SHAFT: Secure, Handy, Accurate, and Fast Transformer Inference

Artifact Evaluated
NDSS SYMPOSIUM
Available
Functional
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Background

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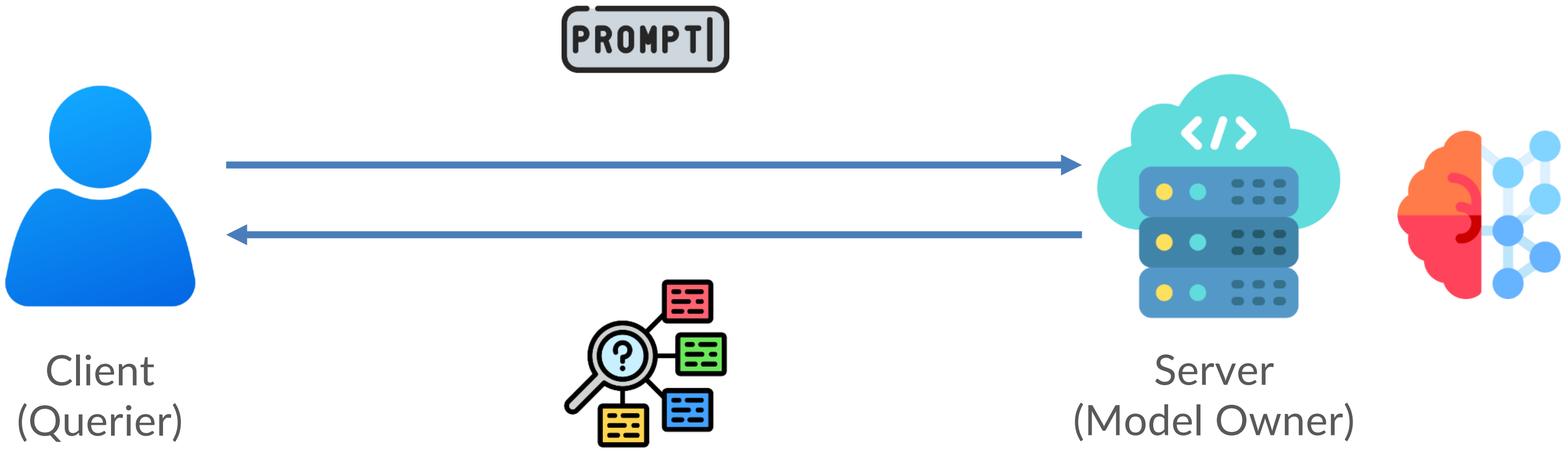

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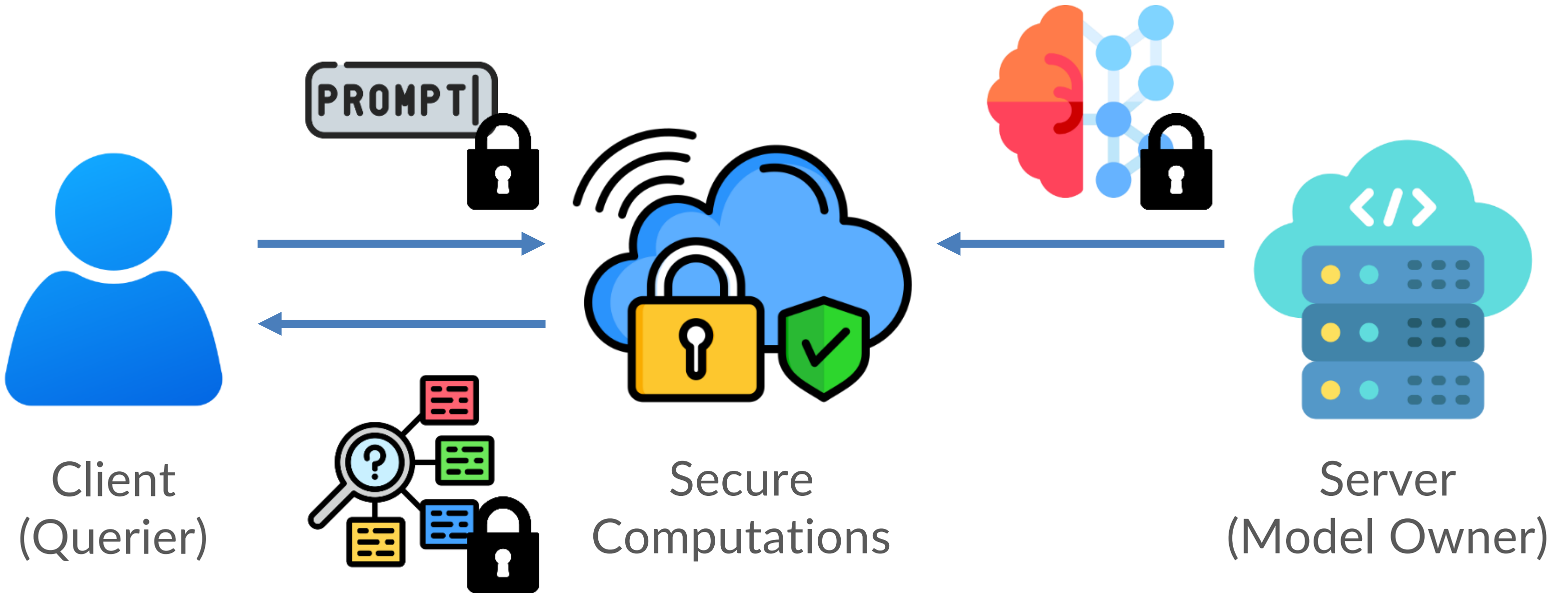
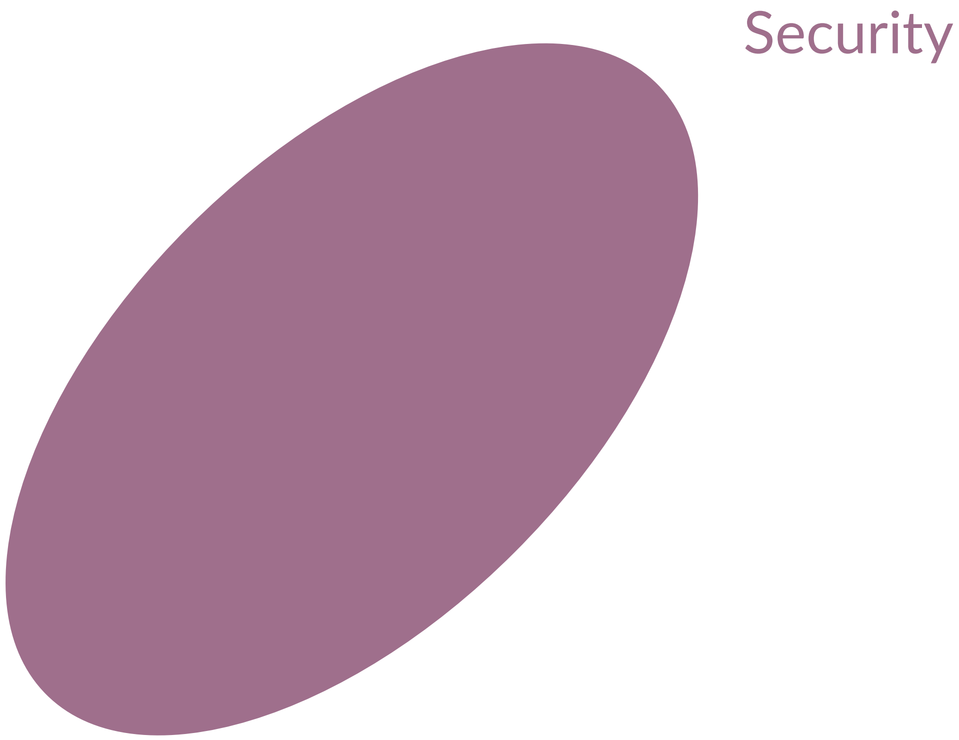
- **Privacy concerns** arise due to the increasing adoption of LLMs (*e.g.*, ChatGPT)
- **Private inference**: performs model inference without leaking the ***model*** or ***query***



L. Ng, **S. Chow**. "GForce: GPU-Friendly Oblivious and Rapid Neural Network Inference." *Usenix Security* 2021.

Desirable Properties for Private Transformer Inference



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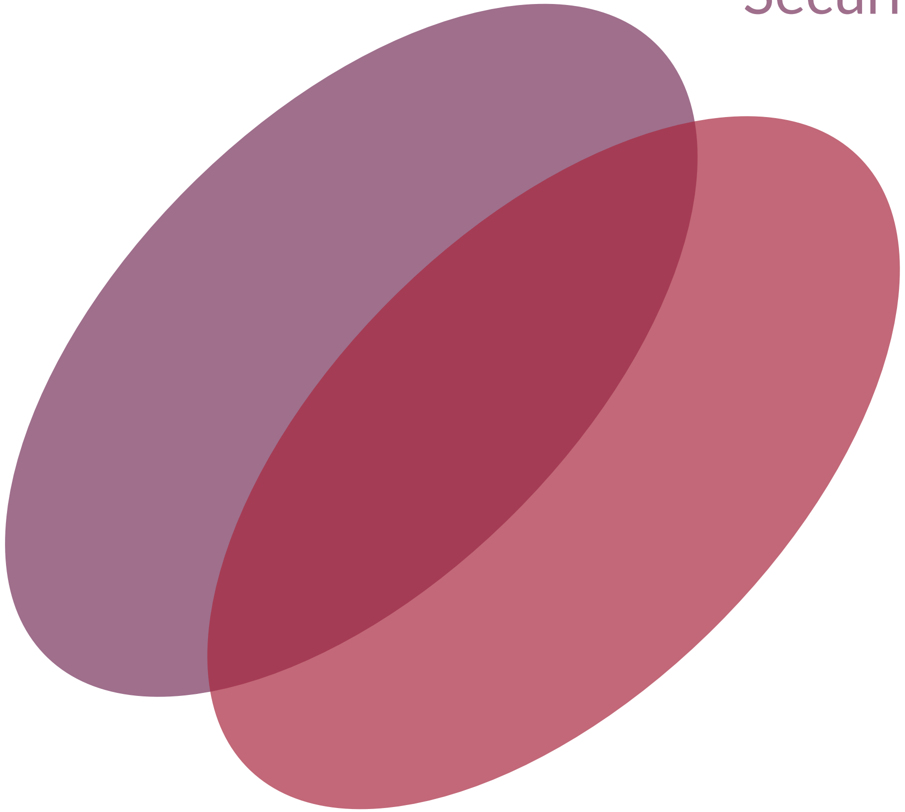

Security

Handiness

deployable ***without*** *knowledge* of cryptography (secure computations or libraries)

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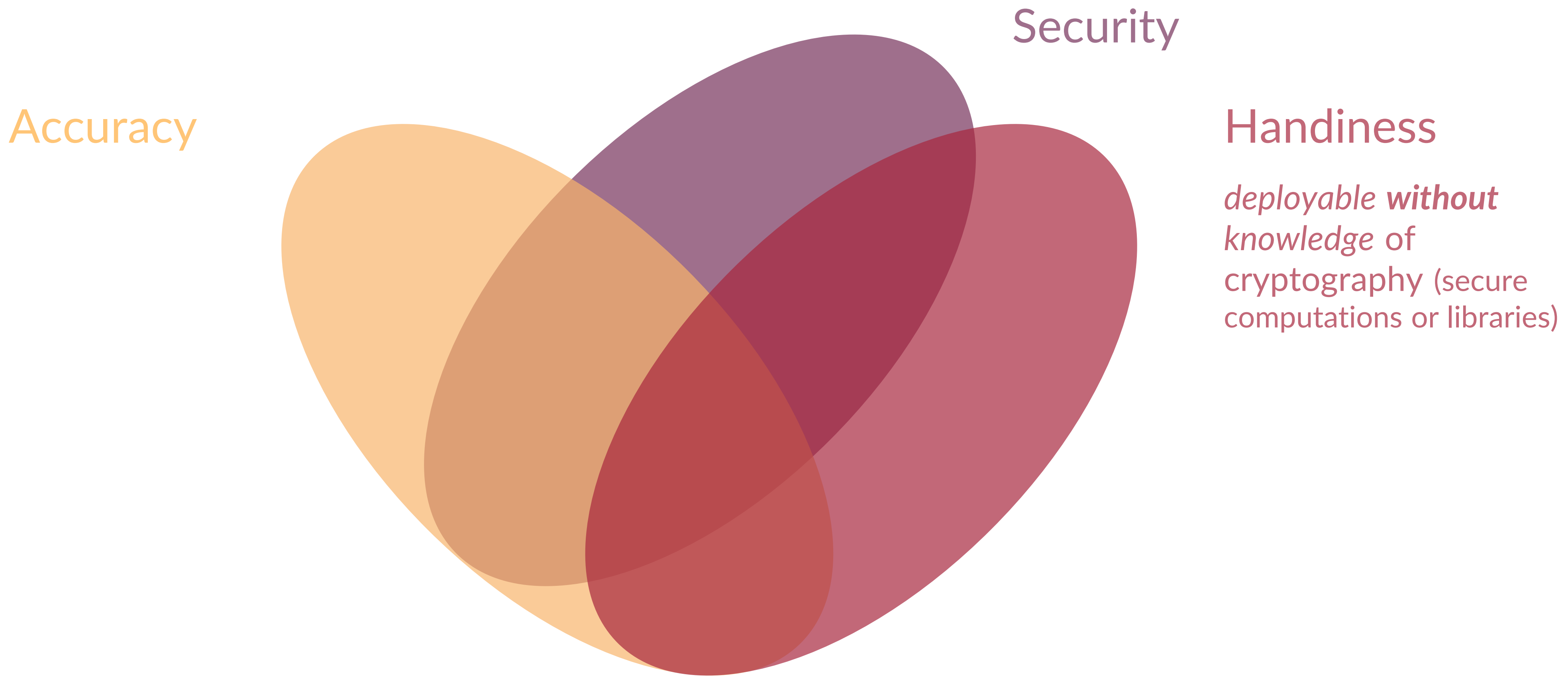
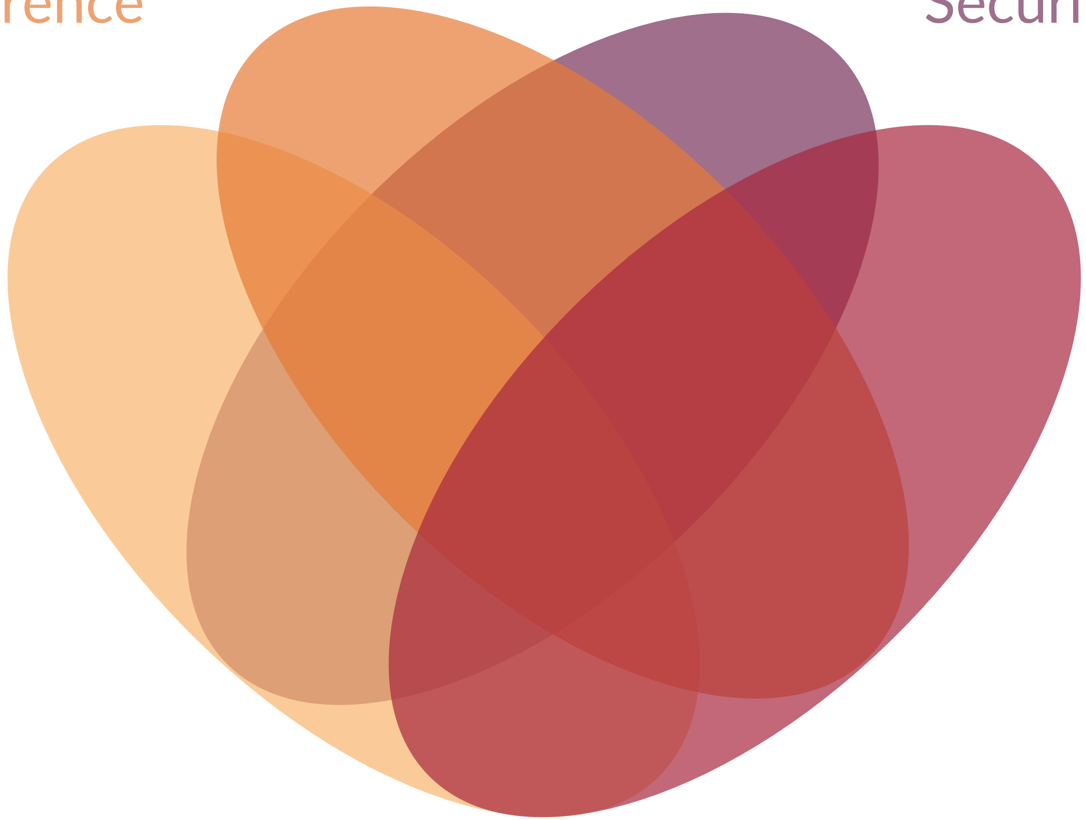


Desirable Properties for Private Transformer Inference

Fast Inference

Accuracy



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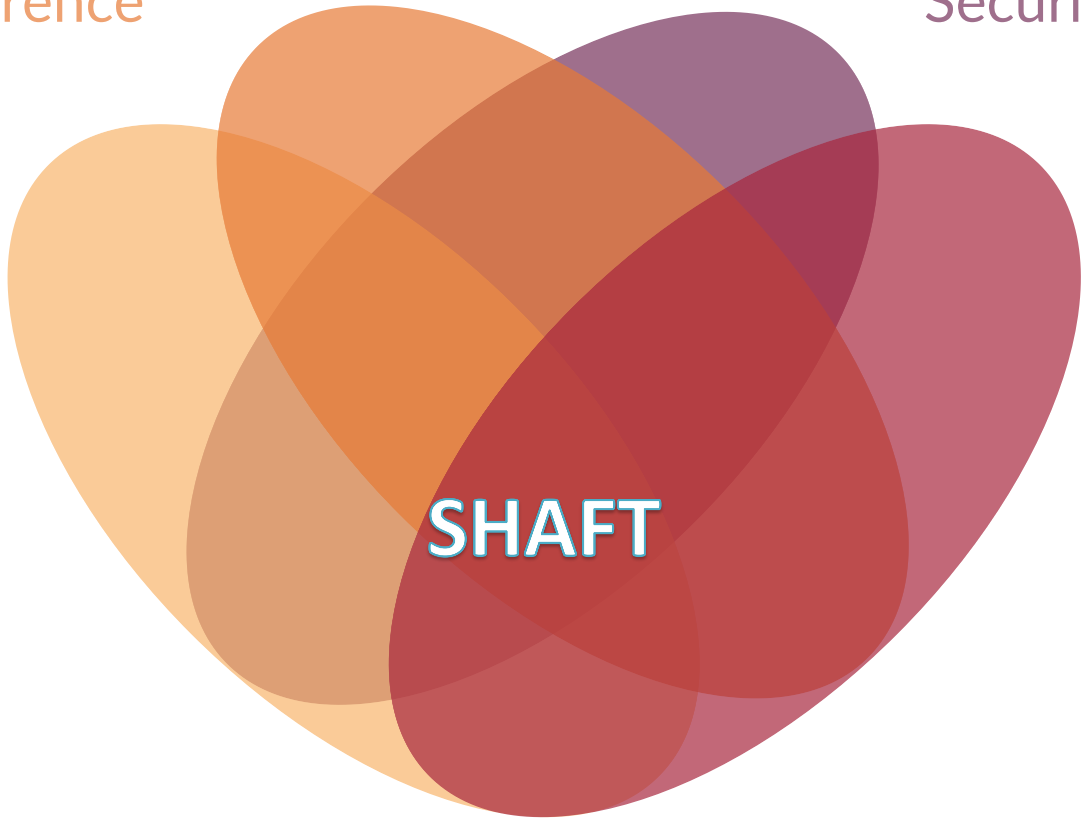
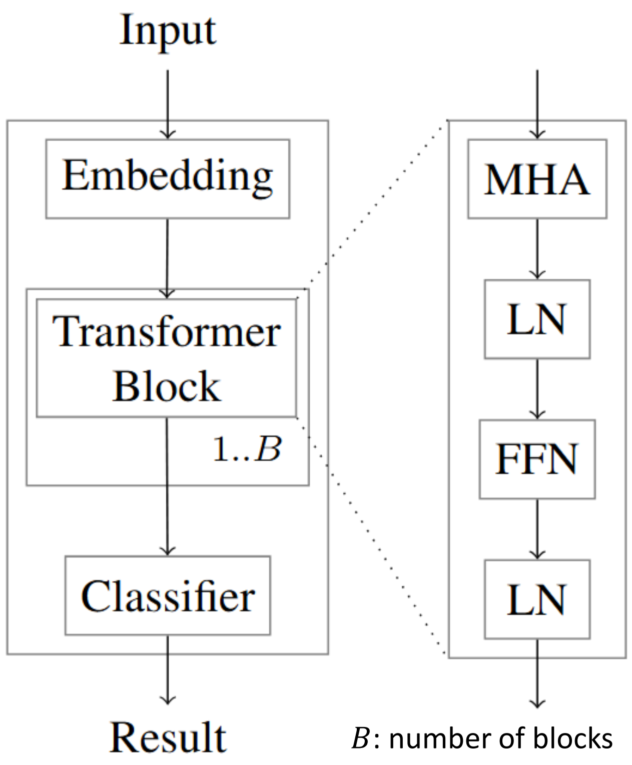


Challenges in Private Transformer Inference

- Embedding
  - One-hot vector conversion
- Multi-head attention (MHA)
  - **Softmax**
- Feed-forward network (FFN)
  - **Gaussian error linear unit (GELU)**
- Layer normalization (LN)
  - Inverse square root



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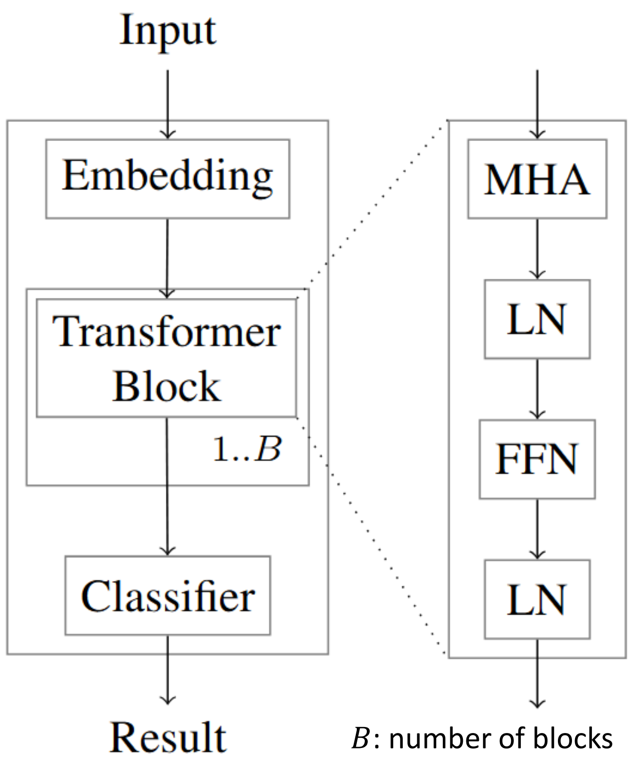
- More challenging than (convolutional) neural networks
  - **Expensive secure softmax** in **every** MHA layer
  - **Sophisticated secure GELU** activation in **every** FFN layer



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Private Transformer Inference Frameworks

Framework	Core Techniques	Accuracy	Efficiency
MPCFormer (ICLR ’23)	Rough Approximations		✓✗
SIGMA (PETS ’24)			
BumbleBee (NDSS ’25)			
SHAFT (Ours)			

D. Li et al. “MPCFormer: Fast, performant and private transformer inference with MPC.” *ICLR* 2023.
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- Observation: ***non-linear*** function approximations remain **under**explored

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- SHAFT outperforms two recent works in **efficiency**
  - vs. SIGMA: **reduces communication** by 25-41% with **similar running time**
  - vs. BumbleBee: 4.6-**5.3× faster** on LAN, 2.9-**4.4× faster** on WAN

OS: Ubuntu 20.04.

CPU: Intel Xeon Gold 5318Y, GPU: two NVIDIA A40, RAM: 256 GB.

Models: BERT-base, BERT-large, GPT-2, ViT-base.

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- SHAFT achieves **comparable accuracy to plaintext inference**

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Datasets: QNLI, CoLA, SST-2 from the GLUE benchmark.

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SHAFT (Ours)	✓	✓	✓	✓

- For **handy** deployment of secure inference, we offer an **open-source** framework
  - **PyTorch-like APIs** smoothly integrate with the **Hugging Face** transformer library

PyTorch Hugging Face

L. Ng, **S. Chow**. “SoK: Cryptographic Neural-Network Computation.” *S&P* 2023.

Importing Hugging Face Transformers

- Existing works like CrypTen (NeurIPS '21) allow importing **simple** models
  - but **lack support** for **transformer-specific** layers (*e.g.*, GELU)
- We implement **code conversion** of these layers

```
from transformers import AutoModelForSequenceClassification
import crypten as ct
# (standard) data loading and preprocessing omitted
model = AutoModelForSequenceClassification.from_pretrained("user/bert-base-cased-qnli")
ct.init()
model_ss = ct.nn.from_pytorch(model, dummy_data).encrypt().cuda()
data_ss = ct.cryptensor(data).cuda()
output_ss = model_ss(data_ss)
output = output_ss.get_plain_text()
```

B. Knott et al. "CrypTen: Secure multi-party computation meets machine learning." *NeurIPS* 2021.

Our Technical Novelties

1. First **constant-round** private **softmax** protocol for transformers
   - Prior works need **logarithmic** rounds (in input length m) for **numerical stability**
   - We guarantee the same in **constant** rounds by uniquely combining **ordinary differential equation (ODE)** and **input clipping**

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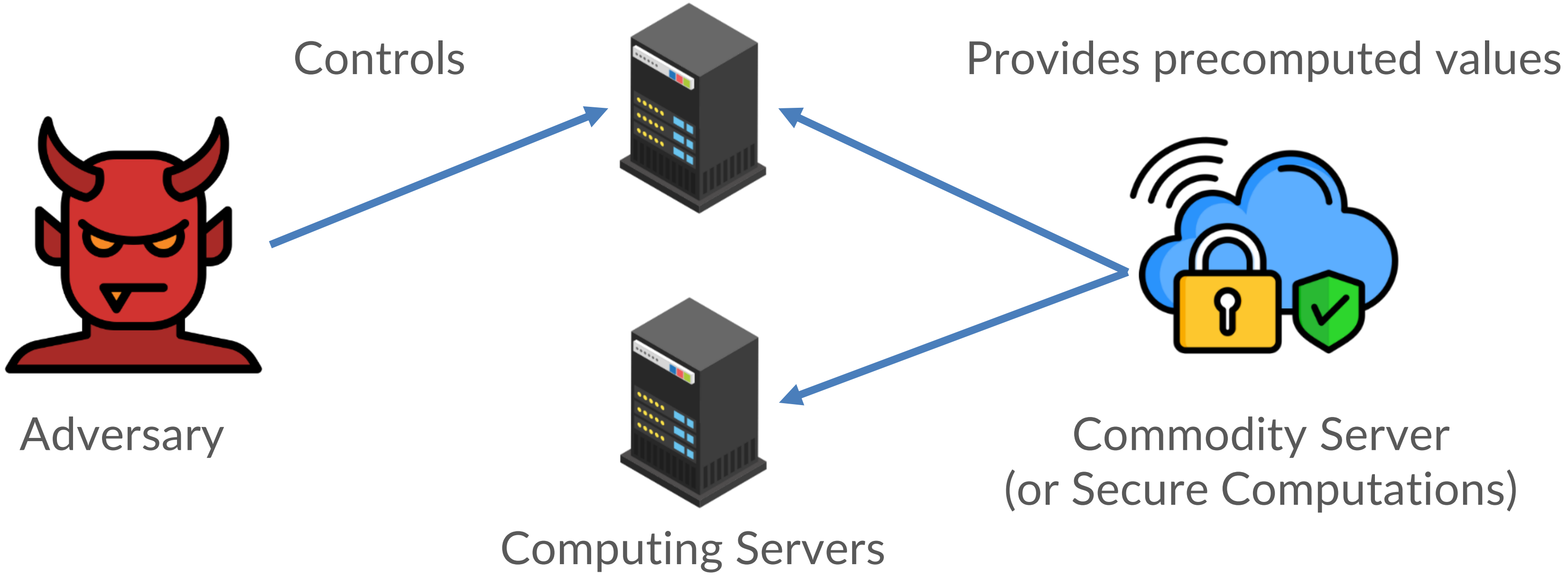
2. A **precise** and **efficient** private **GELU** protocol
   - We design a **GELU characterization** for **Fourier series** approximation
   - **Reduce** round complexity from **two** (S&P ’24) to **one**

hundreds of thousands of softmax & GELU in transformers

Q. Pang et al. “BOLT: Privacy-preserving, accurate and efficient inference for transformers.” *S&P* 2024.

Security Model: 2-Party Outsourced Setting w/ Precomputation

- Well-established 2-party setting, *e.g.*, NDSS ’09
- Model and query are **secret-shared** to two servers
- Adversary: **semi-honest**, controls **one** of the two servers
- **Commodity server** can be replaced by **2-party computation** between servers



S. Chow, J.-H. Lee, L. Subramanian. “Two-Party Computation Model for Privacy-Preserving Queries over Distributed Databases.” *NDSS* 2009.

Private Softmax with Private Max()

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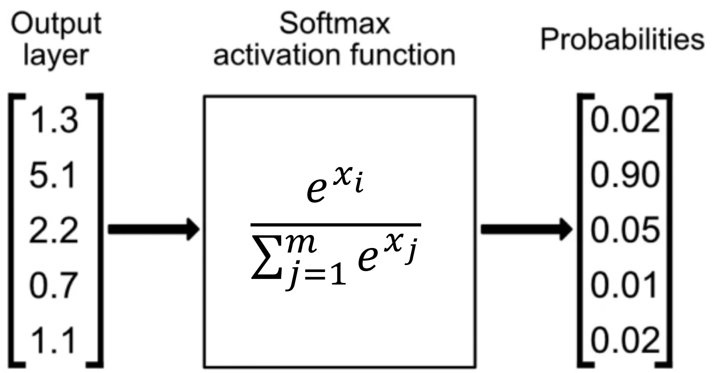
  - Converts values in a vector into probabilities



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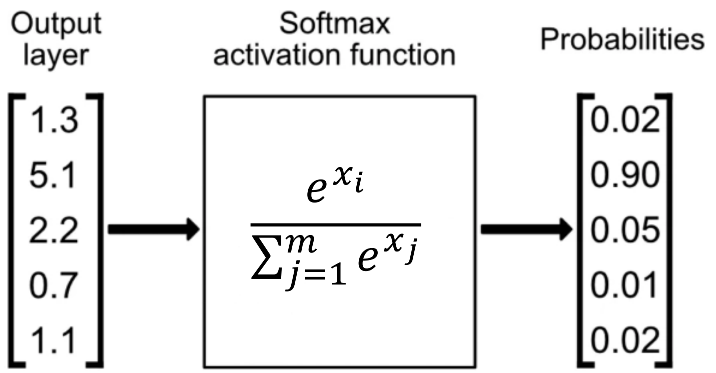
  - Problem: e^x and $1/x$ **overflow easily**



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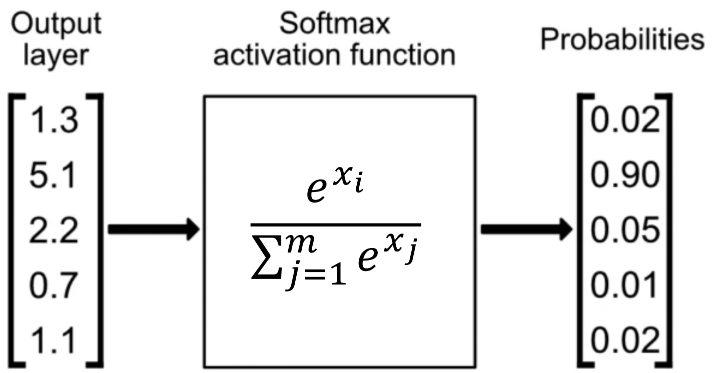

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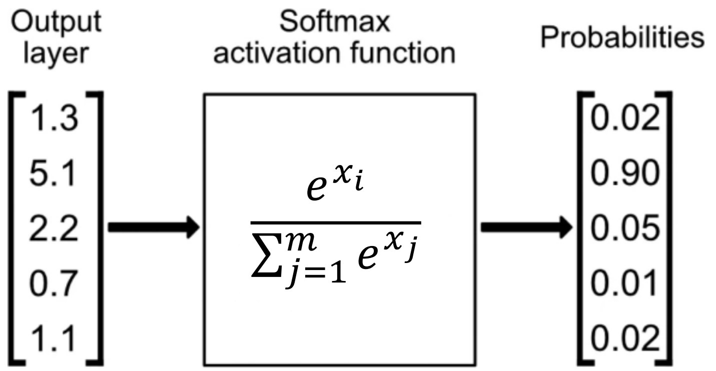

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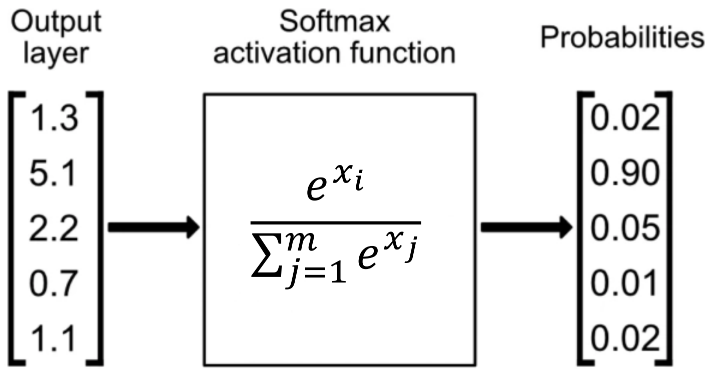

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- Secure evaluation of maximum requires **logarithmic** rounds

Numerically-Unstable Private Softmax with ODE (ACSAC '23)

- Let t be the number of iterations, m be the input length
- **ODE approximation** of $\mathrm{Softmax}(\vec{x})$:
  - Initial guess: $\vec{y}_0 = \vec{1}/m$
  - Iterative updates: $\vec{y}_i = \vec{y}_{i-1} + \frac{1}{t}(\vec{x} - \langle \vec{x}, \vec{y}_{i-1} \rangle \vec{1}) * \vec{y}_{i-1}$

Inner product
All-one vector
Entry-wise product

- Total **2**t rounds (2 per iteration)
- Needs **large** t (*e.g.*, 128) for **unbounded** $\vec{x}$ in transformers
  - Correctness **requires** $\max(\vec{x}) - \min(\vec{x}) \leq t$

Y. Zheng, Q. Zhang, **S. Chow**, Y. Peng, S. Tan, L. Li, S. Yin. "Secure softmax/sigmoid for machine-learning computation." *ACSAC* 2023.

Our Private Softmax with Input-Clipped ODE

- Key idea: **clips** input to a **pre-defined** range $[a, b]$
  - $t = b - a$ ensures correctness, even with **small** t
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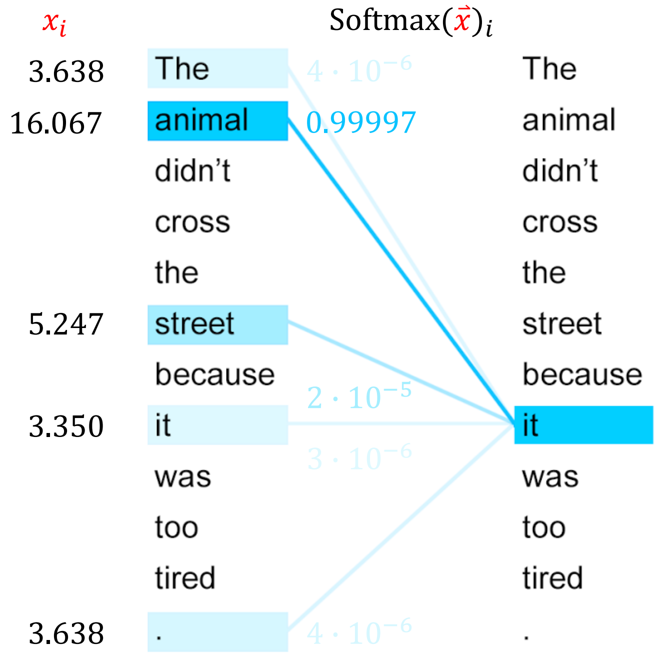

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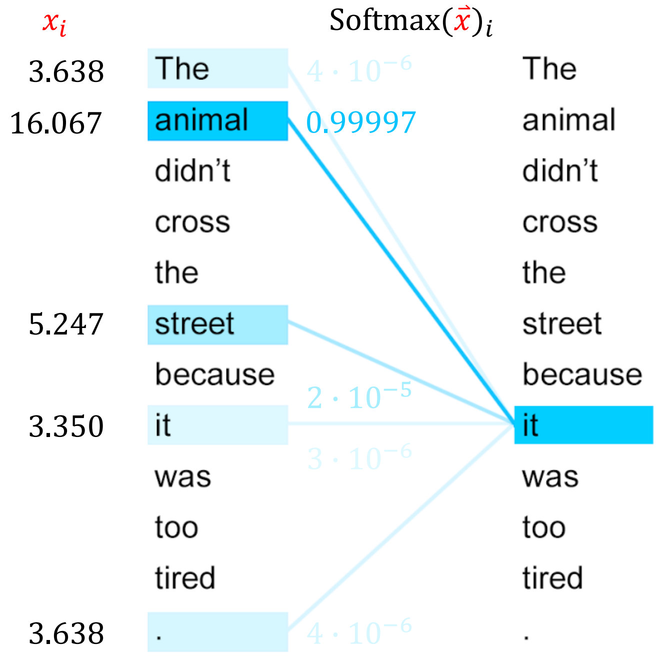

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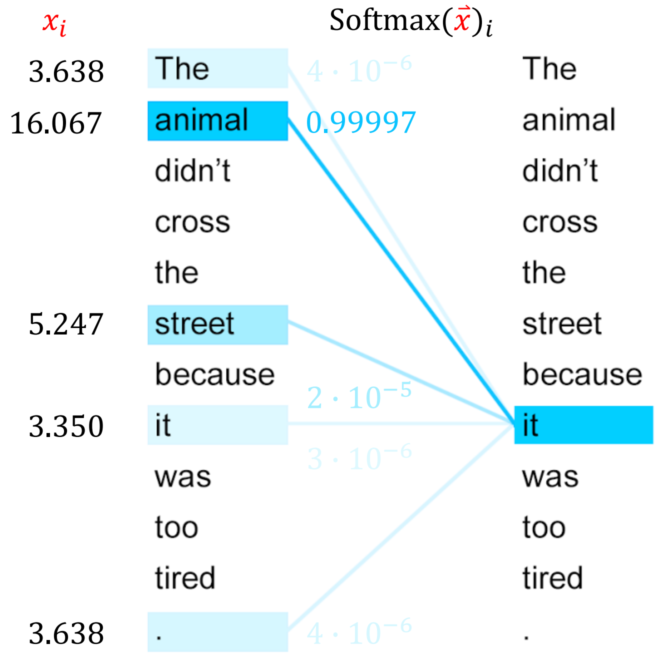

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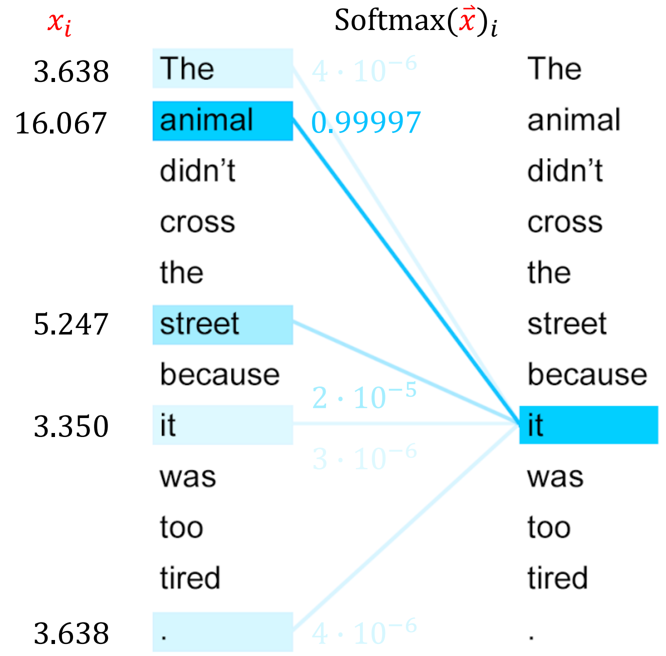

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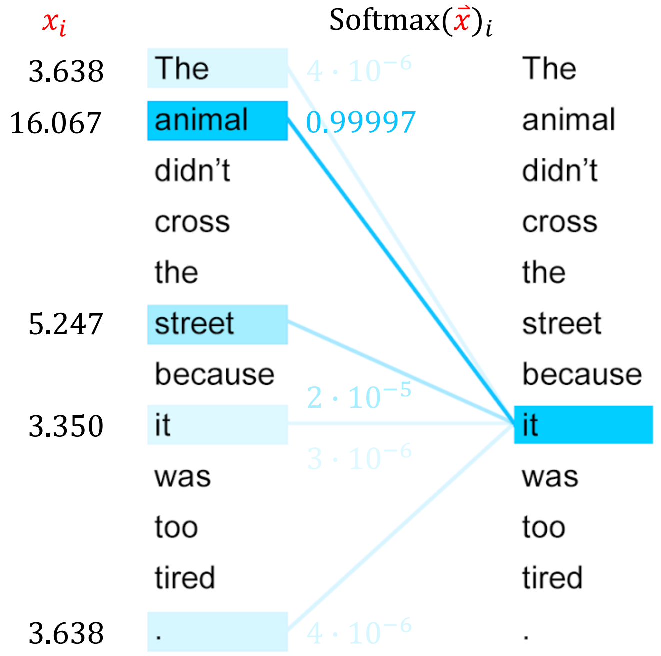

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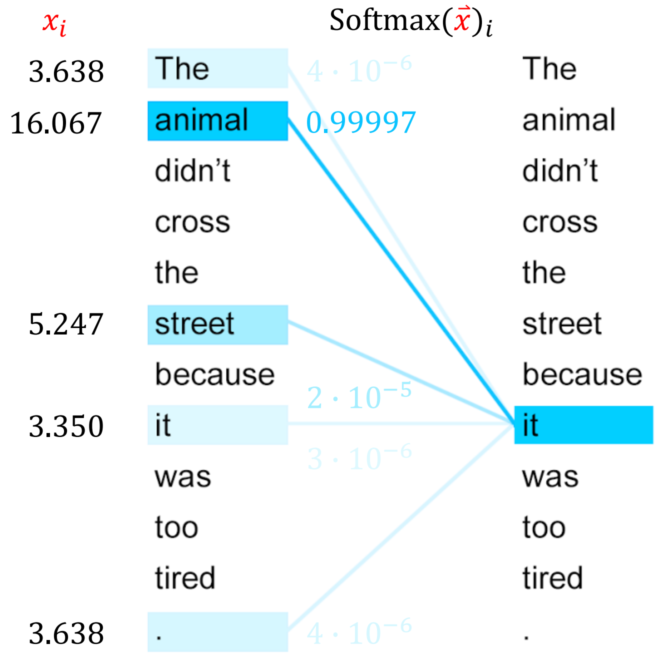
- How to select a and b?
  - Sets a **larger positive** b to **minimize errors** from *large* x_j's
  - Chooses a **slightly negative** a to **include** most *small* x_j's



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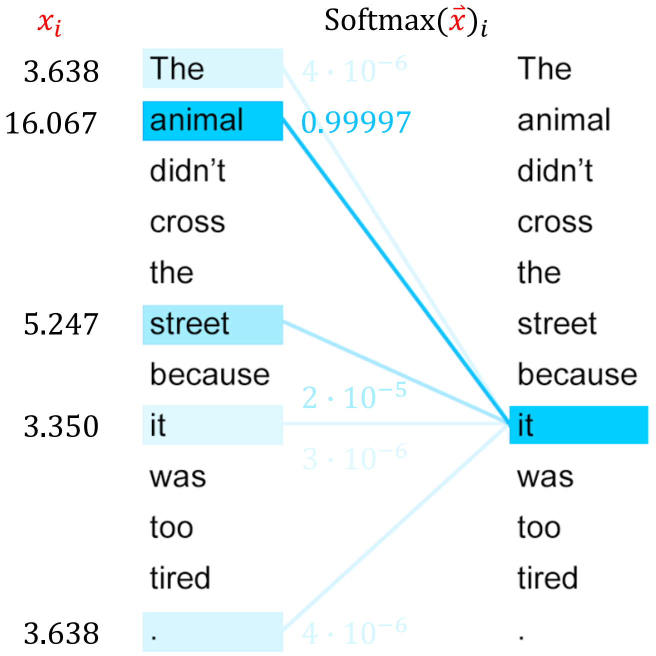
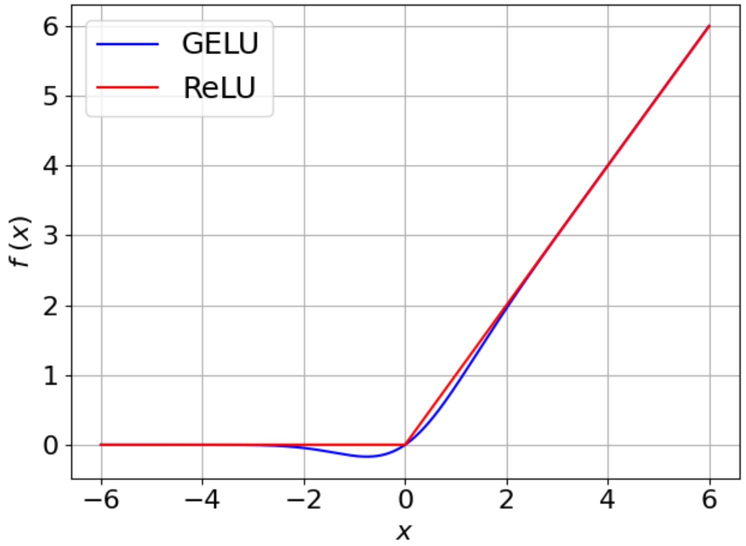
  - **Constant round**!
- Why clipping matters in $\text{Softmax}(\vec{x})_i = e^{x_i} / \sum_j e^{x_j}$?
  - Attention layers map **word relevance** to probabilities
  - Words usually relate to *only a few* others in a sentence
  - **Most** x_j's are **small**, but **a few** large x_j's **dominate** the sum
  - Clipping large x_j aggressively can cause **significant** errors
- How to select a and b?
  - Sets a **larger positive** b to **minimize errors** from *large* x_j's
  - Chooses a **slightly negative** a to **include** most *small* x_j's
  - $t = 16, a = -4, b = 12$ in all our experiments



https://research.google/blog/transformer-a-novel-neural-network-architecture-for-language-understanding

Private GELU with (Piecewise) Polynomial

- $\mathbf{GELU}(x) = 0.5x\left(1 + \mathrm{Erf}\left(x/\sqrt{2}\right)\right)$, $\mathrm{Erf}(x) = (2/\sqrt{x}) \int_0^x e^{-u^2}\, du$
- Standard approach:
  - Idea: $\mathrm{GELU}(x)$ is close to $\mathrm{ReLU}(x) = \max(x, 0)$ when $|x|$ is **relatively large**
  - Approximates $\mathrm{GELU}(x)$ for x near 0 with **polynomial(s)**
  - Sets $\mathrm{GELU}(x) = \mathrm{ReLU}(x)$ for larger $|x|$



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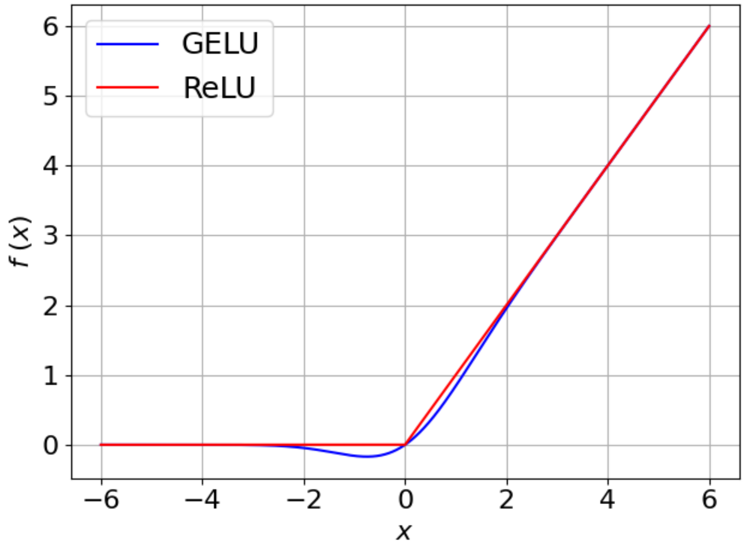
- State-of-the-art: a **degree-4** polynomial (S&P '24)
  - Secure evaluation requires **two** rounds
  - **Substantial** overheads for transformers with **hundreds of thousands** of GELU



Q. Pang et al. "BOLT: Privacy-preserving, accurate and efficient inference for transformers." *S&P* 2024.

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  - with a **sinusoidal** shape for a **bounded** input range

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Y. Zheng, Q. Zhang, **S. Chow**, Y. Peng, S. Tan, L. Li, S. Yin. "Secure softmax/sigmoid for machine-learning computation." *ACSAC* 2023.

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- **Fourier Series (FS)**: provide precise approximations of functions
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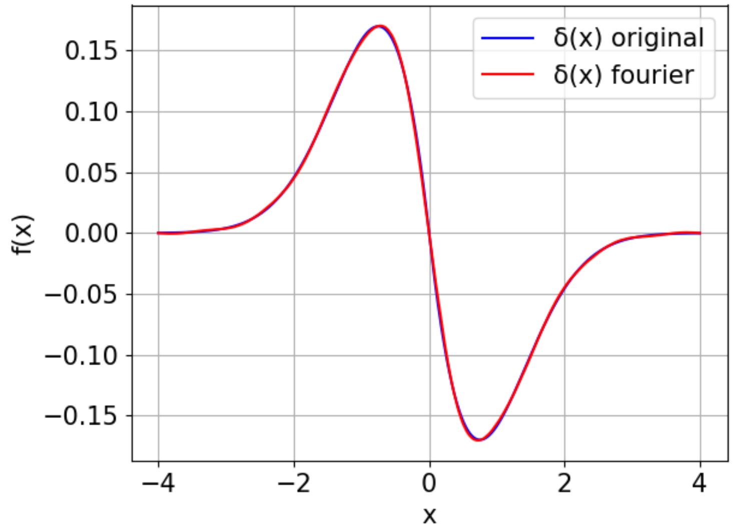
- Securely evaluating an FS takes only **one** round (ACSAC '23)
- Problem: GELU is **not** sinusoidal (*i.e.*, **direct** approximation with FS **fails**)
- Simple solution: approximates $\mathrm{Erf}(x)$ with FS (ACL Findings '24):
  - Recall: $\mathrm{GELU}(x) = 0.5x\left(1 + \mathrm{Erf}\left(x/\sqrt{2}\right)\right)$
  - Requires an **additional** round to **securely multiply** the result by x
  - Increases approximation **error** (when $|x| > 2$)

Y. Zheng, Q. Zhang, **S. Chow**, Y. Peng, S. Tan, L. Li, S. Yin. "Secure softmax/sigmoid for machine-learning computation." *ACSAC* 2023.
J. Luo et al. "SecFormer: Towards fast and accurate privacy-preserving inference for large language models." *ACL (Findings)* 2024.

Our Private GELU with Fourier Series (FS)

- Goal: **designs a suitable function** for FS approximation
- Our formulation: $\delta(x) = \mathrm{sgn}(x)(\mathrm{GELU}(x) - \mathrm{ReLU}(x))$
  - Modified from **non-sinusoidal** $\mathrm{GELU}(x) - \mathrm{ReLU}(x)$ for table lookup (PETS '24)
  - A **sinusoidal** function for x near 0
  - **Ideal** for accurate FS approximation



K. Gupta et al. "SIGMA: Secure GPT inference with function secret sharing." *PETS* 2024.

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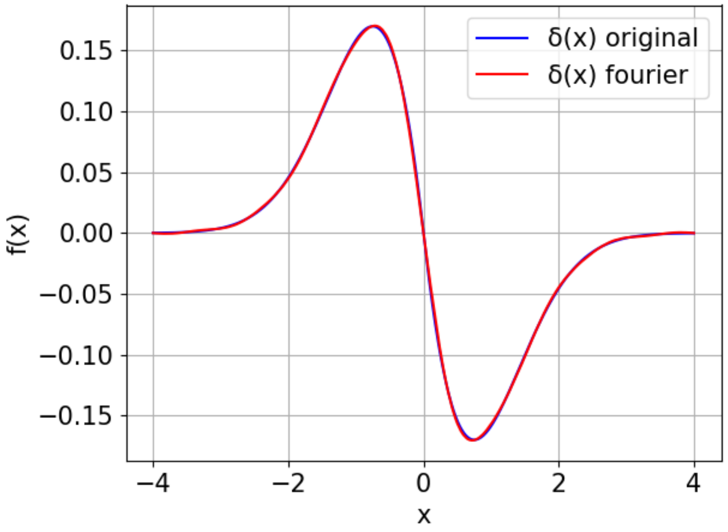
- **FS approximation** of $\delta(x)$ for $|x| < 4$:
  - $\delta(x) \approx \sum_{n=1}^{8} \beta_n \sin\left(\frac{n\pi x}{4}\right), \beta_n = \frac{1}{4}\int_{-4}^{4} \delta(u) \sin\left(\frac{n\pi u}{4}\right) du$
  - Coefficients β_n precomputable via numerical integration
- Enforces $\delta(x) \approx 0$ for $|x| \geq 4$



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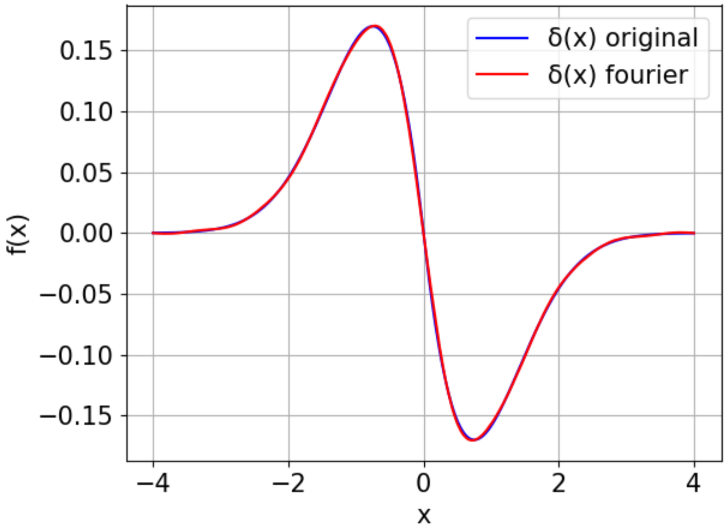
  - Coefficients β_n precomputable via numerical integration
- Enforces $\delta(x) \approx 0$ for $|x| \geq 4$
- GELU characterization: $\mathrm{GELU}(x) = \mathrm{ReLU}(x) + \delta(|x|)$
  - **No extra round** needed: $|x| = 2\mathrm{ReLU}(x) - x$



K. Gupta et al. "SIGMA: Secure GPT inference with function secret sharing." *PETS* 2024.

Other Contributions

1. **First private embedding** protocol **"natively"** taking **indices** as inputs
   - Prior works **assume** inputs are **one-hot vectors**, requiring **extra conversions** by clients
   - Our approach is inspired by **pre-computed one-hot pairs** from Grotto (CCS '23)
   - (unlike Grotto for *spline evaluation*)

2. Extension of our GELU characterization to **other activations**
   - *E.g.*, **sigmoid linear unit/SiLU,** used in the Meta AI's LLaMA model

3. Optimizations for **smaller bitwidth**
   - **Reduces communication** in **mixed-bitwidth** frameworks

K. Storrier et al. "Grotto: Screaming fast $(2 + 1)$-PC for $\mathbb{Z}_{2^n}$ via $(2, 2)$-DPFs." *CCS* 2023.

Final Remarks

- We propose **secure**, **accurate**, and **fast** protocols for **softmax** and **GELU**
- Code: [github.com/andeskyl/SHAFT]
  - Interoperable with **Hugging Face** for **handy transformer** deployment
- Future directions:
  - Private transformer ***fine-tuning/training*** (GPU-TEE co-design?)
  - Security against ***malicious*** adversaries (replicated/authenticated sharing?)
- Contact: {kyl022, sherman}@ie.cuhk.edu.hk

L. Ng, **S. Chow**, A. Woo, D. Wong, Y. Zhao. "Goten: GPU-Outsourcing Trusted Execution of Neural Network Training." *AAAI* 2021.