Privacy-Preserving Logistic Regression based on HEAAN Library

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- 3 Evaluation
- 4 Implementation & Optimization

Task3: HE based Logistic Regression Model Learning

- Logistic Regression
 - Regression model for categorical dependent variable.
 - ► Find a machine learning model for disease prediction using the genotype/phenotype data.
- Implementation Results

Iteration	Learning	AUC
7	10.25min	0.709
14	63.85min	0.715

$$\#(Features) = 19, \#(Samples) = 1421$$

HEAAN* Library

- Homomorphic Encryption for Arithmetic of Approximate Numbers [CKKS, to appear in AC'17]
- Efficient HE scheme over the real/complex numbers.

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- Provide an open-source implementation in C++ language.
 Available at github (https://github.com/kimandrik/HEAAN).

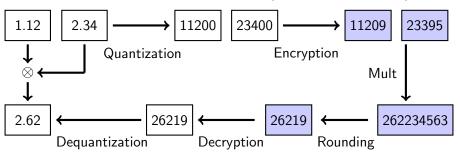
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 Available at github (https://github.com/kimandrik/HEAAN).
- Follow-up researches in applications
 - ► Encrypted Controller of Cyber-Physical System [KLSCKKS, IFAC'16]
 - Privacy-Preserving Logistic Regression [KSWXJ17, preprint]
- * 慧眼: insight, prescience

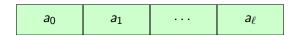
Construction of HEAAN

- A noise of (Ring) LWE is considered to be a part of computation error.
- ct = Enc(m) \Rightarrow Dec(ct) = m + e for some small e.
 - ▶ An approximate value can replace the original message.
- Support arithmetic operations and rounding of encrypted data.
- Linear bitsize of ctx modulus on the depth of a circuit & bit precision



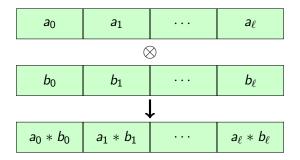
Functionality of HEAAN

- RLWE based construction over the cyclotomic ring $\mathcal{R} = \mathbb{Z}[X]/(X^N+1)$ of a power-of-two dimension N.
- Packing multiple numbers (max. N/2) in a single ciphertext.



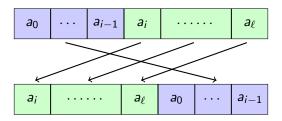
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- Addition, multiplication, and rounding in a SIMD manner.
- Rotation on plaintext slots.



Database Encoding

User	Class (± 1)	Feature Vector (\mathbb{R}^d)			
1	$y_1 = 1$	$x_{11} = 2.78$	$x_{12} = 1.12$		$x_{1d} = 3.05$
2	$y_2 = -1$	$x_{21} = 0.56$	$x_{22} = 1.58$		$x_{2d} = 2.95$
:	:	:	:	٠	:
n	$y_n = 1$	$x_{n1} = 1.22$	$x_{n2} = 2.01$		$x_{nd} = 4.31$

$$\implies Z = \begin{bmatrix} 1 & 2.78 & 1.12 & \cdots & 3.05 \\ -1 & -0.56 & -1.58 & \cdots & -2.95 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & 1.22 & 2.01 & \cdots & 4.31 \end{bmatrix} \in \mathbb{R}^{n \times (d+1)}$$

- Write $\vec{z_i} = y_i \cdot (1, \vec{x_i}) \in \mathbb{R}^{d+1}$ for $i = 1, 2, \dots, n$.
- Generate an encryption of $Z = (\vec{z_i})_i$.

Logistic Regression and Gradient Descent

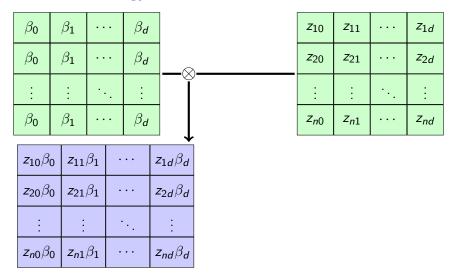
ullet Find a modeling vector $ec{eta} \in \mathbb{R}^{d+1}$ which maximizes the likelihood

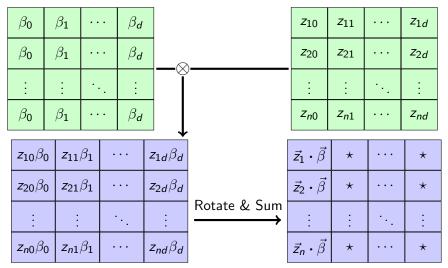
$$\prod_{i=1}^n \Pr[y_i|\vec{x_i}] \quad \text{for} \quad \Pr[y_i|\vec{x_i}] = \frac{1}{1 + \exp(-\vec{z_i} \cdot \vec{\beta})}.$$

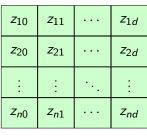
- Loss function $J(\vec{\beta}) = \frac{1}{n} \sum_{i=1}^{n} \log(1 + \exp(-\vec{z}_i \cdot \vec{\beta}))$.
- $\nabla J(\vec{\beta}) = -\frac{1}{n} \sum_{i=1}^{n} \sigma(\vec{z_i} \cdot \vec{\beta}) \cdot \vec{z_i}$ for the sigmoid function σ .
- Repeat $\vec{\beta}_t \leftarrow \vec{\beta}_{t-1} \alpha_t \cdot \nabla J(\vec{\beta}_{t-1})$ for $t = 1, 2, \cdots$.

β_0	β_1	 $\beta_{\sf d}$
β_0	β_1	 $\beta_{\sf d}$
:	:	:
β_0	β_1	 $\beta_{\sf d}$

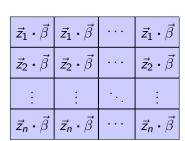
z ₁₀	z ₁₁	 z_{1d}
z ₂₀	z ₂₁	 z _{2d}
:		•••
Z _n 0	Z _{n1}	 Z _{nd}

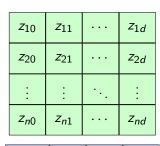






$ec{z_1} \cdot ec{eta}$	*	 *
$\vec{z}_2 \cdot \vec{\beta}$	*	 *
÷		:
$\vec{z}_n \cdot \vec{\beta}$	*	 *





	$ec{z_1} \cdot ec{eta}$	*	• • •	*
D 11 .	$\vec{z}_2 \cdot \vec{\beta}$	*	• • •	*
Replicate				
	:	:		:
	$\vec{z}_n \cdot \vec{\beta}$	*		*

$$\begin{array}{c|ccc}
\sigma(-\vec{z}_1 \cdot \vec{\beta}) & \cdots & \sigma(-\vec{z}_1 \cdot \vec{\beta}) \\
\sigma(-\vec{z}_2 \cdot \vec{\beta}) & \cdots & \sigma(-\vec{z}_1 \cdot \vec{\beta}) \\
\vdots & \ddots & \vdots \\
\sigma(-\vec{z}_n \cdot \vec{\beta}) & \cdots & \sigma(-\vec{z}_1 \cdot \vec{\beta})
\end{array}$$

$\vec{z}_1 \cdot \vec{eta}$	$ec{z_1} \cdot ec{eta}$	•••	$ec{z}_1 \cdot ec{eta}$
$\vec{z}_2 \cdot \vec{\beta}$	$\vec{z}_2 \cdot \vec{\beta}$		$\vec{z}_2 \cdot \vec{\beta}$
i	:	٠	:
$\vec{z}_n \cdot \vec{\beta}$	$\vec{z}_n \cdot \vec{\beta}$		$\vec{z}_n \cdot \vec{\beta}$

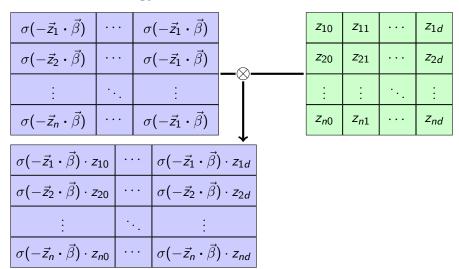
_	Sigmoid
_	Replicate
•	

<i>z</i> ₁₀	<i>z</i> ₁₁	• • •	z _{1d}
z ₂₀	z ₂₁		z _{2d}
:	:	٠	:
Z_{n0}	Z_{n1}		Z _{nd}

$ec{z_1} \cdot ec{eta}$	*	•••	*
$\vec{z}_2 \cdot \vec{\beta}$	*		*
•	i		i
$\vec{z}_n \cdot \vec{\beta}$	*		*

$\sigma(-\vec{z}_1\cdot\vec{eta})$	 $\sigma(-\vec{z_1}\cdot\vec{eta})$
$\sigma(-\vec{z}_2\cdot\vec{eta})$	 $\sigma(-\vec{z_1}\cdot \vec{eta})$
:	:
$\sigma(-\vec{z}_n\cdot\vec{eta})$	 $\sigma(-ec{z_1} \cdot ec{eta})$

z ₁₀	<i>z</i> ₁₁	• • •	z _{1d}
z ₂₀	z ₂₁		z _{2d}
:	:	٠	:
Z _n 0	Z _{n1}		Z _{nd}



$\sigma(-\vec{z}_1\cdot\vec{\beta})\cdot z_{10}$	 $\sigma(-\vec{z_1}\cdot\vec{\beta})\cdot z_{1d}$
$\sigma(-\vec{z}_2\cdot\vec{\beta})\cdot z_{20}$	 $\sigma(-\vec{z}_2\cdot\vec{\beta})\cdot z_{2d}$
:	:
$\sigma(-\vec{z}_n \cdot \vec{\beta}) \cdot z_{n0}$	 $\sigma(-\vec{z}_n \cdot \vec{\beta}) \cdot z_{nd}$

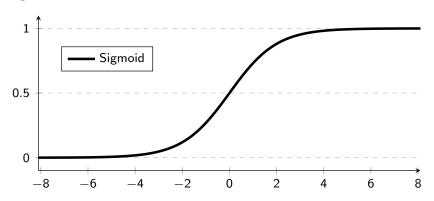
Rotate & Sum
$$\begin{array}{c}
\sum_{i=1}^{n} \sigma(-\vec{z_i} \cdot \vec{\beta}) \cdot z_{i0} & \cdots & \sum_{i=1}^{n} \sigma(-\vec{z_i} \cdot \vec{\beta}) \cdot z_{id} \\
\sum_{i=1}^{n} \sigma(-\vec{z_i} \cdot \vec{\beta}) \cdot z_{i0} & \cdots & \sum_{i=1}^{n} \sigma(-\vec{z_i} \cdot \vec{\beta}) \cdot z_{id} \\
\vdots & \vdots & \vdots \\
\sum_{i=1}^{n} \sigma(-\vec{z_i} \cdot \vec{\beta}) \cdot z_{i0} & \cdots & \sum_{i=1}^{n} \sigma(-\vec{z_i} \cdot \vec{\beta}) \cdot z_{id}
\end{array}$$

$\sigma(-\vec{z}_1 \cdot \vec{\beta}) \cdot z_{10}$	 $\sigma(-\vec{z_1}\cdot\vec{\beta})\cdot z_{1d}$
$\sigma(-\vec{z}_2 \cdot \vec{\beta}) \cdot z_{20}$	 $\sigma(-\vec{z}_2\cdot\vec{\beta})\cdot z_{2d}$
÷	:
$\sigma(-\vec{z}_n \cdot \vec{\beta}) \cdot z_{n0}$	 $\sigma(-\vec{z}_n \cdot \vec{\beta}) \cdot z_{nd}$

$\sigma(-\vec{z}_1\cdot\vec{\beta})\cdot z_{10}$	 $\sigma(-\vec{z_1}\cdot\vec{\beta})\cdot z_{1d}$
$\sigma(-\vec{z}_2\cdot\vec{\beta})\cdot z_{20}$	 $\sigma(-\vec{z}_2\cdot\vec{\beta})\cdot z_{2d}$
:	:
$\sigma(-\vec{z}_n \cdot \vec{\beta}) \cdot z_{n0}$	 $\sigma(-\vec{z}_n \cdot \vec{\beta}) \cdot z_{nd}$

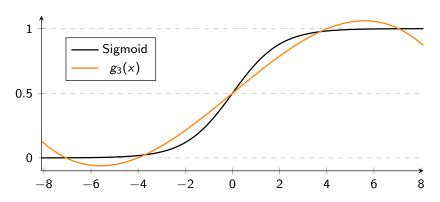
β_0	β_1	•••	β_d
β_0	β_1		β_{d}
:			:
β_0	β_1		β_d

Sigmoid Function



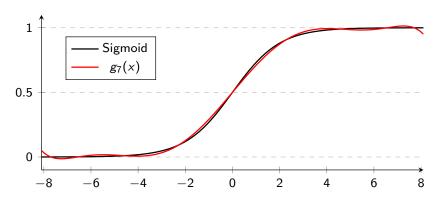
- The most widely used activation function.
- Use the least squares on [-8,8] to find an approximate polynomial.

Degree 3



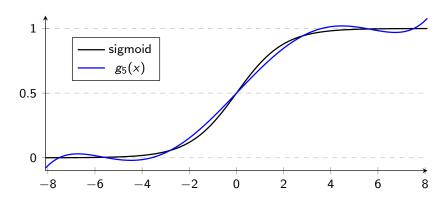
- Pros: Small depth
- Cons: Maximum error > 0.1.

Degree 7



- Pros: Maximum error ≈ 0.03
- Cons: Computation cost.

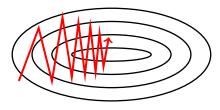
Degree 5



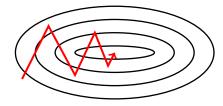
• Maximum error ≈ 0.06 .

Momentum Method

- Momentum is a method that accelerates GD in the relevant direction and dampens oscillations.
- Add a fraction of the update vector of the past time step to the current update vector.



Standard GD



Momentum method

Nesterov Accelerated Gradient

- Guarantee a better rate of convergence $O(1/t^2)$ (vs. O(1/t))
- Evaluate the gradient at this "looked-ahead" position.

$$\vec{v}_t = \gamma \cdot \vec{v}_{t-1} + \alpha_t \cdot \nabla J(\vec{\beta}_{t-1} - \gamma \cdot \vec{v}_{t-1})$$

$$\vec{\beta}_t = \vec{\beta}_{t-1} - \vec{v}_t$$

Experimental Results

Intel(R) Xeon(R) CPU E5-2670 v2 @ 2.50GHz processor.

Parameters				Results					
Iter	Deg	log N	log q	Enc	Learn	PK	Encrypted	Correctness	AUC
				Time	Time	Size	Database		
7	5	16	1229	0.95min	10.25min	1.2GB	38 MB	815 / 1421	0.709
14	5	17	2405	2.33min	63.85min	2.4GB	75 MB	888 / 1421	0.715

#(Features) = 19, #(Samples) = 1421

