



BLAZE: BLAZING FAST PRIVACY-PRESERVING MACHINE LEARNING

ARPITA PATRA AND **AJITH SURESH**

Ajith Suresh

CrIS Lab, IISc

<https://www.csa.iisc.ac.in/~cris>



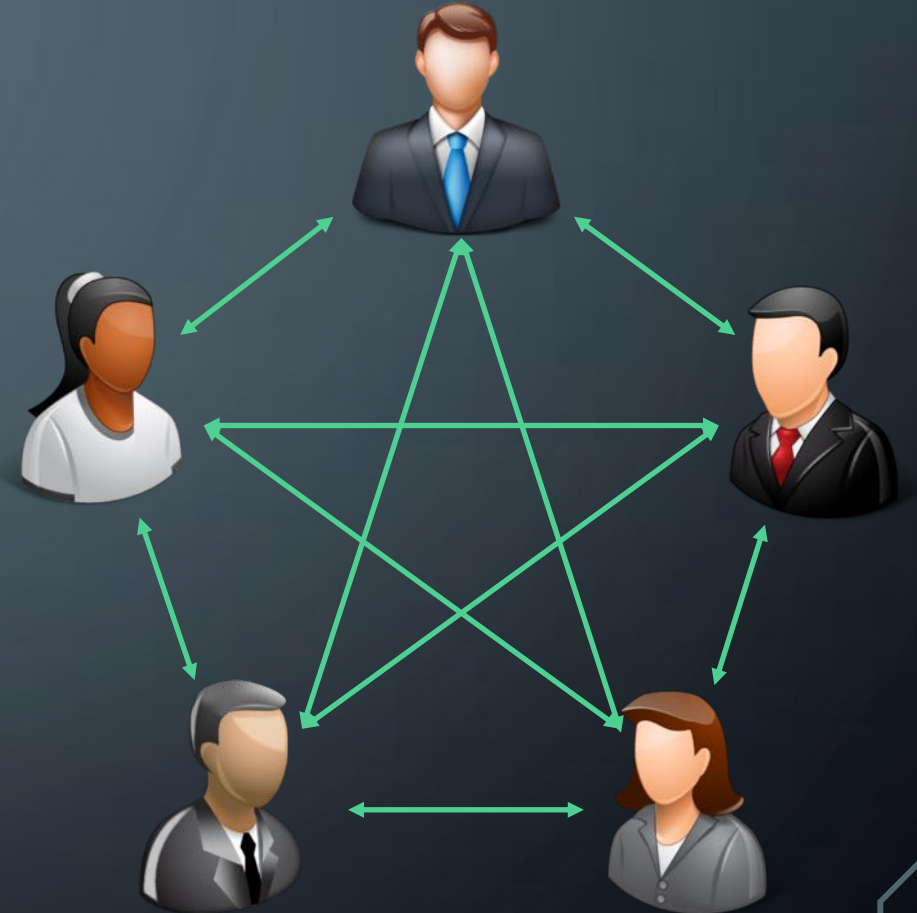
Outline



- ❑ Secure Multi-party Computation (MPC)
- ❑ MPC for small number of parties (3PC)
- ❑ Our Efficient BLAZE Protocol (Results)
- ❑ Privacy Preserving Machine Learning (PPML)

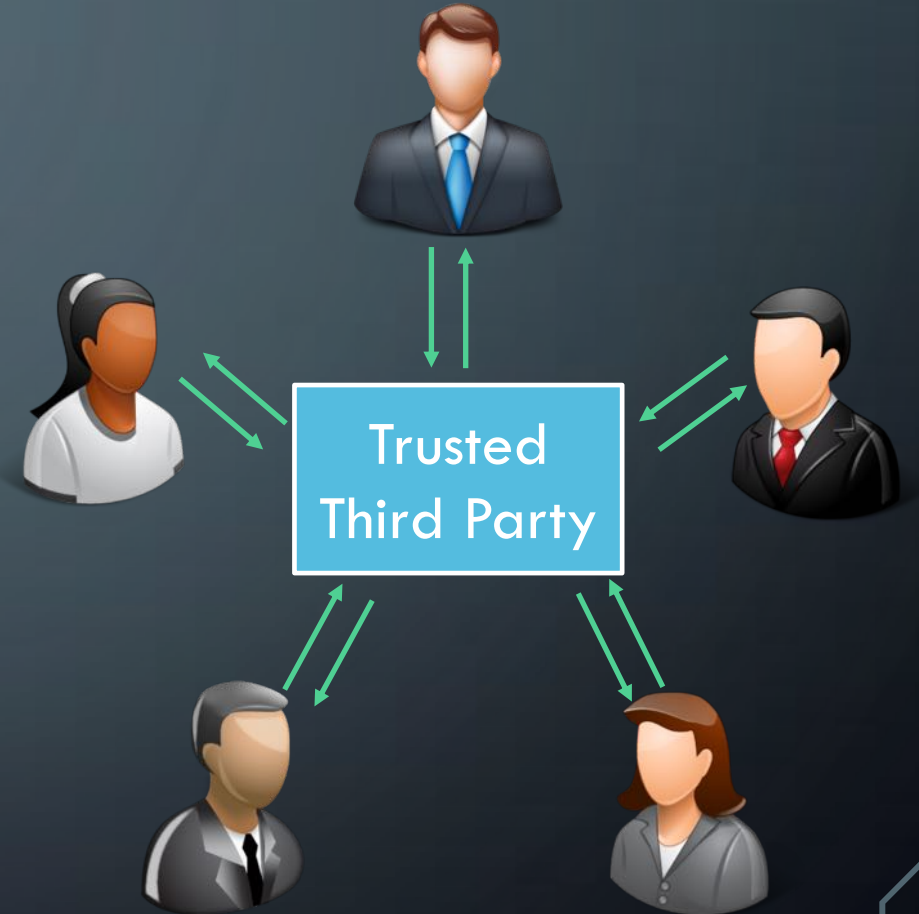
Secure Multi-party Computation (MPC) [Yao'82]

- ✓ A set of parties with private inputs wish to compute some joint function of their inputs.
- ✓ Goals of MPC:
 - **Correctness** – Parties should correctly evaluate the function output.
 - **Privacy** – Nothing more than the function output should be revealed



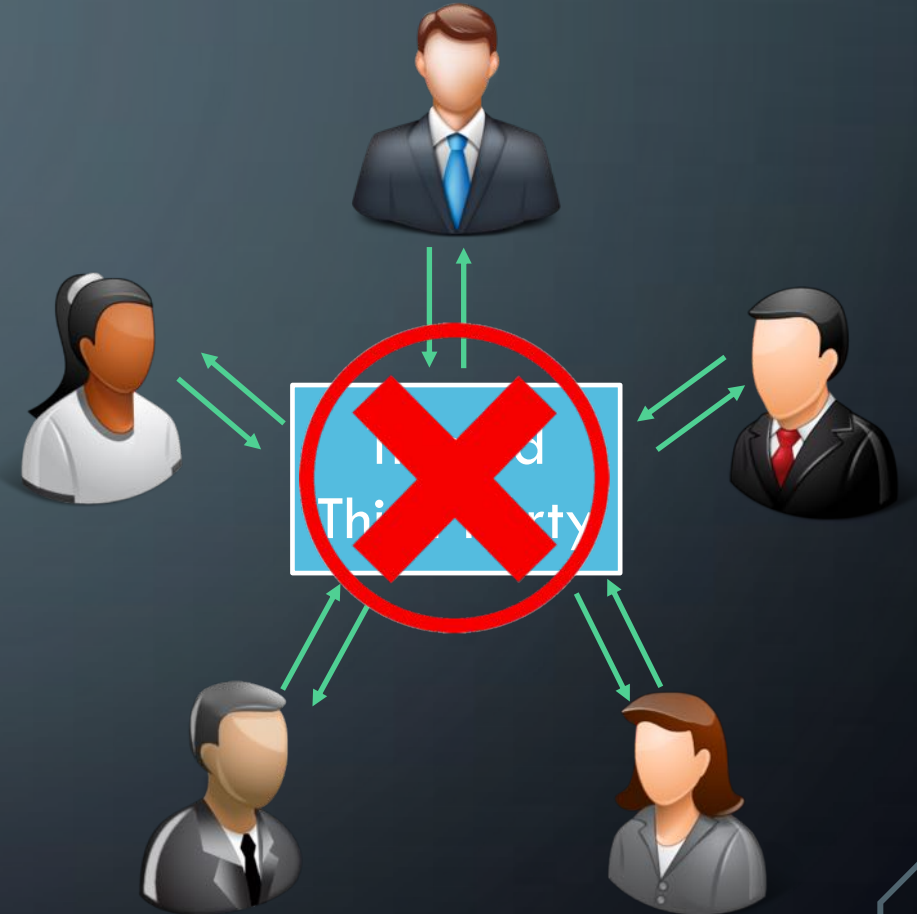
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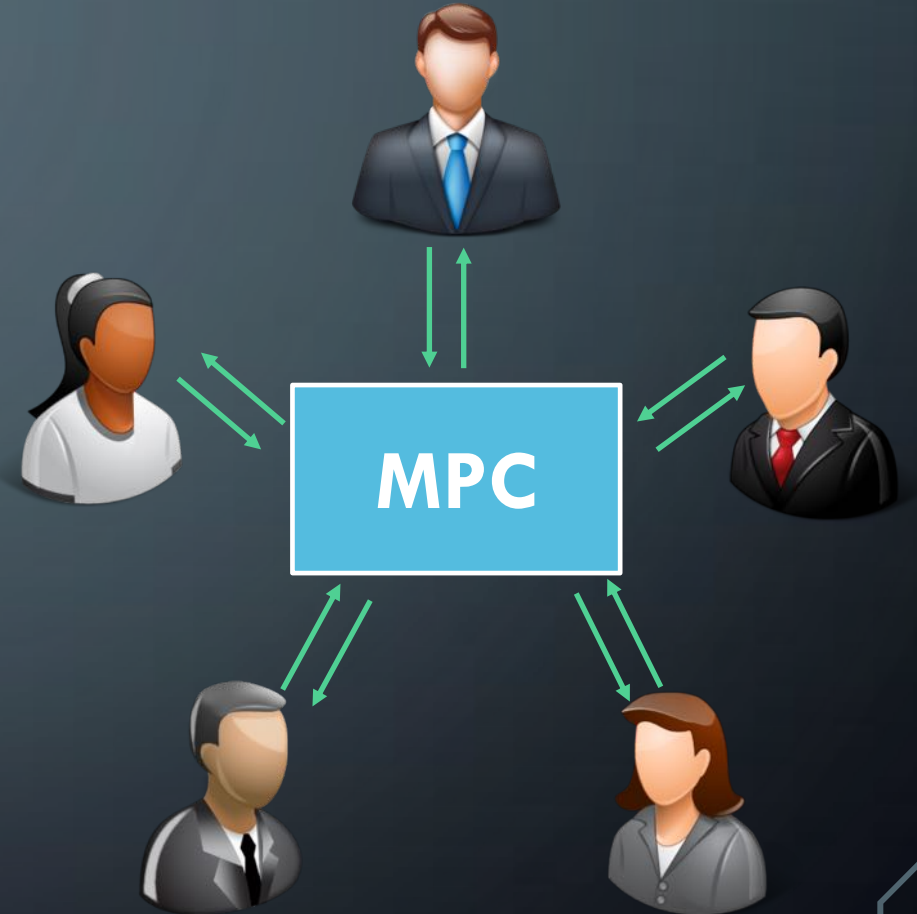
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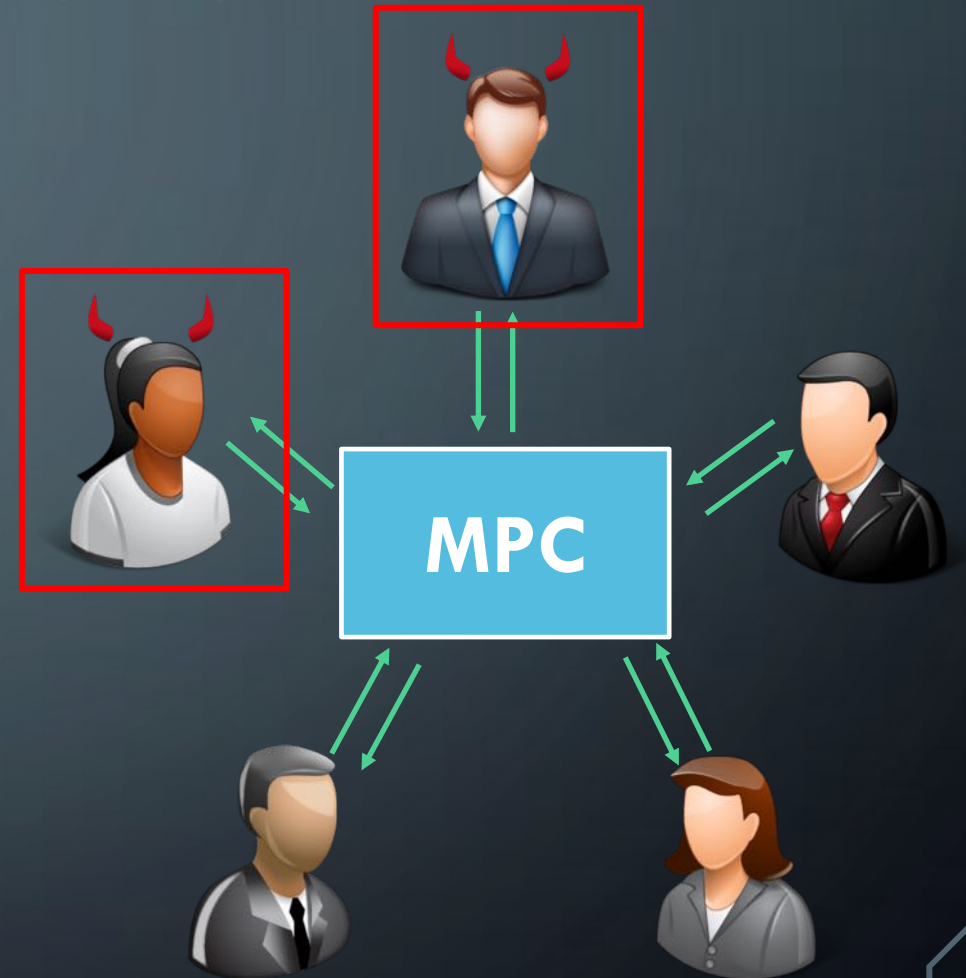


Secure Multi-party Computation (MPC) [Yao'82]



ADVERSARY

- Semi – honest:
 - Follows the protocol but tries to learn more
- Malicious:
 - Can arbitrarily deviate from the protocol

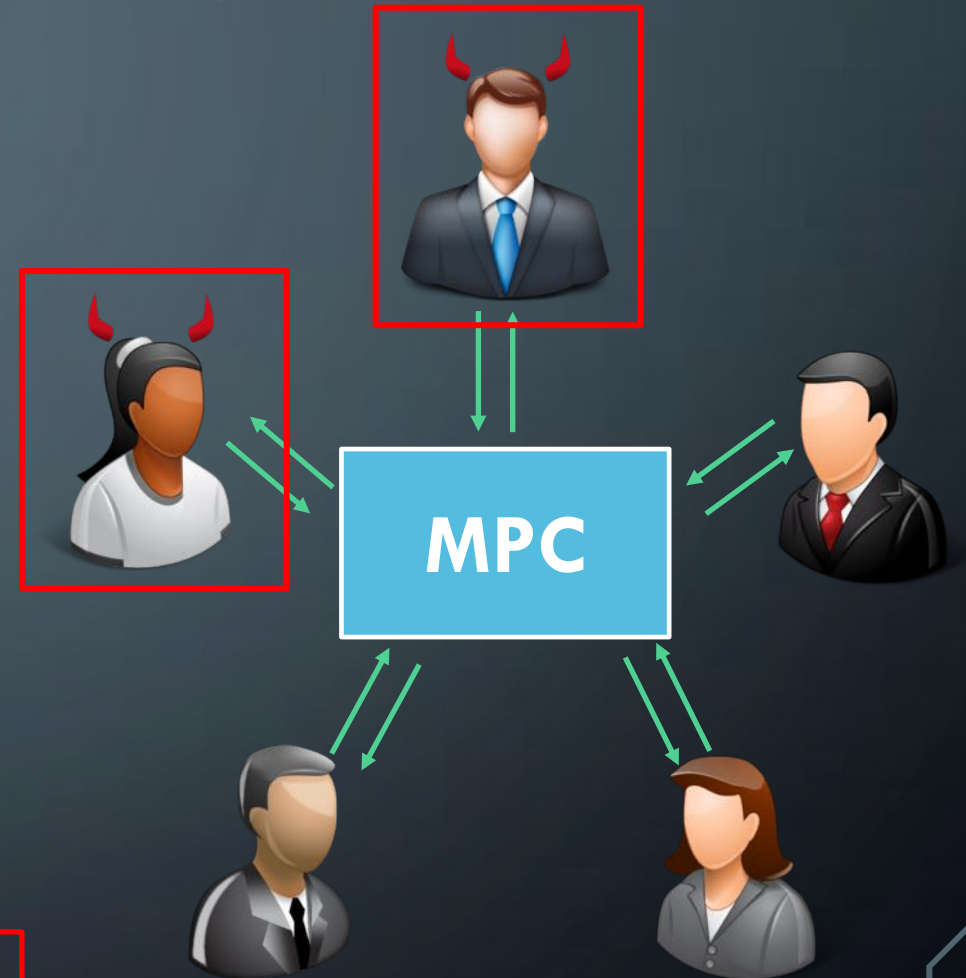


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Malicious Corruption

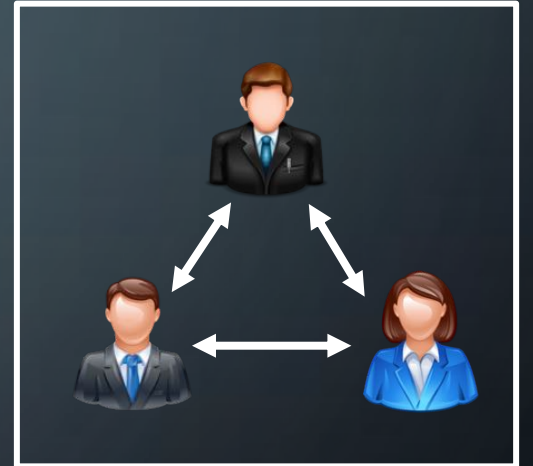


MPC for small number of parties

- **Efficiency and Simplicity** [MRZ15,AFLNO16,FLNW17,CGMV17]

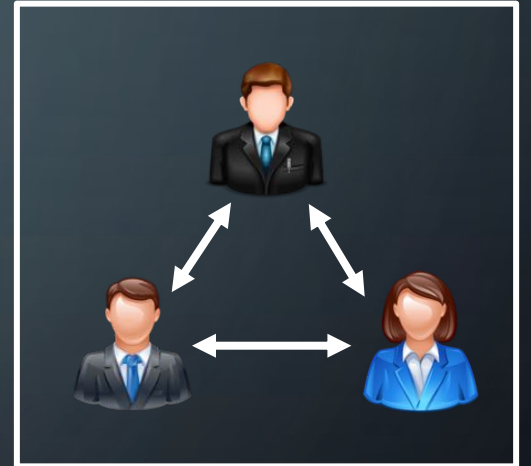
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- Our focus: MPC with 3 parties



MPC for small number of parties

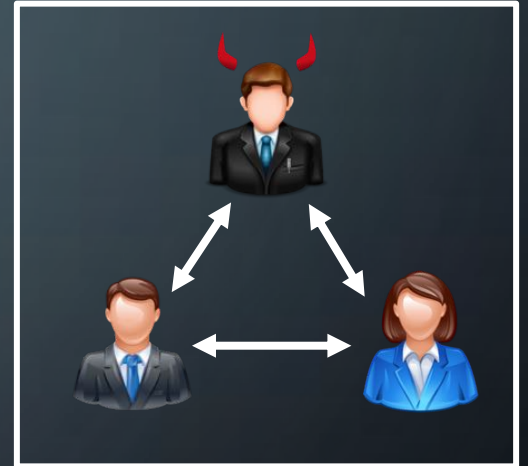
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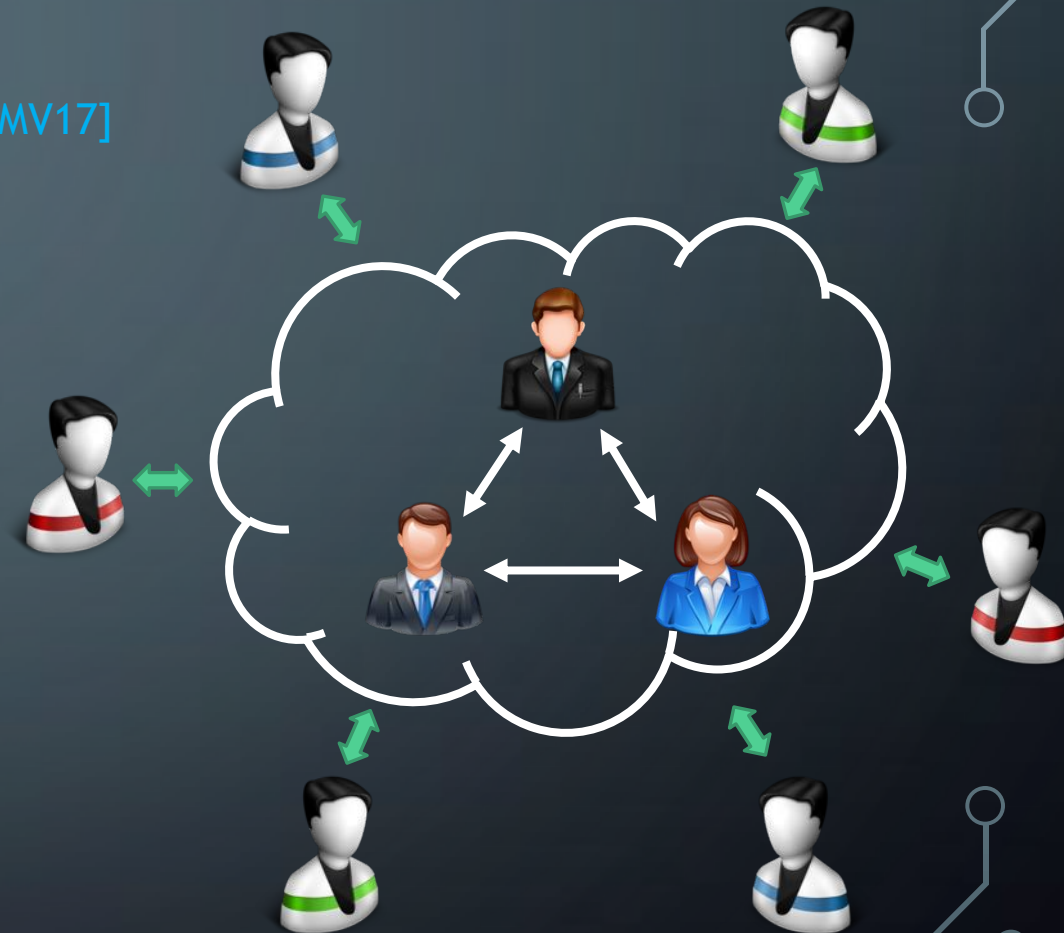
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- Our focus: MPC with 3 parties
- Corruption : **honest majority**

- ❑ Majority of the parties are honest
- ❑ 3PC - at most 1 corruption



MPC for small number of parties

- **Efficiency and Simplicity** [MRZ15,AFLNO16,FLNW17,CGMV17]
- Our focus: MPC with 3 parties
- Corruption : honest majority
- Outsourced Computation





MPC for small number of parties

- **Efficiency and Simplicity** [MRZ15,AFLNO16,FLNW17,CGMV17]
- Our focus: MPC with 3 parties
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- Outsourced Computation
- Pre-processing Model

MPC for small number of parties

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- Pre-processing Model
 - Pre-processing phase

MPC for small number of parties

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- Pre-processing Model
 - **Pre-processing phase**



- Data-independent Computation
- Relatively slow and expensive



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- Pre-processing Model
 - Pre-processing phase
 - Online Phase

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- Our focus: MPC with 3 parties
- Corruption : honest majority
- Outsourced Computation
- Pre-processing Model
 - Pre-processing phase
 - Online Phase
 - ❑ Minimized communication
 - ❑ Blazing fast





BLAZE PROTOCOL

BLAZE Protocol

S_0



S_1



S_2





BLAZE Protocol



S_0



S_1



S_2



BLAZE Protocol

S_0



S_1



S_2



BLAZE Protocol

S_0



S_1



S_2



BLAZE Protocol

S₀



S₁



S₂



BLAZE Protocol

S_0



S_1



S_2



BLAZE Protocol



Communication Cost per
Multiplication Gate (malicious)

Mult: $x.y$

BLAZE : <https://eprint.iacr.org/2020/042>

Ref	Pre-processing (#elements)	Online (#elements)	Security
Araki et al'17	12	9	Abort



Communication Cost per
Multiplication Gate (malicious)

Mult: $x.y$

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Araki et al'17	12	9	Abort
ASTRA	21	4	Fair



Communication Cost per
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BLAZE Protocol



Ref	Pre-processing (#elements)	Online (#elements)	Security
Araki et al'17	12	9	Abort
ASTRA	21	4	Fair
Boneh et al'19	0	3	Abort

Communication Cost per
Multiplication Gate (malicious)

Mult: $x.y$

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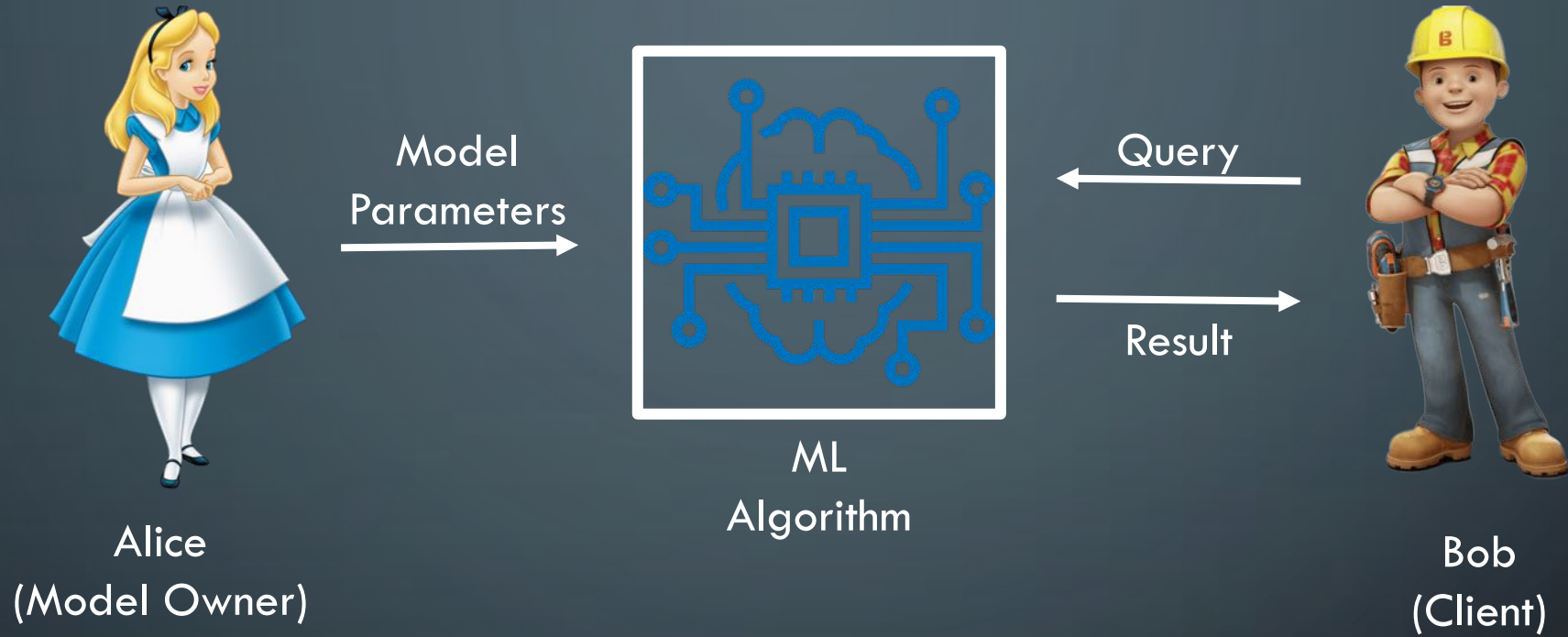
Ref	Pre-processing (#elements)	Online (#elements)	Security
Araki et al'17	12	9	Abort
ASTRA	21	4	Fair
Boneh et al'19	0	3	Abort
BLAZE	3	3	Fair

Communication Cost per
Multiplication Gate (malicious)

Mult: $x.y$

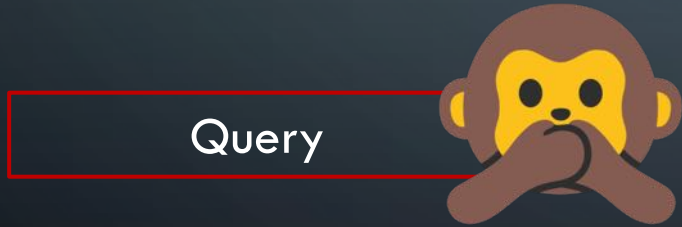
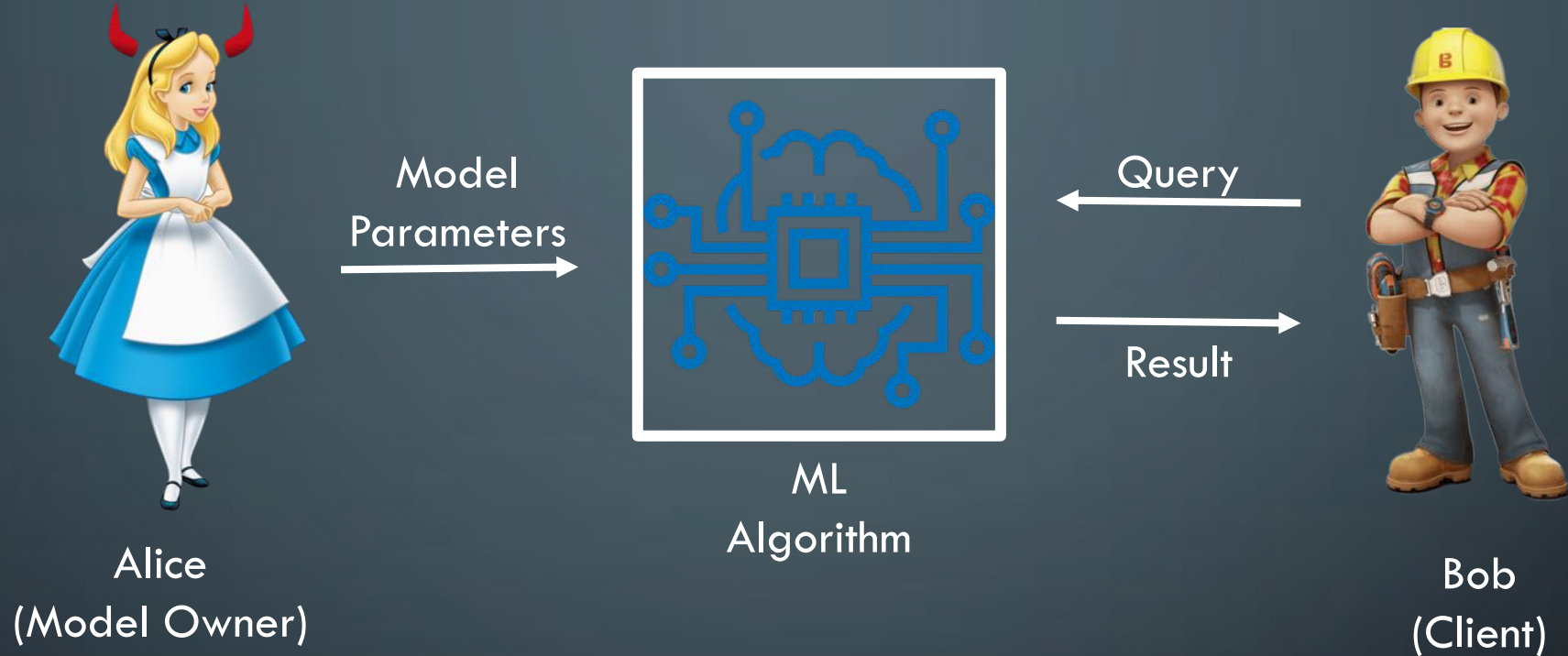
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Privacy Preserving Machine Learning (PPML)

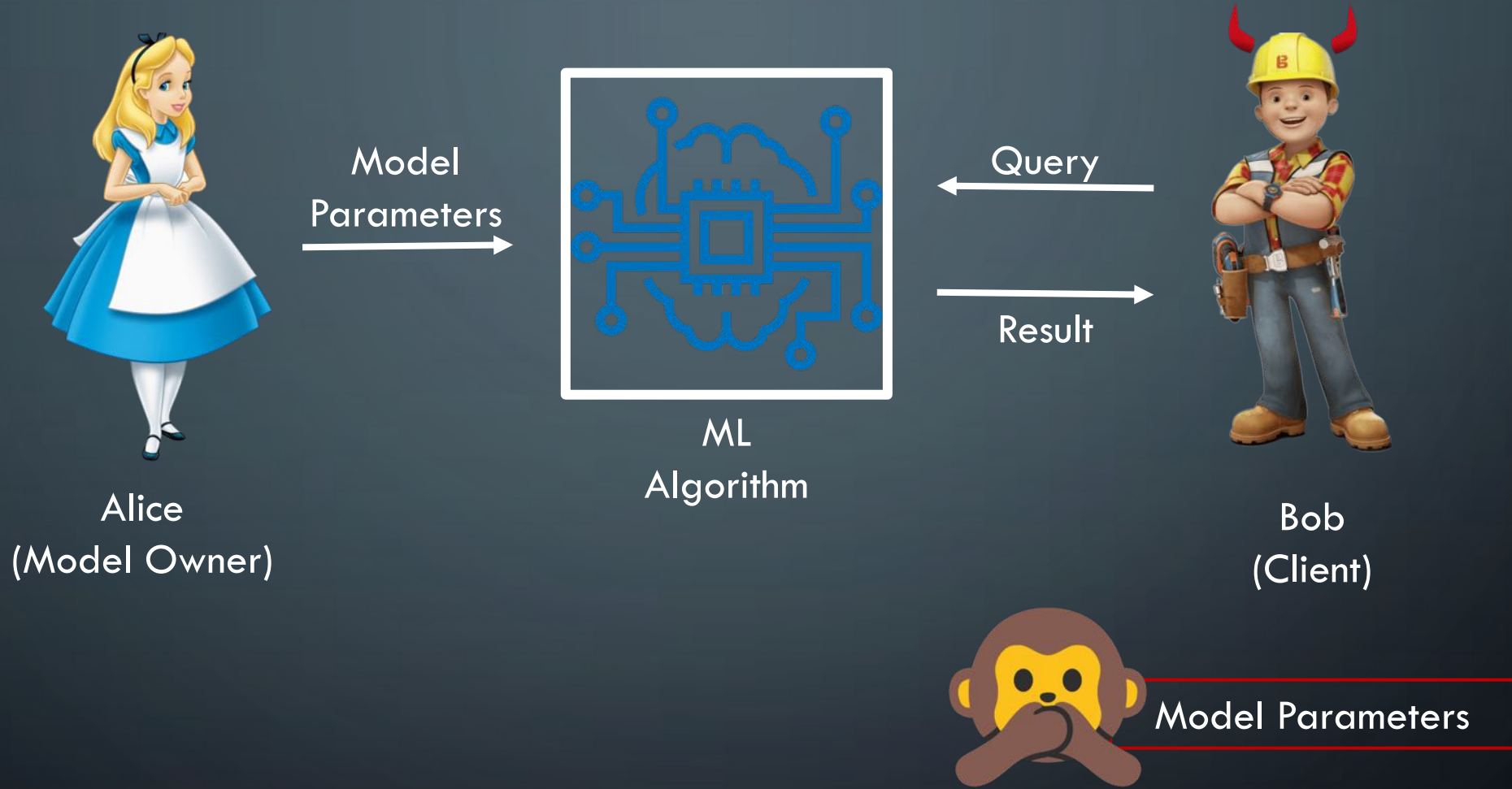


Privacy ??

Privacy Preserving Machine Learning (PPML)



Privacy Preserving Machine Learning (PPML)



Solution ??

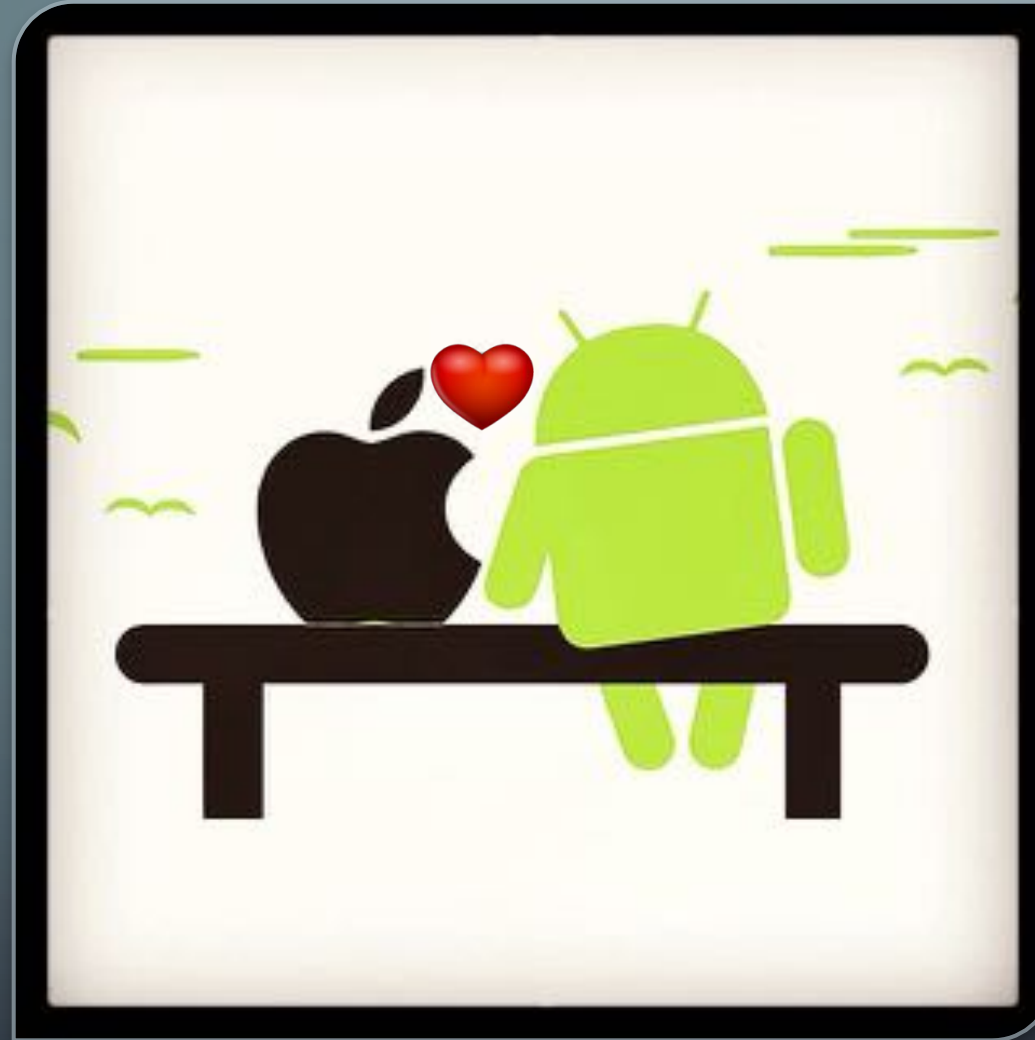


ML

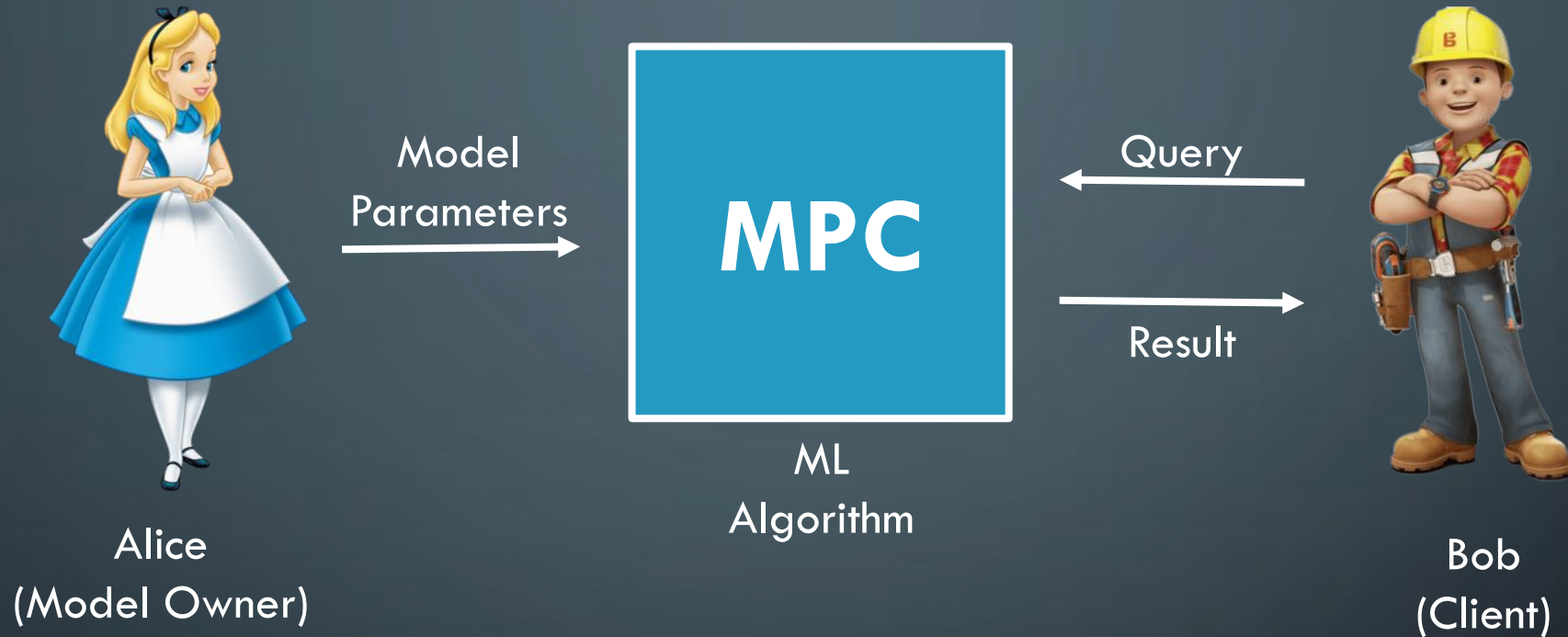


MPC

MPC MEETS ML



Privacy Preserving Machine Learning (PPML)

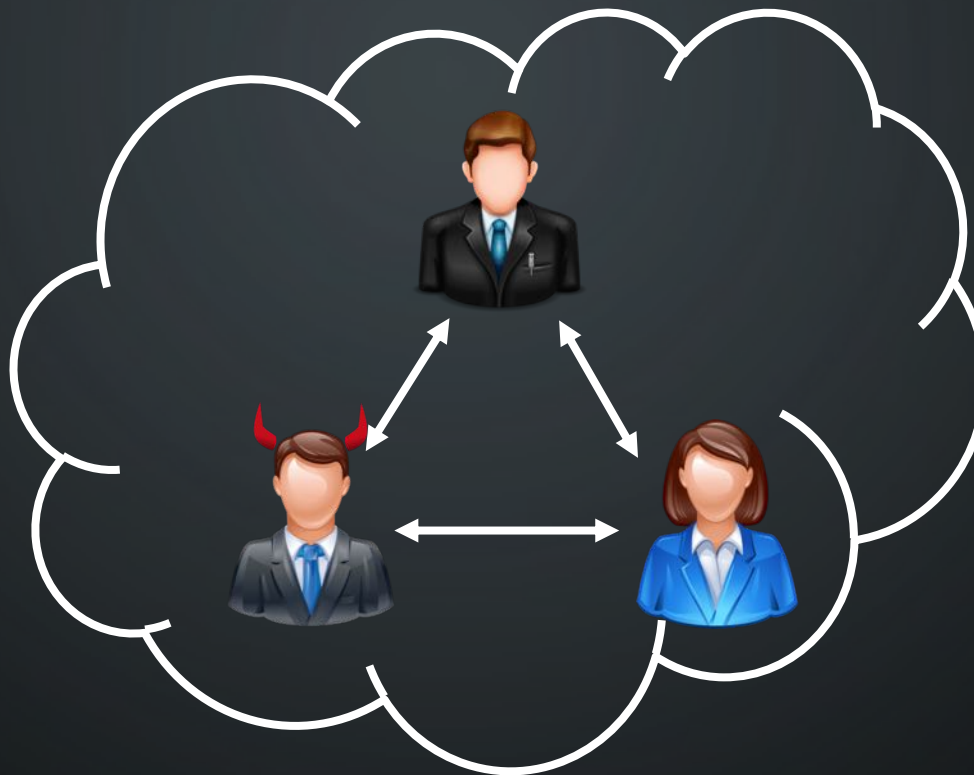


Use MPC to achieve privacy



Alice
(Model Owner)

Model
Parameters



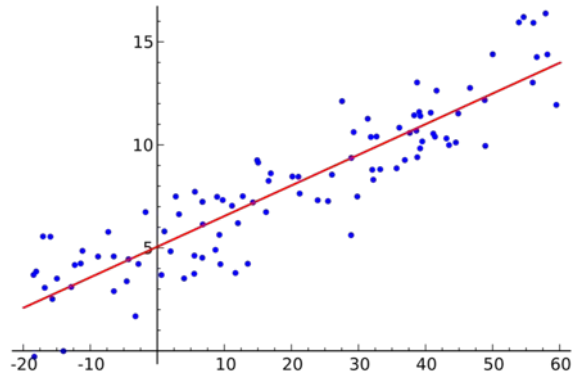
Query

Result

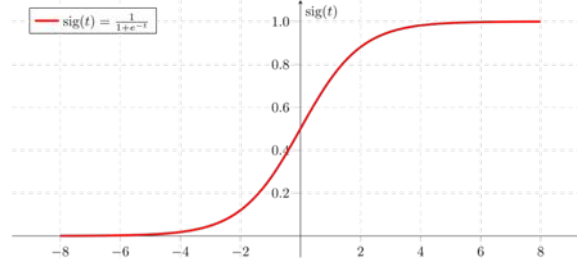


Bob
(Client)

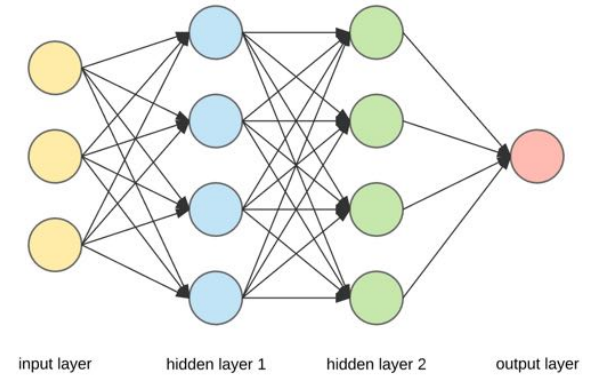
SECURE OUTSOURCED SETTING (SOC)



Linear Regression



Logistic Regression



Neural Networks

ML ALGORITHMS CONSIDERED



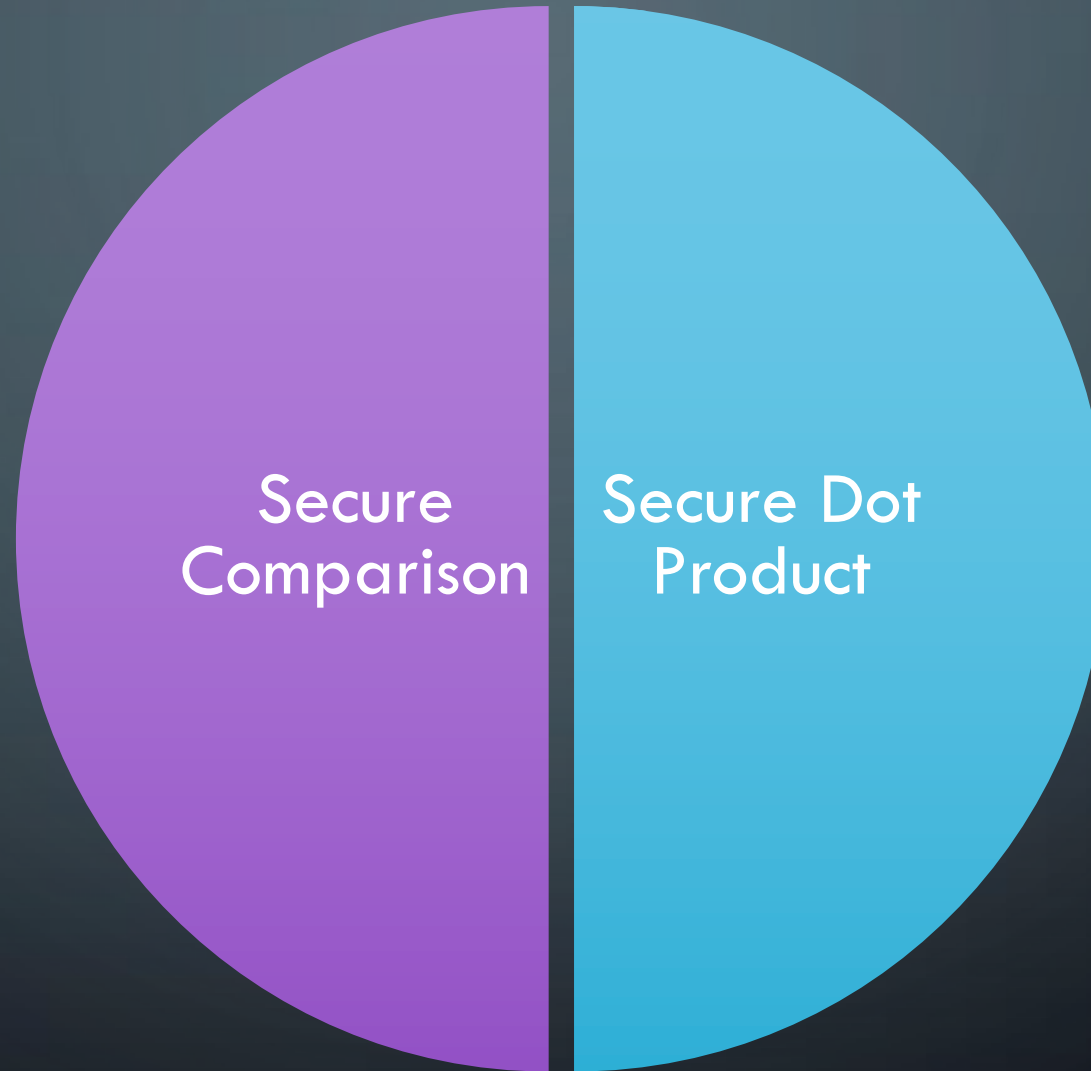
PPML using MPC: Hurdles to Clear



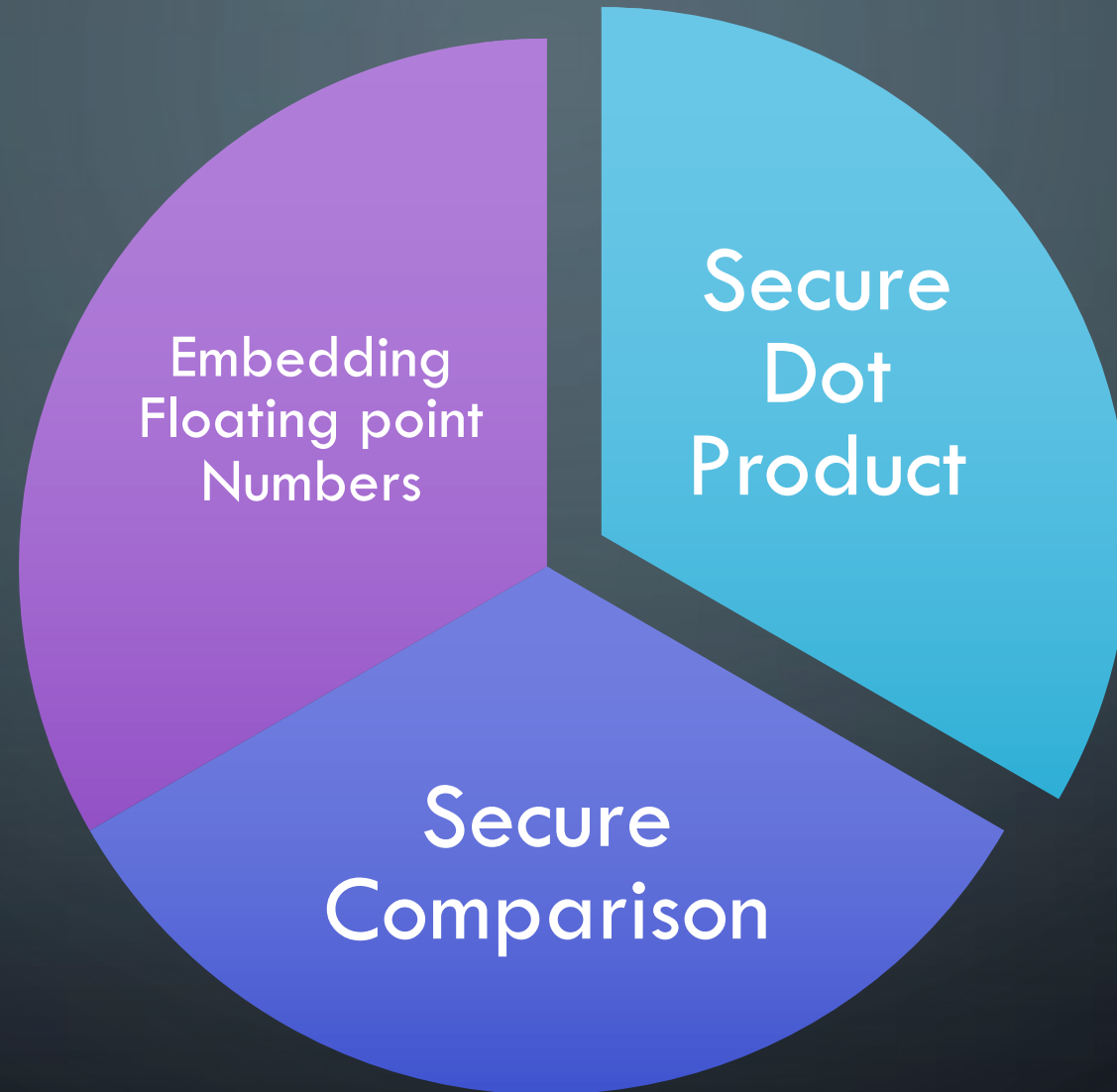
Secure Dot Product



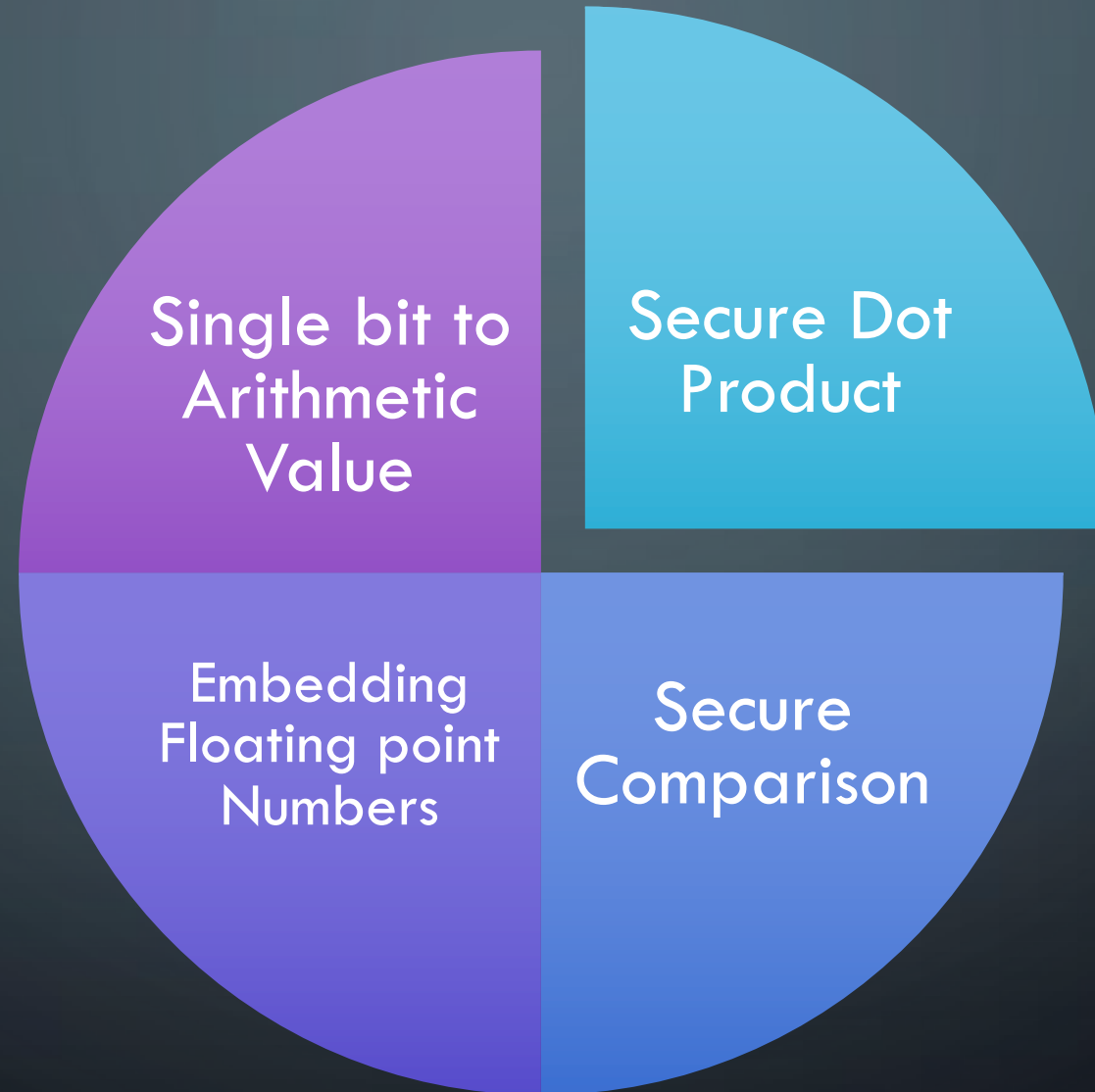
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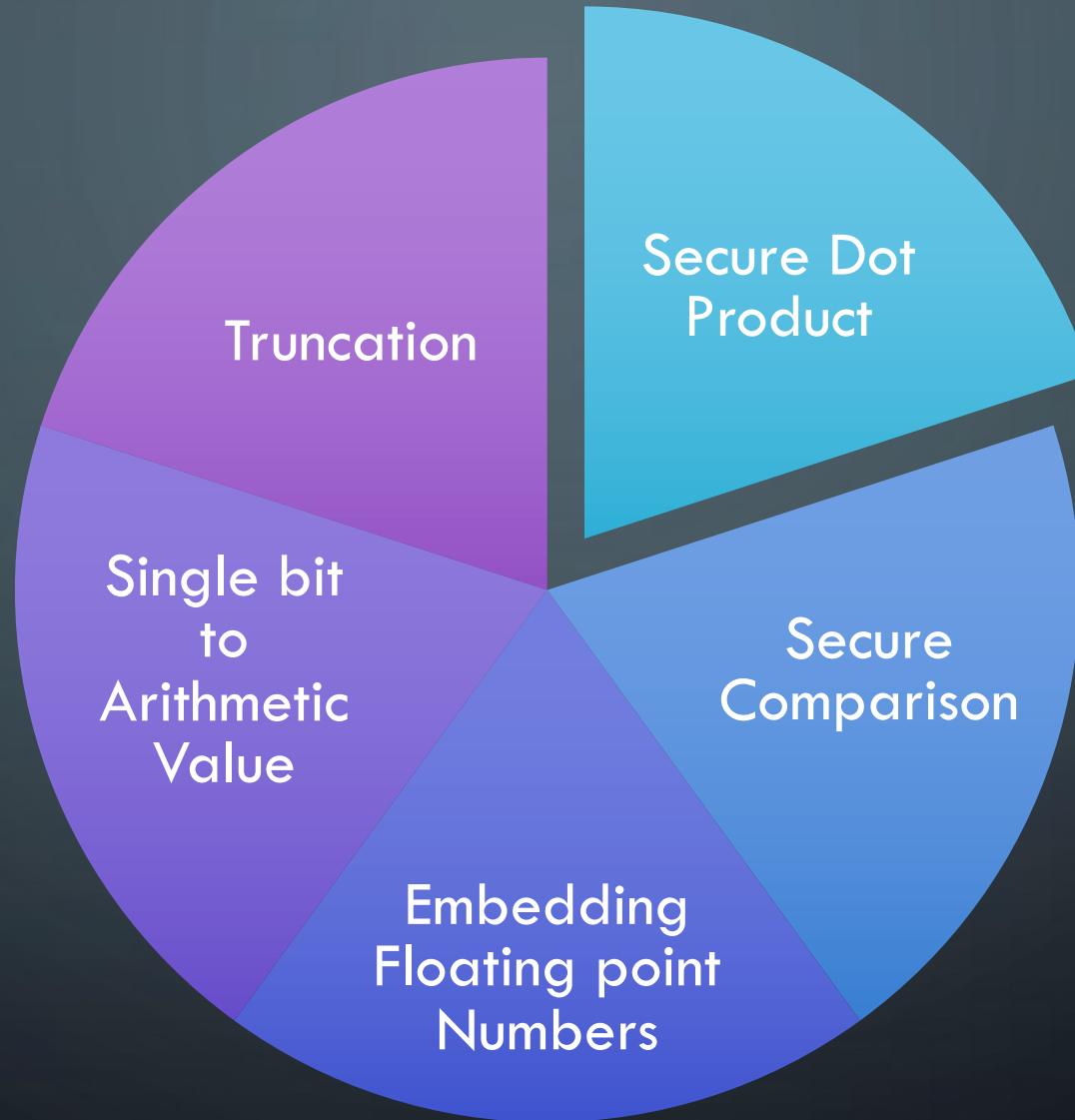
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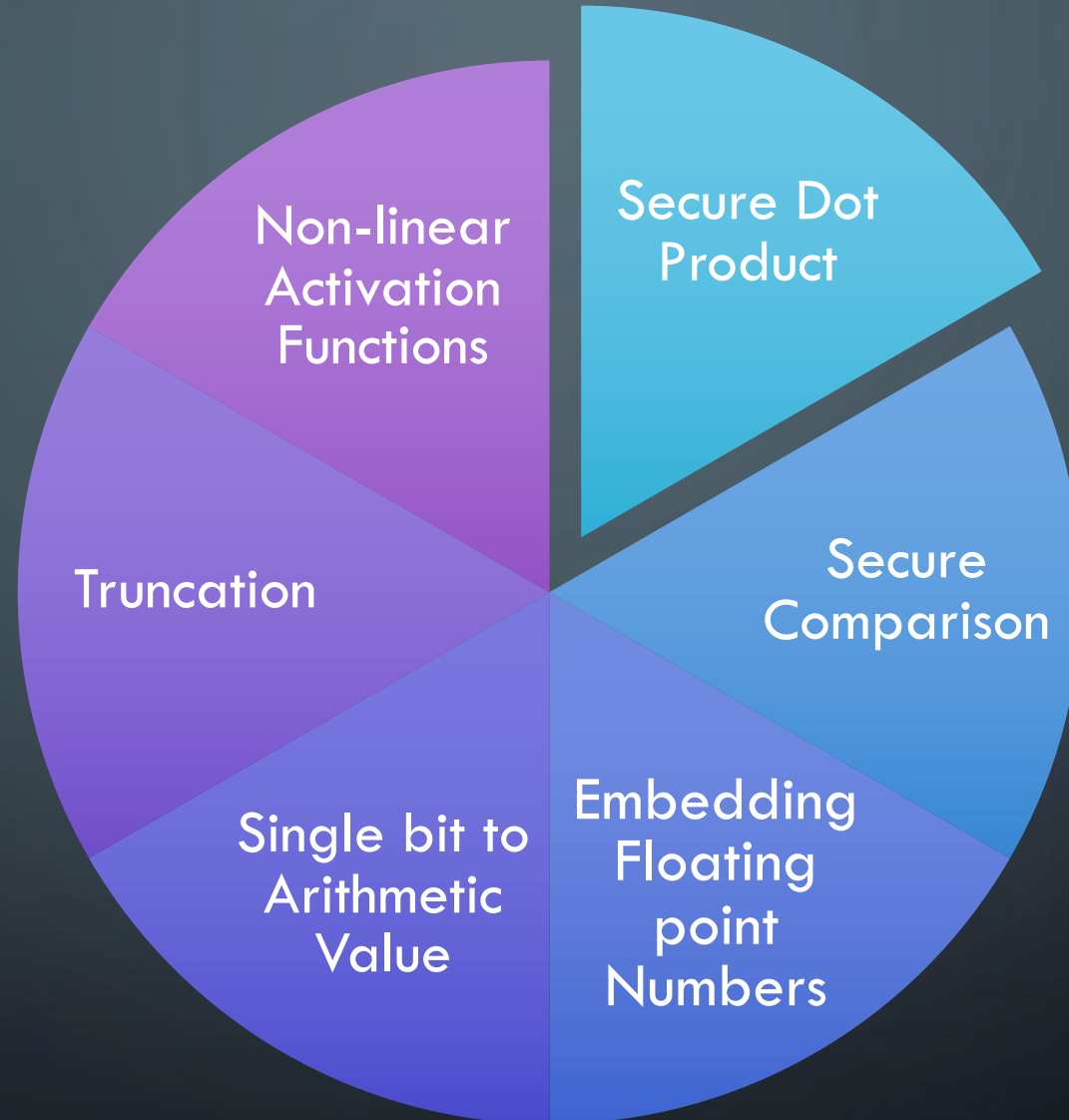
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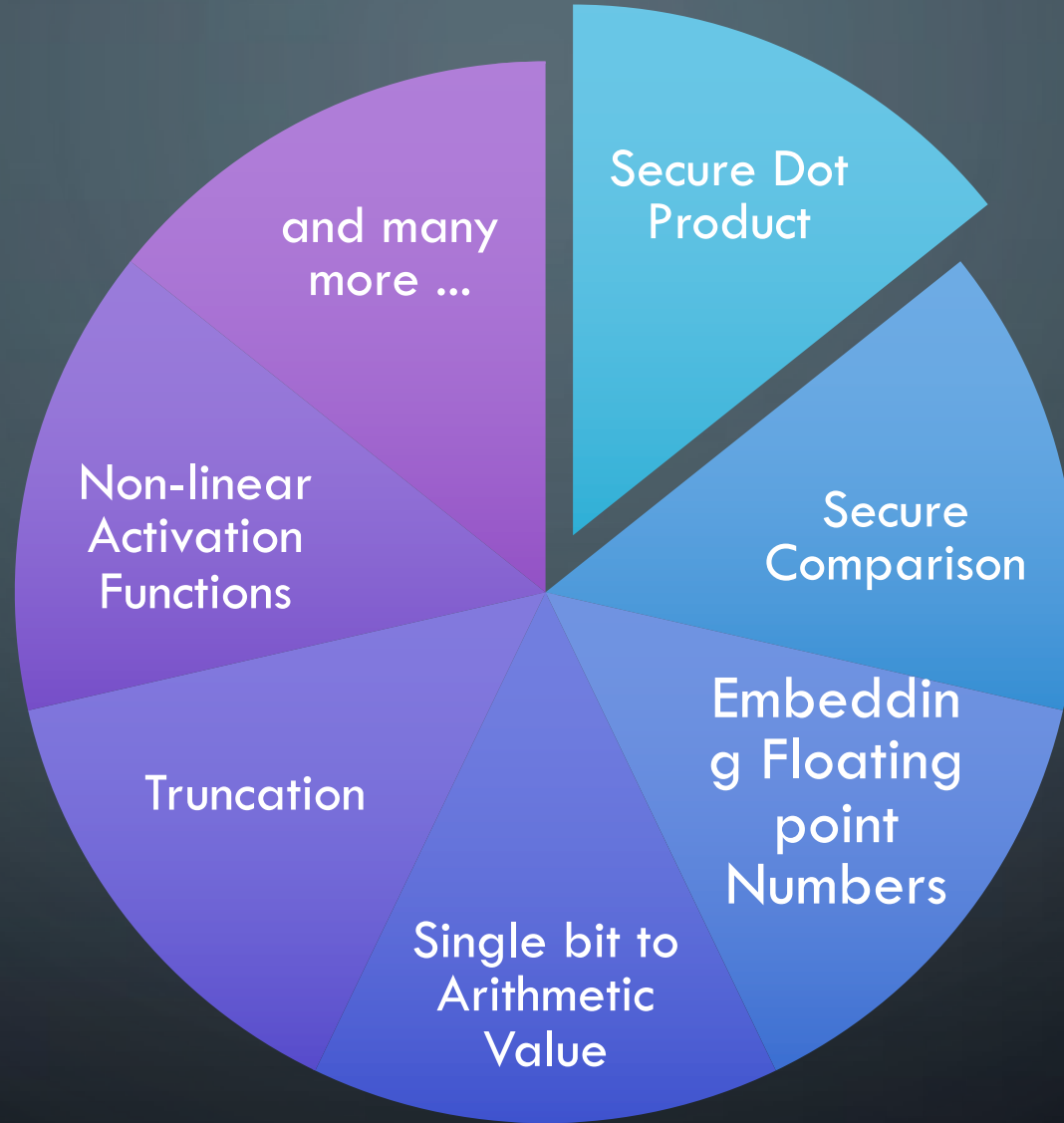
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PPML using MPC: Hurdles to Clear



BLAZE Protocol

Ref	Pre-processing (#elements)	Online (#elements)	Security
ABY3	12d	9d	Abort



Communication Cost per
Dot Product

$$X \blacksquare Y = \sum_{i=1}^d x_i \cdot y_i$$

BLAZE : <https://eprint.iacr.org/2020/042>

d – #elements in each vector

BLAZE Protocol



Ref	Pre-processing (#elements)	Online (#elements)	Security
ABY3	12d	9d	Abort
ASTRA	21d	2d+2	Fair

Communication Cost per
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d – #elements in each vector



Summary of Our Benchmarking Results

Algorithm	Improvement in terms of Online Throughput over State-of-the-art protocols over WAN	
	Training	Prediction
Linear Regression	333.22 x	194.86 x
Logistic Regression	53.19 x	27.52 x
Neural Networks	-	276.31 x

*Throughput for Training - #iterations processed by servers / minute

*Throughput for Prediction - #queries processed by servers / minute

Algorithm	Ref.	Preprocessing		Online	
		TP	Gain	TP	Gain
Linear Regression	ABY3	61.02	4.01×	30.61	145.35×
	BLAZE	244.74		4449.55	
Logistic Regression	ABY3	60.71	4.02×	60.99	31.89×
	BLAZE	243.81		1945.24	

TABLE VI: Throughput (TP) for ML Training for a batch size B-128 and feature size n-784

Summary of Our Benchmarking Results

Algorithm	Ref.	Preprocessing		Online	
		TP ($\times 10^3$)	Gain	TP ($\times 10^3$)	Gain
Linear Regression	ABY3	15.57	4.02×	15.67	169.75×
	BLAZE	62.61		2660.53	
Logistic Regression	ABY3	15.41	4.03×	15.55	23.57×
	BLAZE	62.13		366.68	
Neural Networks	ABY3	0.10	4.01×	0.14	245.74×
	BLAZE	0.41		33.74	

TABLE VII: Throughput (TP) for ML Inference for a feature size of n-784



**THANK
YOU!**



References

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2. P. Mohassel, M. Rosulek, and Y. Zhang. *Fast and Secure Three party Computation: Garbled Circuit Approach*. In CCS, 2015.
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