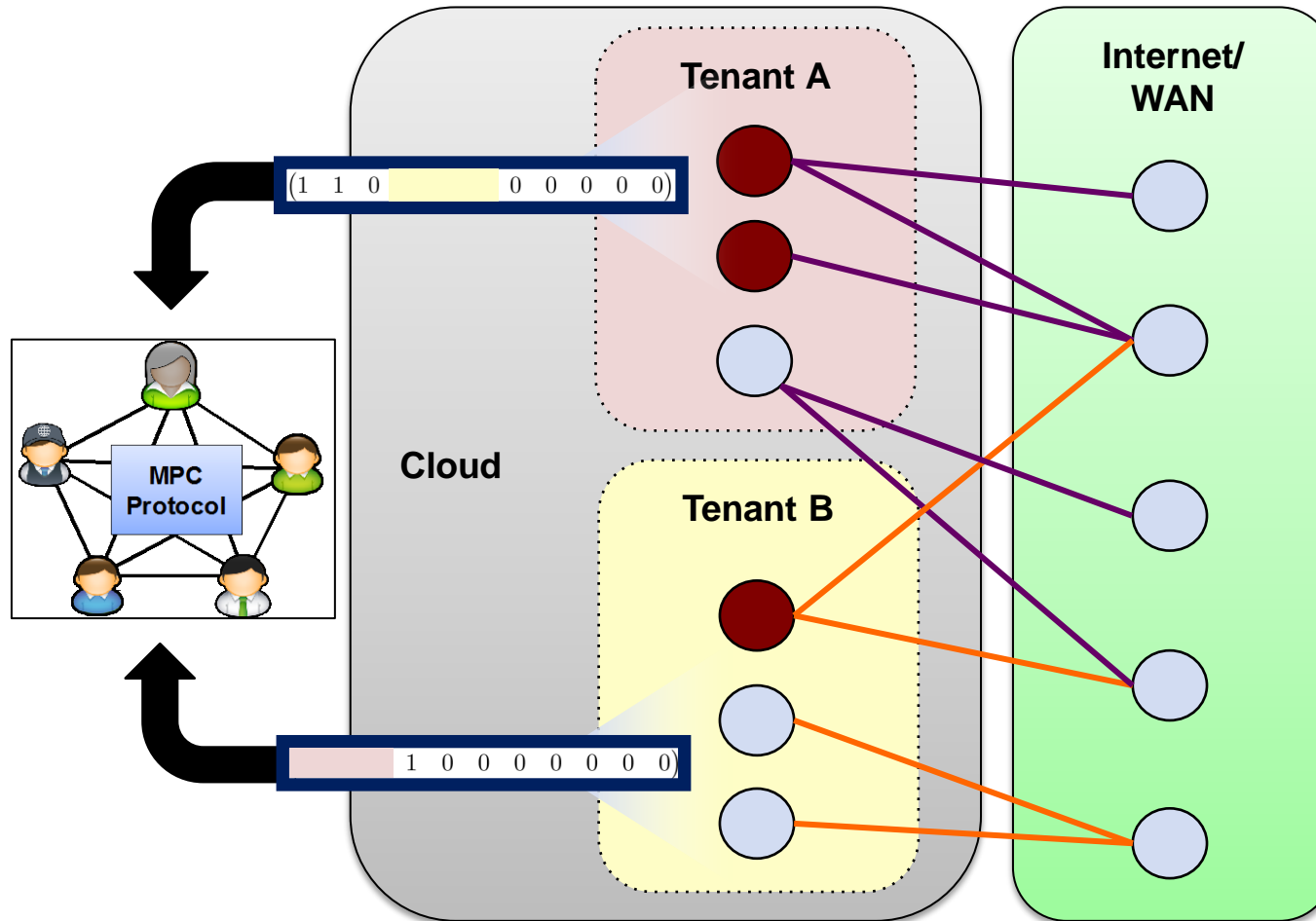
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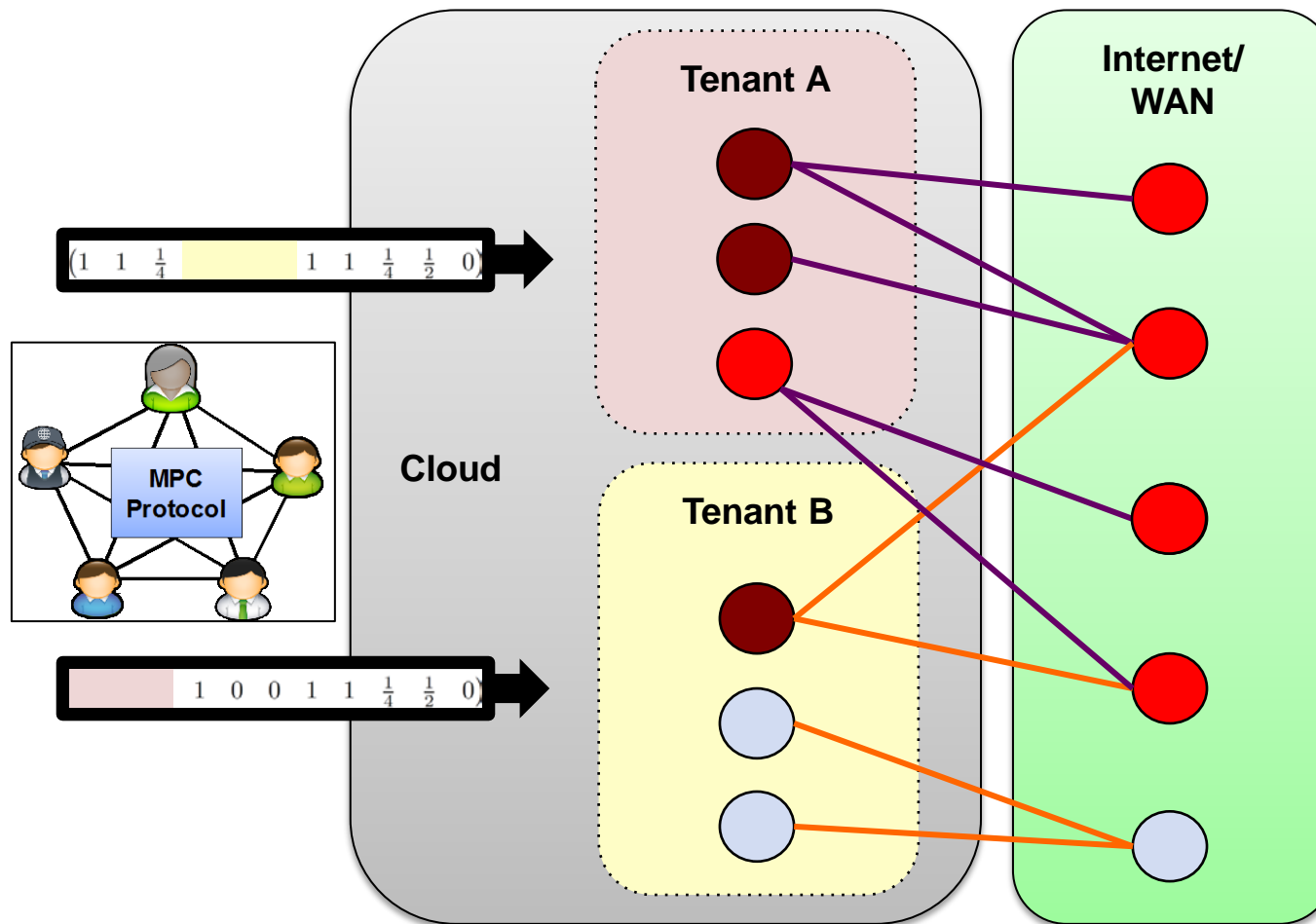
Secure Multi-Party Computation of PTP



Tenants secret-share compromised host info with other tenants, jointly compute PTP securely



Secure Multi-Party Computation of PTP



Each party learns about compromised hosts in its own network and on the Internet



Secure Multi-Party Computation of PTP

Probabilistic Threat Propagation Algorithm

Require: $W, \{tips\}, \gamma, \alpha$
 $P \leftarrow \alpha^N, P(\{tips\}) \leftarrow \gamma$
 $C \leftarrow 0^{N \times N}$ **MPC Operations**
repeat
 $T \leftarrow W \otimes P^T$ **N^2 mult-by-const**
 $C \leftarrow T - W \circ C^T$ **N^2 mult-by-const, adds**
 $P \leftarrow \langle C, \bar{1} \rangle$ **N^2 adds**
 $C(\{tips\}, \cdot) \leftarrow 0$ **N^2 mults**
 $P(\{tips\}) \leftarrow \gamma$ **N mults, N adds**
until P has converged **N mults, $2N$ adds, 1 comp**
return P

- Map high-level algorithm to mathematical operations
- Low overhead: add; multiply by constants
- High overhead: multiply, compare



MPC Optimization Techniques

1 Fixed Point Arithmetic

Efficiently compute on non-integer values using secure fixed point arithmetic

Representation	$a \rightarrow \tilde{a} := \lfloor a \cdot 2^{30} \rfloor$
Addition	$a + b \rightarrow \tilde{a} + \tilde{b} \approx \lfloor (a + b) \cdot 2^{30} \rfloor$
Multiplication	$a \cdot b \rightarrow \tilde{a} \cdot \tilde{b} / 2^{30} \approx \lfloor (a \cdot 2^{30}) \cdot (b \cdot 2^{30}) / 2^{30} \rfloor = \lfloor (a \cdot b) \cdot 2^{30} \rfloor$

All MPC computation done on integer values

2 Oblivious Selection

Select/assign values to/from secret indices using secret-shared indicator vector

$$\begin{pmatrix} 1 \\ 3 \\ 0 \\ 2 \\ 3 \end{pmatrix} * \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ 2 \\ 3 \end{pmatrix}$$

↓

$$\begin{pmatrix} 92134 \\ 41431 \\ 19384 \end{pmatrix} * \begin{pmatrix} 14321 \\ 3413 \\ 7324 \end{pmatrix} = \begin{pmatrix} 34549 \\ 3412 \\ 23412 \end{pmatrix}$$

Original shares Indicator vector New shares

MPC hides selection/assignment indices

3 Sparse Matrices

Reduce computation on sparse matrices by storing only nonzero entries

Original $\begin{pmatrix} 0 & 0 & 3 & 3 & 0 \\ 0 & 0 & 0 & 0 & 6 \\ 2 & 0 & 0 & 2 & 2 \\ 3 & 0 & 3 & 0 & 0 \\ 0 & 3 & 3 & 0 & 0 \end{pmatrix}$

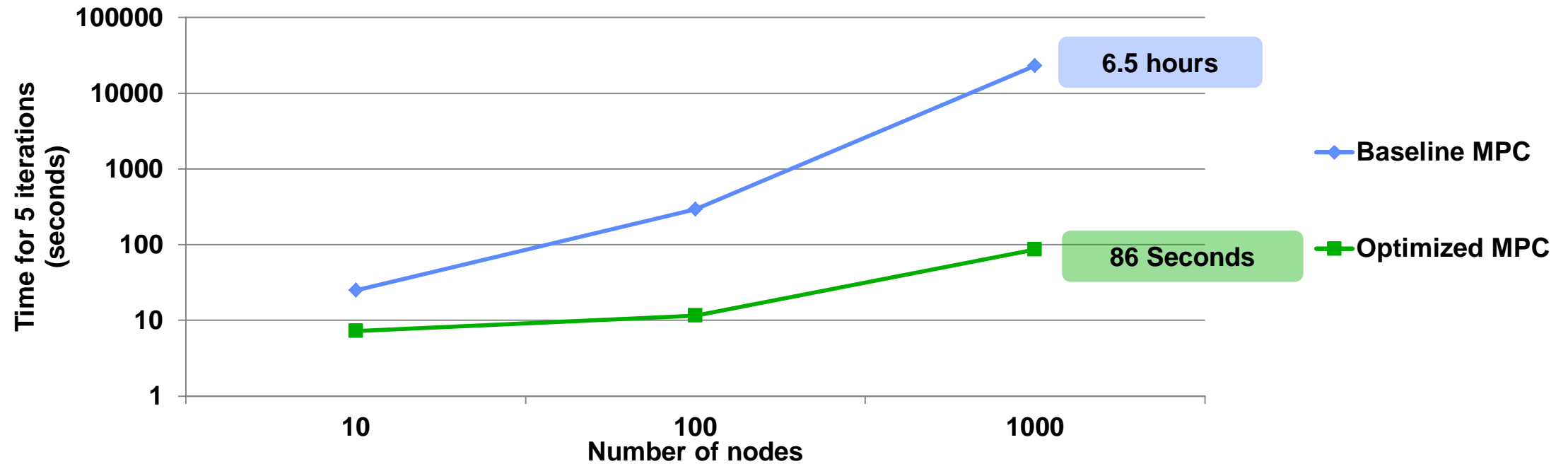
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Sparse $\begin{pmatrix} 3 & 3 & 6 & 2 & 2 & 2 & 3 & 3 & 3 & 3 \\ 1 & 1 & 2 & 3 & 3 & 3 & 4 & 4 & 5 & 5 \\ 3 & 4 & 5 & 1 & 4 & 5 & 1 & 3 & 2 & 3 \end{pmatrix}$ Nonzeros
Row indices
Col indices

MPC operations only needed on nonzero entries



Performance of Secure Multi-Party Computation of PTP



Optimizations result in >250× speedup over baseline MPC



Summary

- **Graph analytics (e.g., probabilistic threat propagation) have important applications to cyber security**
- **Privacy concerns may restrict ability to perform joint analytics**
- **Secure multi-party computation enables privacy-preserving computation of analytics**
- **Designed and optimized MPC for PTP, achieving significant speedup over baseline MPC**
- **Future work: design and optimize secure computation other useful graph analytics**