OblivGNN: Oblivious Inference on Transductive and Inductive Graph Neural Network

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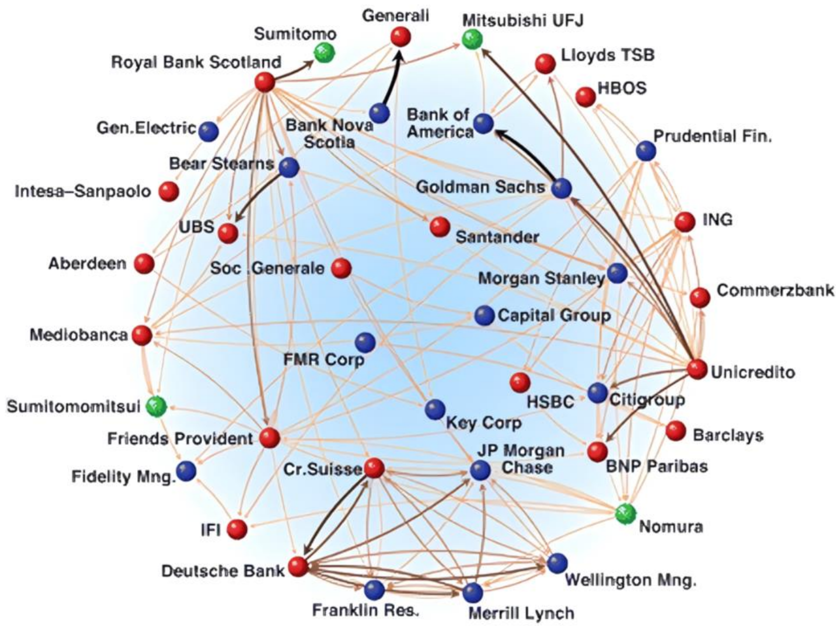
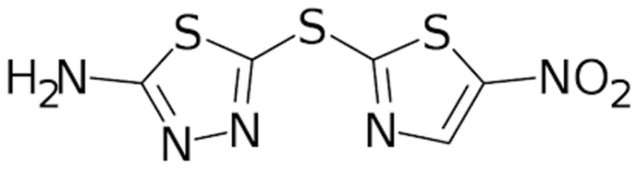
GNN Tasks

Node Classification
(Graph Convolutional Network [Kipf *et al.* (ICLR'17)])

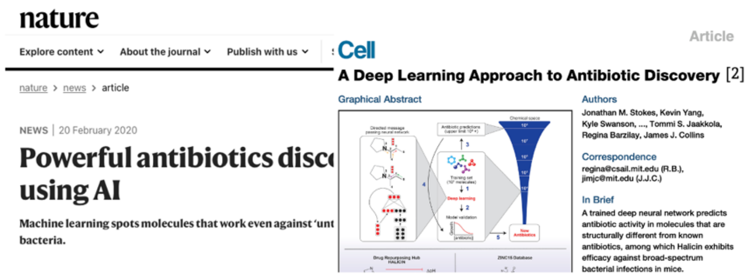


Bank

Graph Classification
(GraphSAGE [Hamilton *et al.* NIPS'17])

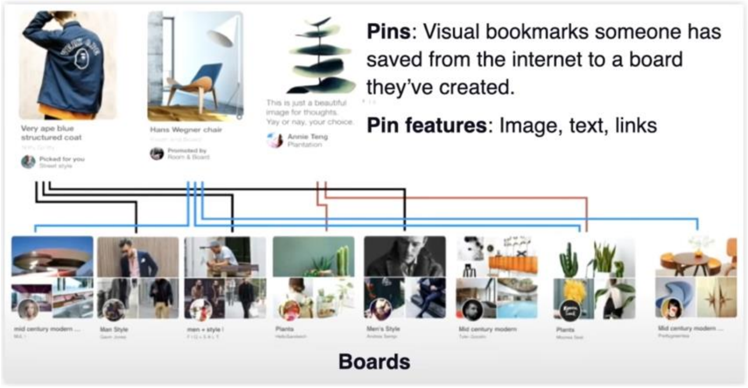


Halicin [3]



Drug discovery

Link Prediction
(GraphSAGE [Hamilton *et al.* NIPS'17])



Recommendation systems

Graph Neural Networks are specifically designed neural architectures operated on graph-structure data

--*Graph Neural Networks: Foundations, Frontiers, and Applications* by Lingfei et al.

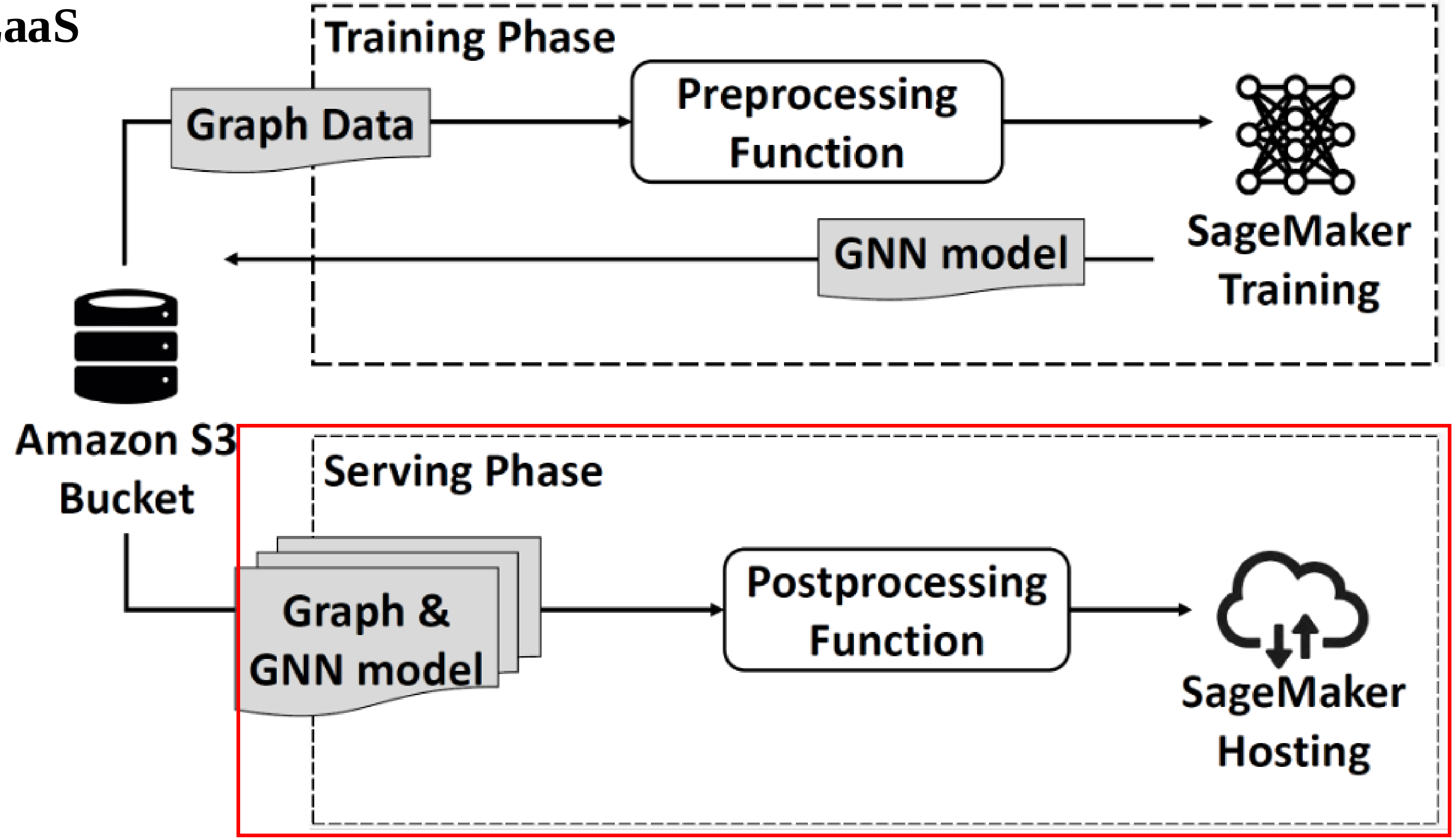
GNNs in Machine Learning as a Service (MLaaS)

GNN is increasingly featured on MLaaS platforms

Amazon: SageMaker Support for DGL

Google: Neo4j & Google Cloud Vertex AI

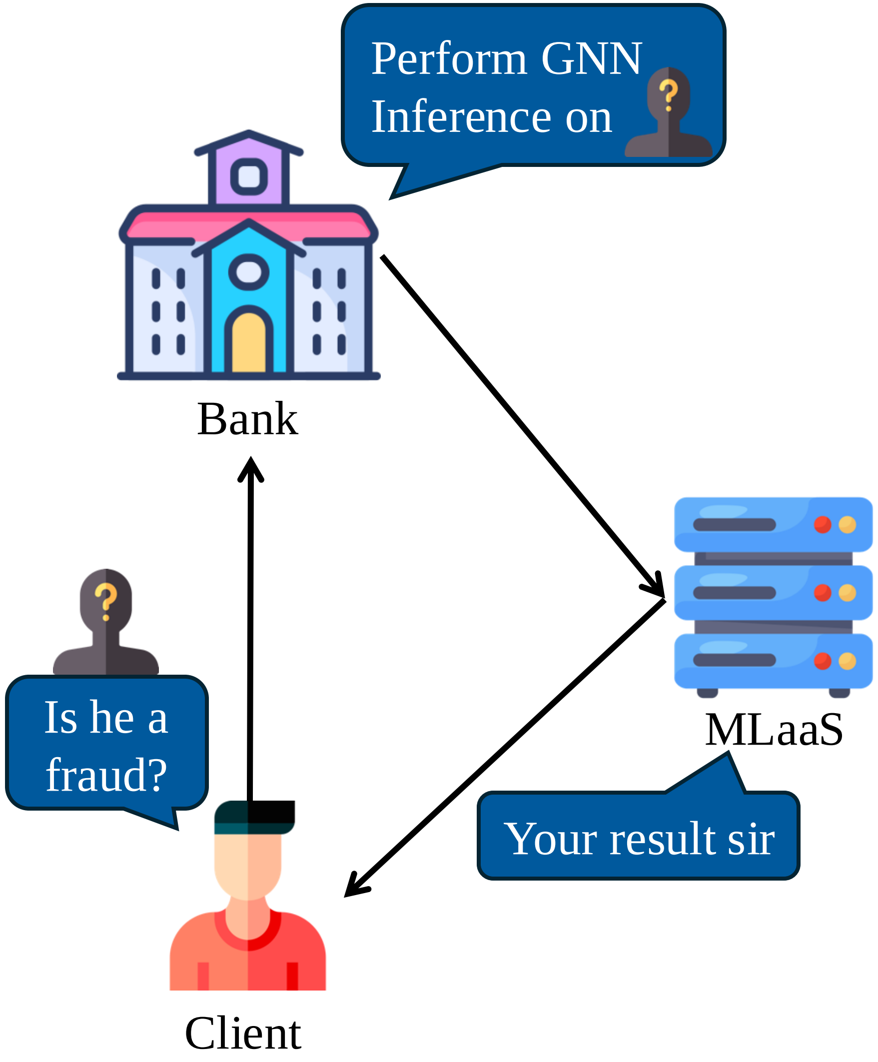
Microsoft: Azure ML Spektral



AWS SageMaker for GNN training and inference

Build a GNN-based real-time fraud detection solution using Amazon SageMaker, Amazon Neptune, and the Deep Graph Library: https://aws.amazon.com/blogs/machine-learning/build-a-gnn-based-real-time-fraud-detection-solution-using-amazon-sagemaker-amazon-neptune-and-the-deep-graph-library/

Privacy Concerns



Privacy Concerns:

- Expose sensitive training/inference graph to MLaaS
  - Collecting training graphs often requires a large amount of human, computing, and economic resource
  - Graph data is sensitive by nature, e.g., users' financial transactions, private friendships
- Expose proprietary GNN model parameters and node features to MLaaS

Related Works in PPML

Traditional PPML Frameworks

Trident, Chameleon, Falcon, GAZELLE, MiniONN, Delphi, ABY^3, SecureML, BLAZE, XONN, AriaNN, CryptGPU, SecureNN

- Cannot support graph-structured data

Existing Secure GNN Frameworks

SecGNN, CryptoGCN, LinGCN

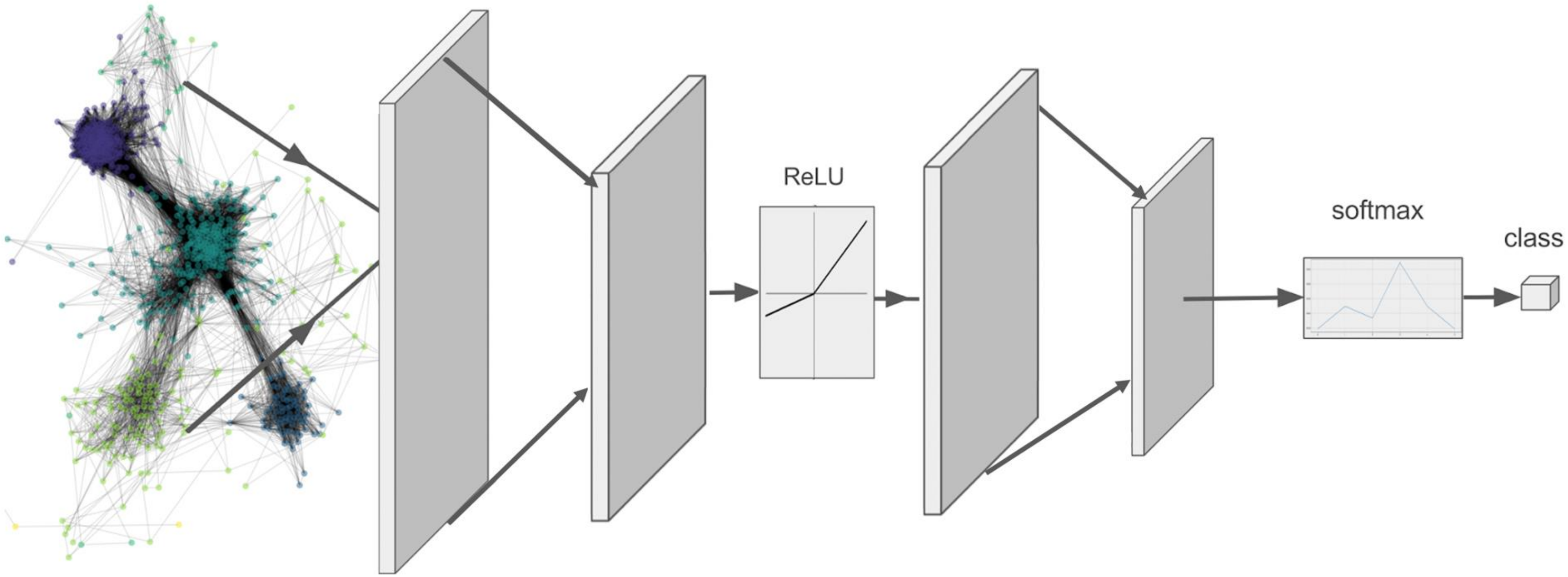
- Do not offer full protection of graph structure information
- Leak degree information
- Not support the diverse settings of GNN deployment
- Heavy computation cost (via FHE), heavy communication cost (via ASS) due to the large size of the graph

GNNs

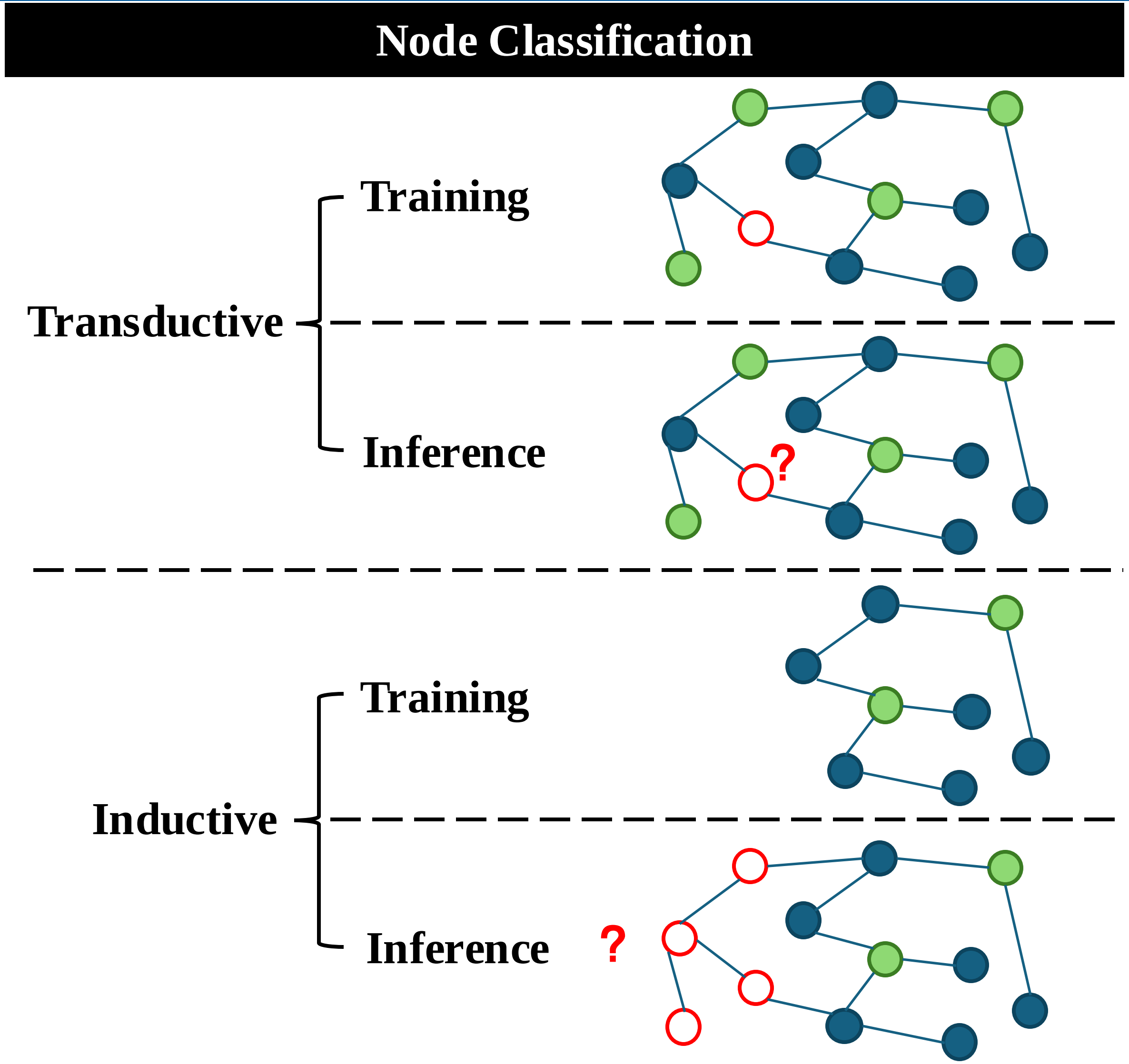
$\mathbf{Z}$=Softmax($\hat{\mathbf{A}}$ ReLU($\hat{\mathbf{A}}\hat{\mathbf{F}}\mathbf{W_0}$)$\mathbf{W_1}$)

- $\mathbf{W_0}$ and $\mathbf{W_1}$ are two trainable weights
- $\hat{\mathbf{A}}$ is the symmetric normalized adjacency matrix
- $\hat{\mathbf{F}}$ is the normalized feature matrix

- Activation functions:
  - $\mathrm{ReLU}(x) = \begin{cases} x & \text{if } x \geq 0 \\ 0 & \text{if } x < 0 \end{cases}$
  - Softmax: $z_i = \frac{e^{x_i}}{\sum_{j\in[1,C]} e^{x_i}}, i \in [1, C]$



GNN Settings



Transductive:

- Unlabelled nodes and their connections exist in the training
- Graph for training and inference remains the same

Inductive:

- *New/updated* nodes, features, connections appear in the *inference*

Function Secret Sharing

Function Secret Sharing

Distributed Point Functions:

$\text{KeyGen}(\alpha, \beta) \rightarrow k_0, k_1$

$\text{Eval}(k_b, x) \rightarrow [\![y]\!]_b$

$$\text{Eval}(k_0, x) + \text{Eval}(k_1, x) = \begin{cases} \beta, if x = \alpha \\ 0, otherwise \end{cases}$$

Equality Test:

$\text{KeyGen}^{=}(\alpha = \gamma, \beta = 1) \rightarrow k_0^{=}, k_1^{=}$

$\text{Eval}^{=}(k_b^{=}, x) \rightarrow [\![y]\!]_b$

$$\text{Eval}^{=}(k_0, x') + \text{Eval}^{=}(k_1, x') = \begin{cases} y = 1, if x' = \gamma \\ 0 \quad, otherwise \end{cases}$$

Comparison:

$\text{KeyGen}^{<}(\alpha = \gamma, \beta = 1) \rightarrow k_0^{<}, k_1^{<}$

$\text{Eval}^{<}(k_b^{<}, x) \rightarrow [\![y]\!]_b$

$$\text{Eval}^{<}(k_0, x') + \text{Eval}^{<}(k_1, x') = \begin{cases} y = 1, if x' \leq \gamma \\ 0 \quad\quad, if x' > \gamma \end{cases}$$

Arithmetic FSS:

Multiplication:

$\text{KeyGen}^{\times}\left(\mathrm{g}^{\circ}, r_{in}^1, r_{in}^2, r_{out}\right) \rightarrow k_0^{\times}, k_1^{\times}$

$\text{Eval}^{\times}(k_b^{\times}, x_1', x_2') \rightarrow \mathrm{g}_b^{\circ}(x_1 \times x_2) + r_{out}$

$$\text{Eval}^{\times}(k_0^{\times}, x_1', x_2') + \text{Eval}^{\times}(k_1^{\times}, x_1', x_2') = x_1 \times x_2 + r_{out}$$

Addition:

$\text{KeyGen}^{+}\left(\mathrm{g}^{\circ}, r_{in}^1, r_{in}^2, r_{out}\right) \rightarrow k_0^{+}, k_1^{+}$

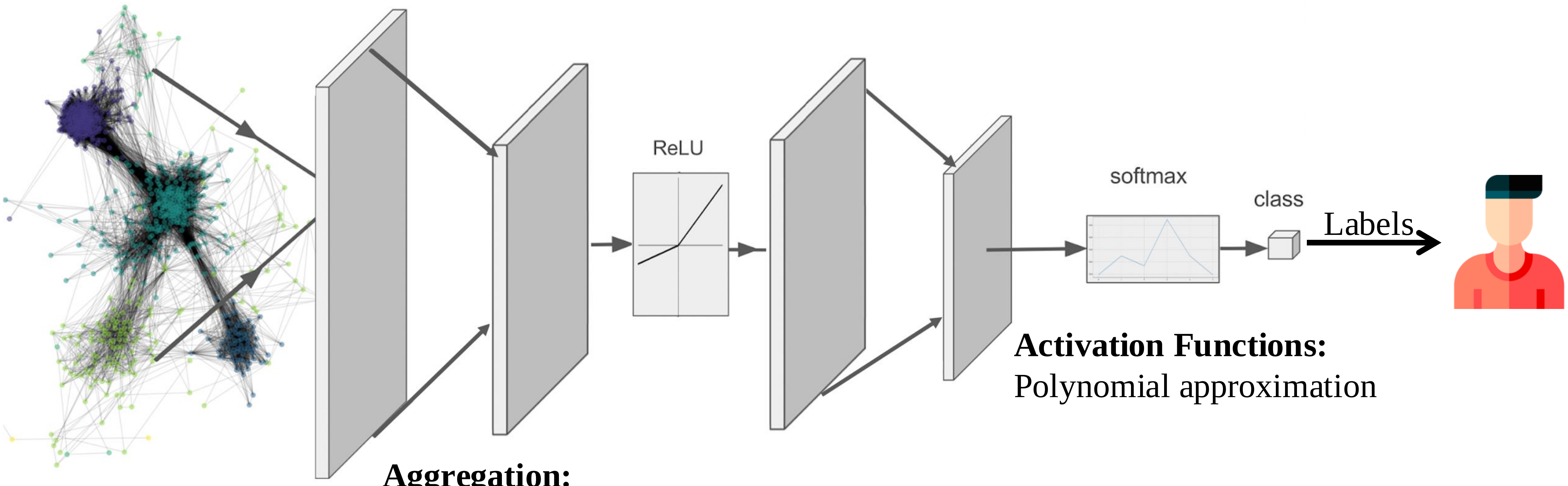
$\text{Eval}^{+}(k_b^{+}, x_1', x_2') \rightarrow \mathrm{g}_b^{\circ}(x_1 + x_2) + r_{out}$

$$\text{Eval}^{+}(k_0^{+}, x_1', x_2') + \text{Eval}^{+}(k_1^{+}, x_1', x_2') = x_1 + x_2 + r_{out}$$

Strawman Approach

Transductive setting

Sharing:
Additive Secret Sharing



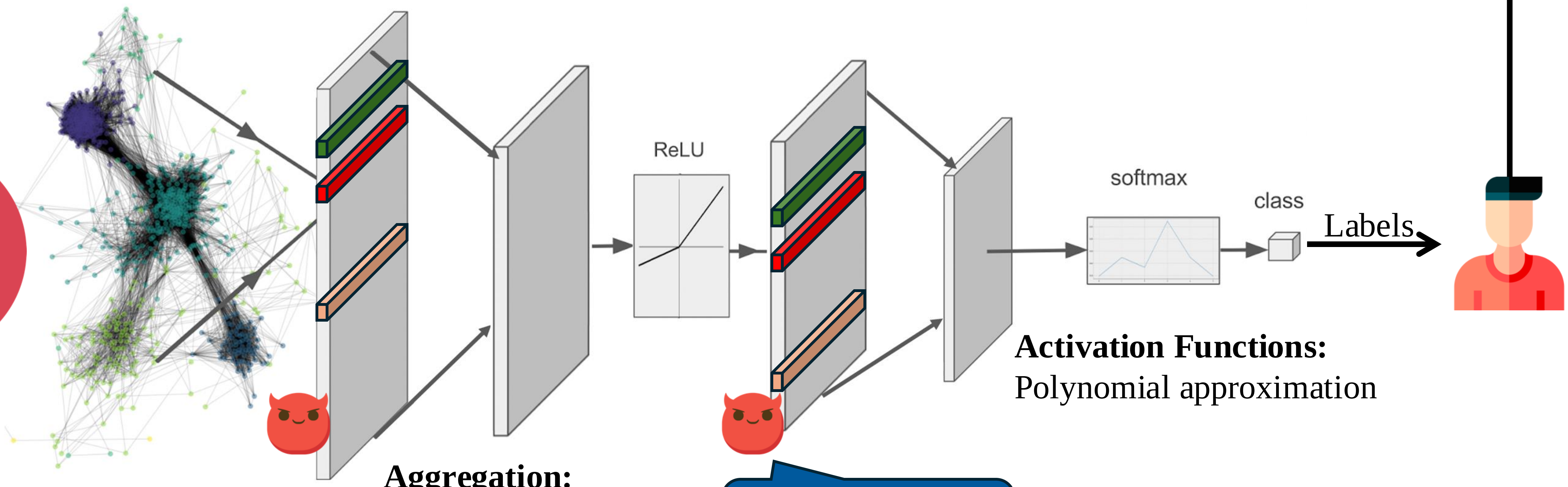
Activation Functions:
Polynomial approximation

Aggregation:
Beaver's triple

Strawman Approach

Inductive setting

Graph update:
update the graph



Activation Functions:
Polynomial approximation

Aggregation:
Beaver's triple

I can observe the update pattern

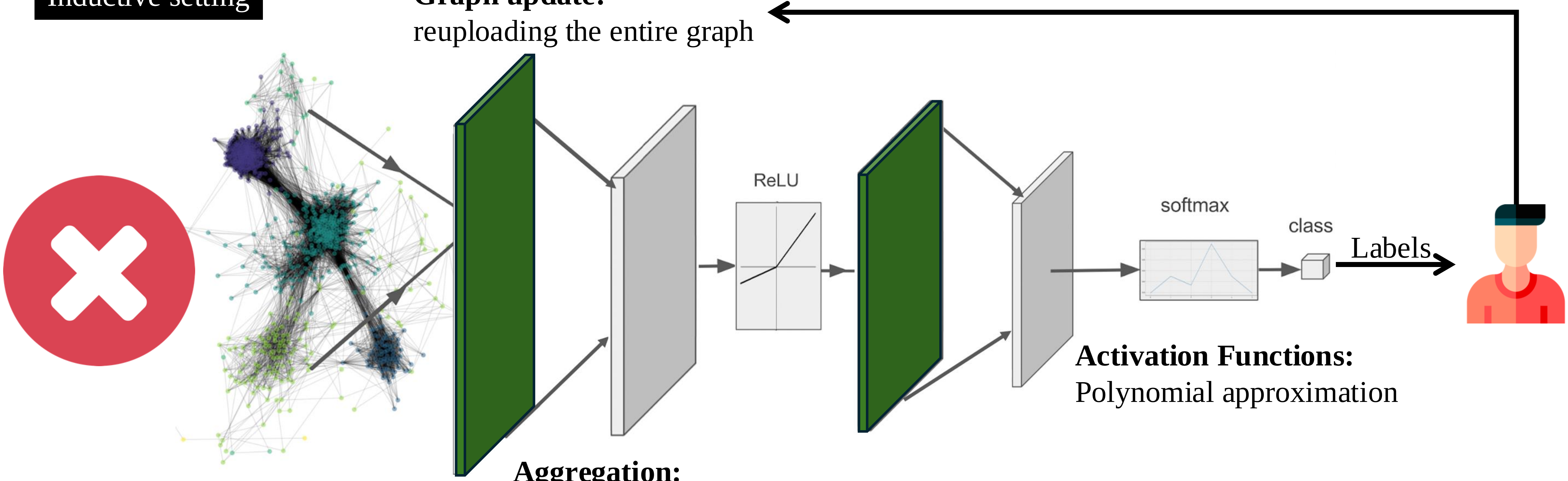
Problem:

1. Leak graph update access, suffering from leakage attack [Falzon and Paterson, ESORICS'22]

Strawman Approach

Inductive setting

Graph update:
reuploading the entire graph



Activation Functions:
Polynomial approximation

Aggregation:
Beaver's triple

Problems:
The communication/computation cost is significant when re-uploading the updated graph to update obliviously.

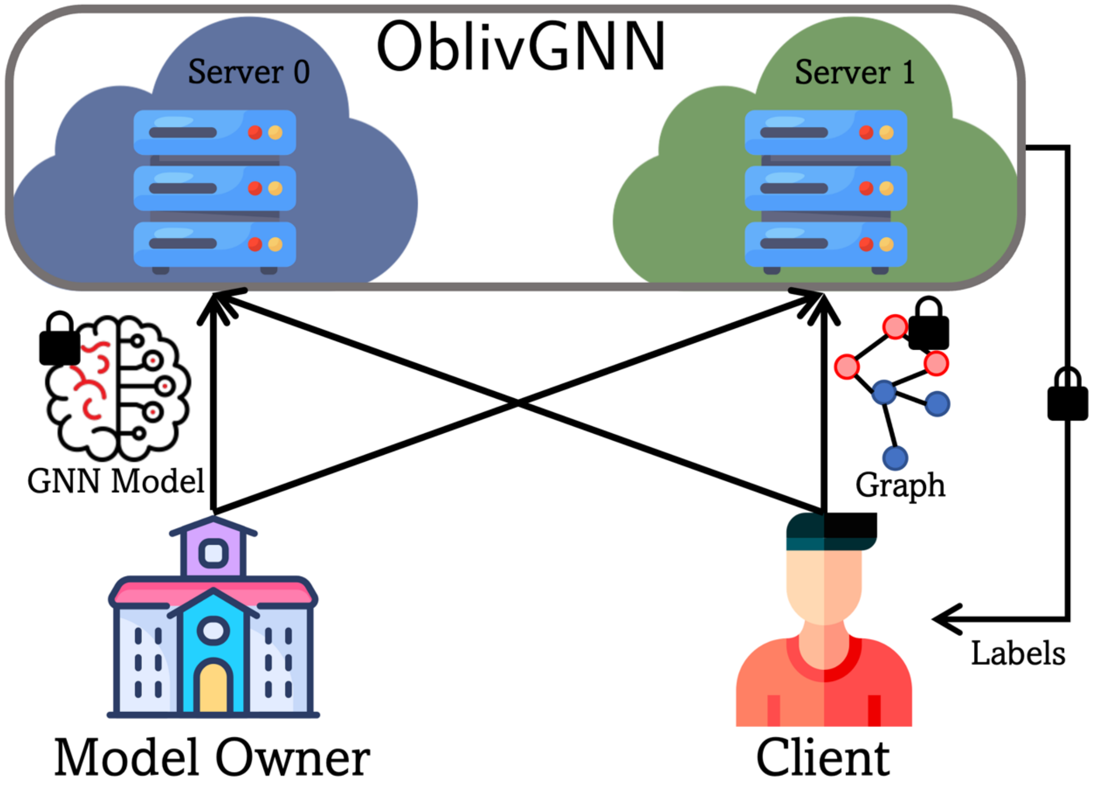
Research Questions

1. How to enable secure GNN inference for the *transductive* and *inductive* settings?

2. How to offer data *obliviousness* with semi-honest security?

3. How to *achieve* efficiency while achieving the above?

OblivGNN Architecture



- Semi-honest
- Outsource
- Non-colluding

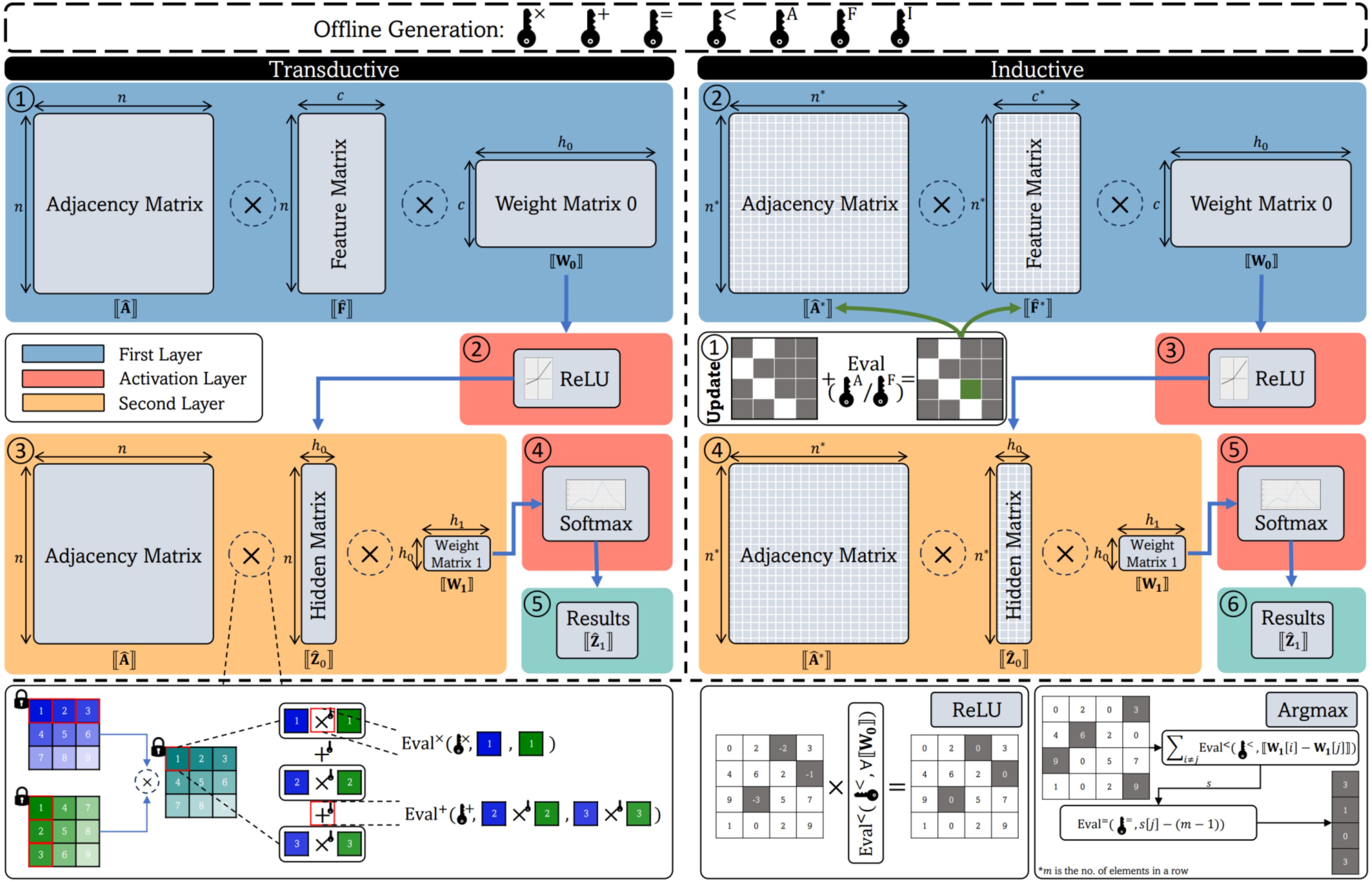
Security Guarantee

- Protect graph information
  - Adjacency Matrix $\widehat{\mathbf{A}}$
  - Feature Matrix $\widehat{\mathbf{F}}$
- Protect model information
  - Weight Matrix $\mathbf{W_0}$ and $\mathbf{W_1}$
- Protect access pattern to the graph structure and node feature
- Protect client query, intermediate results, and inference results

OblivGNN Approach

Offline

Online



OblivGNN Approach

Offline

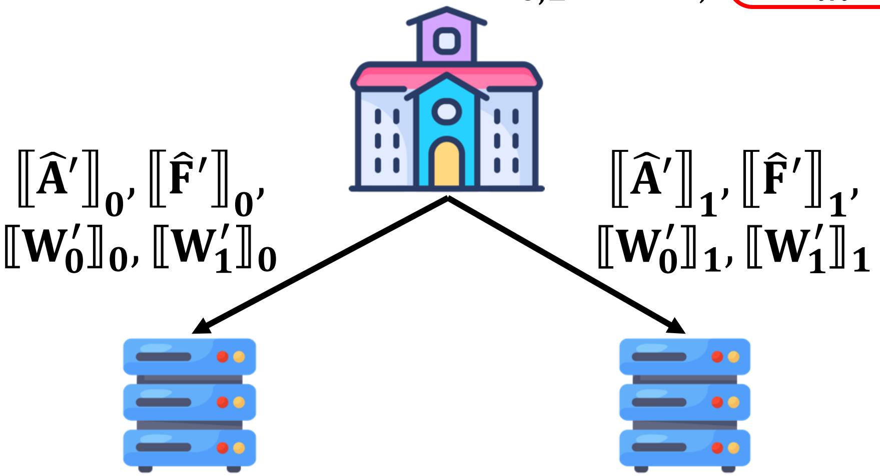
- <u>Masking & secret share GNN model</u>

Masks for Arithmetic FSS gates

Adjacency matrix: $\widehat{\mathbf{A}}' \leftarrow \widehat{\mathbf{A}} + r_{in}^1/r_{in}^2$

Feature matrix: $\hat{\mathbf{F}}' \leftarrow \hat{\mathbf{F}} + r_{in}^1/r_{in}^2$

Weight matrices: $\mathbf{W}_{0,1}' \leftarrow \mathbf{W}_{0,1} + r_{in}^1/r_{in}^2$



- Two servers need to *recover* the ASS shares before operating FSS circuits
- The linear layer results (in *shares*) will be used in oblivious activation functions
- The oblivious updates are performed on the shares

OblivGNN Approach

Offline

- Key generation

FSS Key Pool Generation

Multiplication:

$\text{KeyGen}^{\times}(g^{\circ}, r_{in}^{1}, r_{in}^{2}, r_{out}) \rightarrow \boxed{k_0^{\times}, k_1^{\times} : \text{FSS Multiplication keys}}$

$\text{Eval}^{\times}(k_b^{\times}, x_1', x_2') \rightarrow g_b^{\circ}(x_1 \times x_2) + r_{out}$

Addition:

$\text{KeyGen}^{+}(g^{\circ}, r_{in}^{1}, r_{in}^{2}, r_{out}) \rightarrow \boxed{k_0^{+}, k_1^{+} : \text{FSS Addition keys}}$

$\text{Eval}^{+}(k_b^{+}, x_1', x_2') \rightarrow g_b^{\circ}(x_1 + x_2) + r_{out}$

DPF Key Pool Generation

$\left.\begin{array}{l} k^{\mathrm{A}}\text{: DPF Node Update keys} \\ k^{\mathrm{F}}\text{: DPF Feature Update keys} \\ k^{\mathrm{I}}\text{: DPF Client Inquiry keys} \end{array}\right\}$ Online keys

$k^{=}$: DPF Equality Test keys

$k^{<}$: DPF Comparison keys

OblivGNN Approach

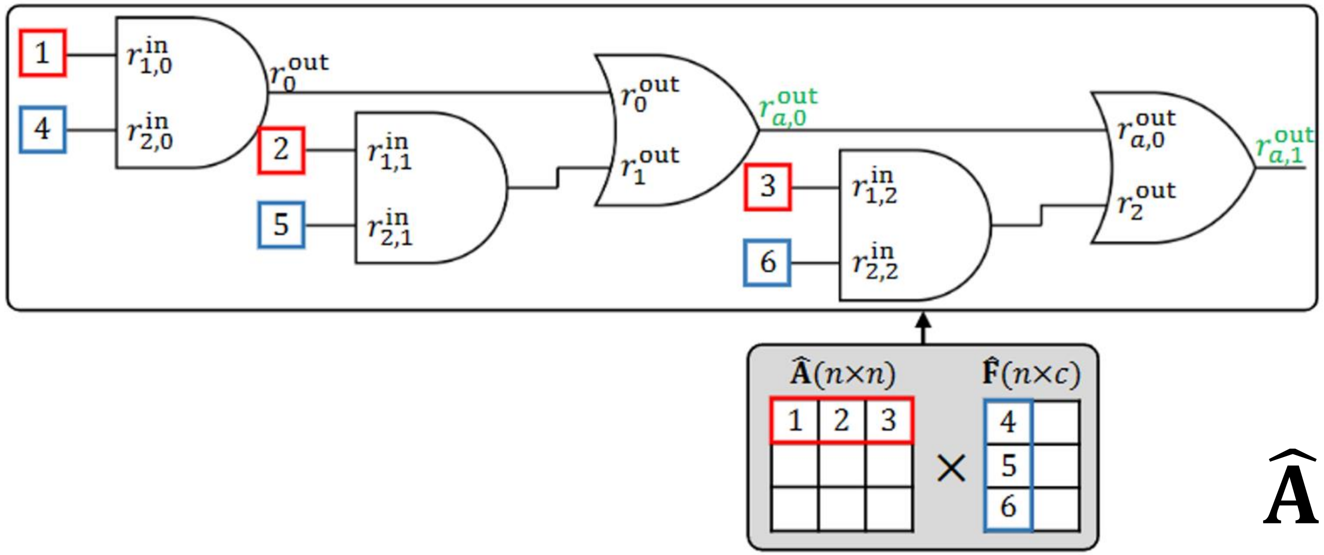
Online – Oblivious Aggregation

$$\mathrm{Eval}^{\times}(k_0^{\times}, x_1', x_2') + \mathrm{Eval}^{\times}(k_1^{\times}, x_1', x_2') = x_1 \times x_2 + r_{out}$$

$$\mathrm{Eval}^{+}(k_0^{+}, x_1', x_2') + \mathrm{Eval}^{+}(k_1^{+}, x_1', x_2') = x_1 + x_2 + r_{out}$$

Example:

$$x_1' = x_1 + r_{in}^1$$
$$x_2' = x_2 + r_{in}^2$$



$$\hat{\mathbf{A}} \times \hat{\mathbf{F}} \times \mathbf{W} \quad \ldots$$

$$\boxed{1} \times \boxed{4} = \mathrm{Eval}^{\times}(k^{\times}, \boxed{1}, \boxed{4})$$

$$\boxed{2} \times \boxed{5} = \mathrm{Eval}^{\times}(k^{\times}, \boxed{2}, \boxed{5})$$

$$\boxed{3} \times \boxed{6} = \mathrm{Eval}^{\times}(k^{\times}, \boxed{3}, \boxed{6})$$

$$\mathrm{Eval}^{+}(k^{+},\ )$$

$$\mathrm{Eval}^{+}(k^{+},\ )$$

$$= \text{output} + r_{out}$$

OblivGNN Approach – *Inductive* Exclusive Ops

Online – Oblivious Graph Update

New Node Insertion

- Introduce *new* nodes
- Do NOT modify the existing graph

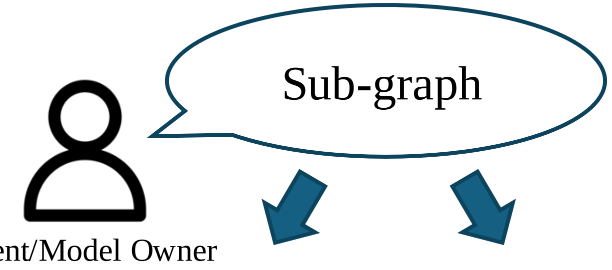
Existing Graph Update

- Modify the *existing* graph
  - Oblivious update adjacency matrix
  - Oblivious update feature matrix

OblivGNN Approach – *Inductive* Exclusive Ops

Online – Oblivious Graph Update

Existing Graph Update



Sub-graph Adjacency Matrix

Sub-graph Feature Matrix

$\mathrm{KeyGen}(0||1,1) \rightarrow k_0^{\mathrm{A}}, k_1^{\mathrm{A}}$

$\mathrm{KeyGen}(1||0,1) \rightarrow k_0^{\mathrm{A}}, k_1^{\mathrm{A}}$

$$
\begin{array}{c|cccc|}
 & 0 & 1 & \dots & n \\
\hline
0 & 1 & 0 & \dots & 0 \\
1 & 0 & 1 & \dots & 0 \\
\dots & \dots & \dots & \dots & \dots \\
n & 0 & 0 & \dots & 1 \\
\hline
\end{array}
+
\begin{array}{l}
\leftarrow \mathrm{Eval}(k_b^{\mathrm{A}}, 0||0) \\
\leftarrow \boxed{\mathrm{Eval}(k_b^{\mathrm{A}}, 1||0)} \\
\leftarrow \mathrm{Eval}(k_b^{\mathrm{A}}, \dots) \\
\leftarrow \mathrm{Eval}(k_b^{\mathrm{A}}, n||0)
\end{array}
\Rightarrow
\begin{array}{c|cccc|}
 & 0 & 1 & \dots & n \\
\hline
0 & 1 & 1 & \dots & 0 \\
1 & 1 & 1 & \dots & 0 \\
\dots & \dots & \dots & \dots & \dots \\
n & 0 & 0 & \dots & 1 \\
\hline
\end{array}
$$

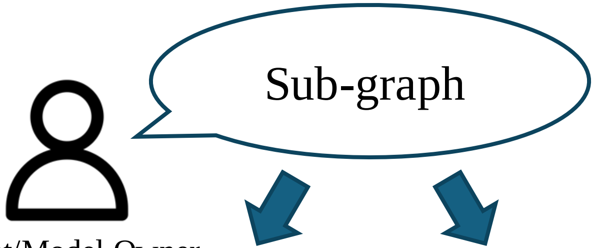
Adjacency Matrix $[\widehat{\mathbf{A}}]$ (secret shared)

Updated Adjacency Matrix

OblivGNN Approach – *Inductive* Exclusive Ops

Online – Oblivious Graph Update

Existing Graph Update



Sub-graph Adjacency Matrix

Sub-graph Feature Matrix

$\mathrm{KeyGen}(1||0, F_{\triangle}(v_i)) \rightarrow k_0^{\mathrm{F}}, k_1^{\mathrm{F}}$

$$\begin{array}{c} \\ 0 \\ 1 \\ \dots \\ n \end{array}\begin{array}{c} \begin{array}{ccc} 0 & \dots & c \end{array} \\ \begin{bmatrix} 1 & \dots & 0 \\ \boxed{1} & \dots & 1 \\ \dots & \dots & \dots \\ 0 & \dots & 1 \end{bmatrix} \end{array} + \begin{array}{l} \leftarrow \mathrm{Eval}(k_b^{\mathrm{F}}, 0||0) \\ \leftarrow \boxed{\mathrm{Eval}(k_b^{\mathrm{F}}, 1||0)} \\ \leftarrow \mathrm{Eval}(k_b^{\mathrm{F}}, \dots) \\ \leftarrow \mathrm{Eval}(k_b^{\mathrm{F}}, n||0) \end{array} \Rightarrow \begin{array}{c} \\ 0 \\ 1 \\ \dots \\ n \end{array}\begin{array}{c} \begin{array}{ccc} 0 & \dots & c \end{array} \\ \begin{bmatrix} 1 & \dots & 0 \\ \boxed{0} & \dots & 1 \\ \dots & \dots & \dots \\ 0 & \dots & 1 \end{bmatrix} \end{array}$$

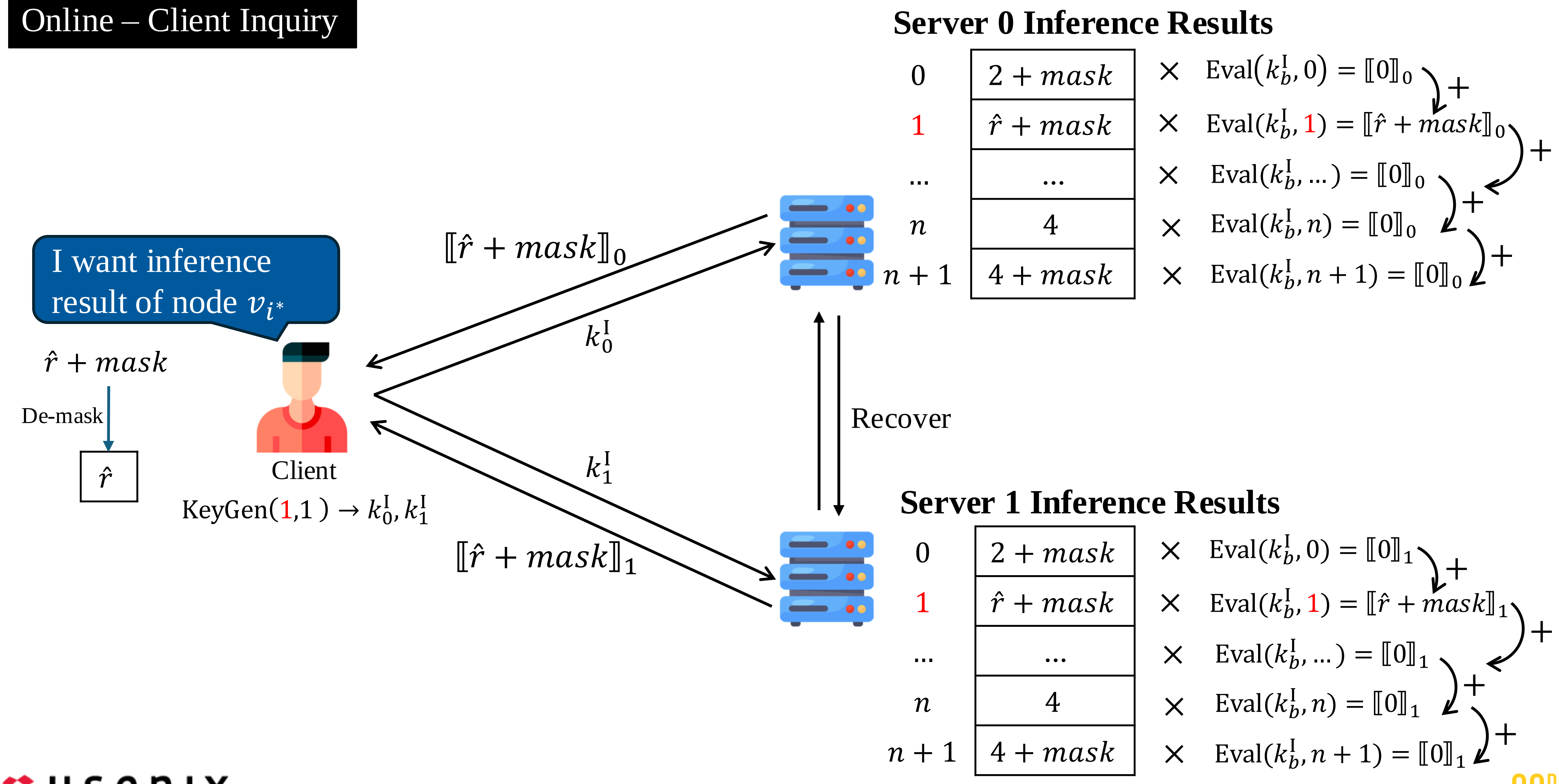
Feature Matrix [$\hat{\mathbf{F}}$] (secret shared)

Updated Feature Matrix

By employing DPF keys to perform graph updates, we now achieve *oblivious* and *efficient* graph updates

OblivGNN Approach

Online – Client Inquiry



Experiments

- **Platform**
  - Python and C++
  - Server
    - 3.70GHz Intel(R) Xeon(R) E-2288G CPU
    - 64GB RAM and 128GB external storage
    - Ubuntu 20.04.5 LTS
  - MP-SPDZ [Keller et al. (CCS'20)]

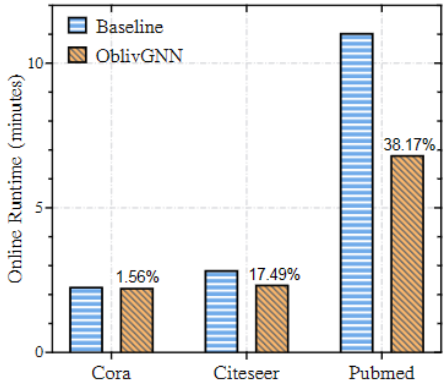
- **Datasets**
  - Cora, Citeseer and Pubmed

Dataset	Nodes	Feature	Edge	Classes
Cora	2708	1433	5429	7
Citeseer	3327	3703	4732	6
Pubmed	19717	500	44338	3

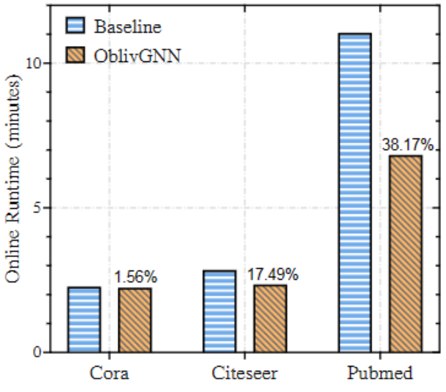
- **Baseline**
  - Baseline: pure additive secret shares for inference.
  - OblivGNN: additive secret shares with FSS for oblivious inference.

Experiments – System

System Runtime: Average Reduction: 38%



(a) Transductive

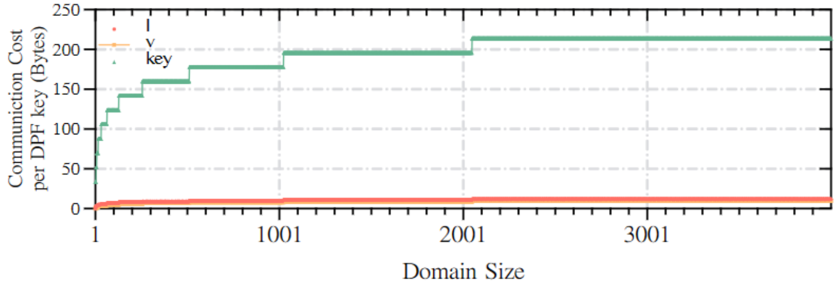


(b) Inductive

System Communication (GB): Reduction: 10× - 151×

	Baseline	**OblivGNN**
Cora	34.21	**0.29**
Citeseer	61.81	**0.41**
Pubmed	16.33	**1.65**

Graph Update Cost: Logarithm growth towards large graph



(a) Node/Feature Update Key Size

(b) Node/Feature Update Time Cost

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Q&A

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