# Privacy-Preserving Machine Learning

## Zama is a cryptography company providing open source homomorphic encryption solutions for blockchain and AI.

Founded in 2020 in Paris

80 people, including 50 in France and 75 in EU

23 patents

73 M€ in funding (including from BPI)



# Privacy-Preserving Machine Learning

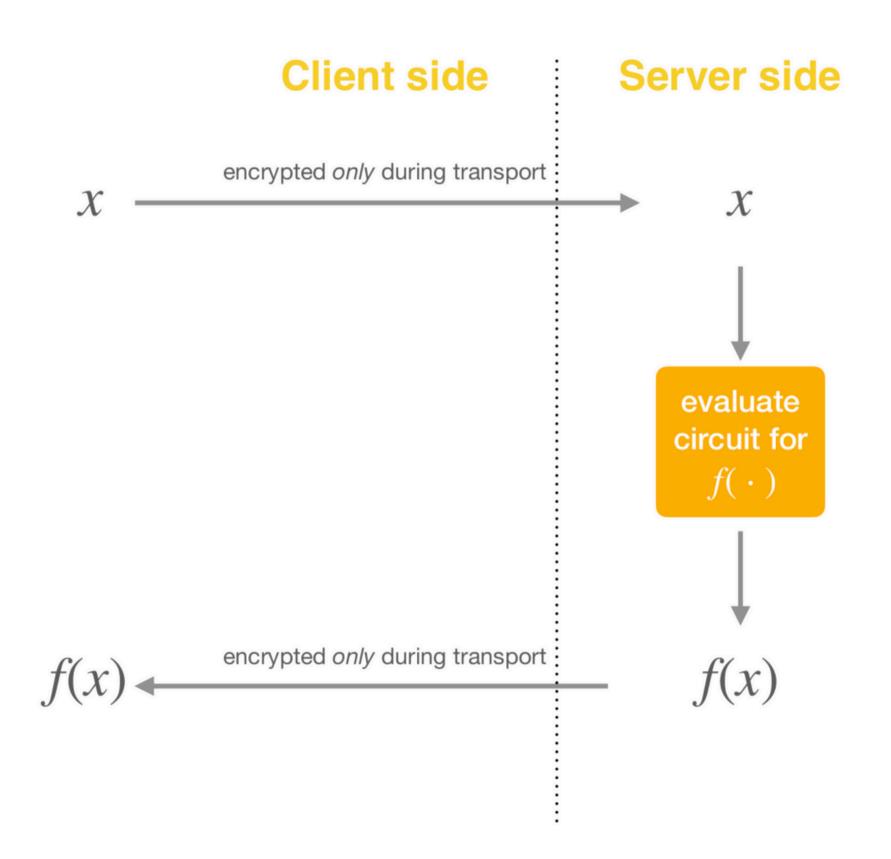
## Security breaches

#### Source: https://www.verizon.com/business/resources/reports/dbir/

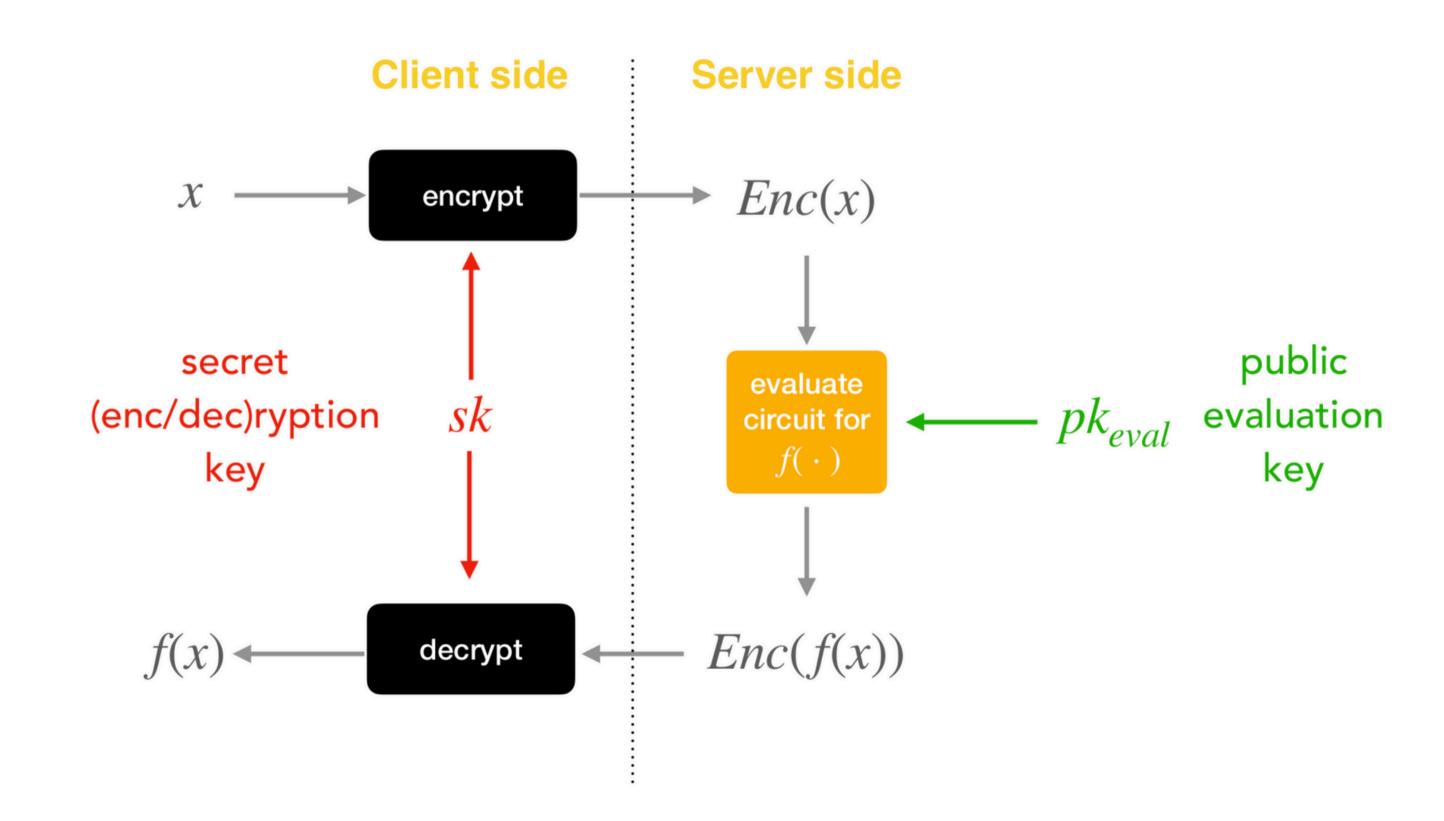
Br	eaches																
	Basic Web Application Attacks	12	1	10	30	30	161	55	124	71	12	21	113	76	21	30	22
	Denial of Service	1						1							1		
E	Everything Else	1	1		13		12	8	1	6	1		3	32		15	4
Pattern	Lost and Stolen Assets				21	2	18	24	4	7		11	22	64	7	1	
	Miscellaneous Errors	2	1	5	375	86	270	585	84	154	20	185	238	493	140	10	18
	Privilege Misuse	6		4	97	39	63	266	38	68	12	45	71	86	41	5	5
	Social Engineering	35	7	158	764	79	251	141	116	190	47	71	500	119	118	119	35
	System Intrusion	52	12	43	860	70	427	168	250	373	64	90	409	245	78	201	59
	Environmental	1								1							
	Error	3	1	5	393	88	280	588	87	161	20	195	255	551	144	10	18
Action	Hacking	66	11	172	872	119	598	204	315	405	94	110	603	341	126	204	84
Ac	Malware	50	11	43	881	71	457	165	277	379	77	94	429	292	79	215	65
	Misuse	7		4	97	39	63	266	38	69	12	45	74	86	41	5	5
	Physical	2			3		8	5	1	1			5	3	2	13	
	Social	37	7	158	764	79	261	142	117	190	47	71	504	119	118	121	37
	Embedded																
	Klosk/Term						5									9	
ĕ	Media			3	89	10	71	238	6	46	5	44	68	197	22	1	
Asset	Network						4	3	1	2				1		2	
	Person	37	7	158	764	79	262	142	118	190	47	71	505	119	119	121	37
	Server	92	20	211	1,228	232	914	601	473	641	108	271	1,032	586	279	323	109
	User Dev	11	2	4	51	16	77	55	76	53	28	43	108	111	8	35	14

Commodation
(72)
Administrative
(56)
Construction
(23)
Education
(61)
Finance (52)
Information
(51)
Mining +
Utilities
(21+22)
Other
Services (81)
Professional
(54)
Professional
(54)
Real Estate
(92)
Retail
(44-45)

### Data is encrypted only during the transport



## With FHE, the data remains encrypted during processing



## Typical use cases where privacy is needed



#### **Healthcare**

Enable private AI diagnostics and collaborative R&D



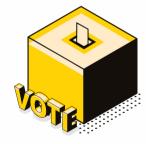
#### **Advertising**

Match privacy-preserving ad based on encrypted profiles



#### **Defense**

Collaborate between agencies without revealing secrets



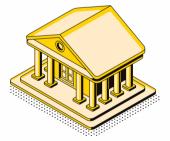
#### Government

Digitalize government services without trusting cloud providers



#### **Biometrics**

Authenticate users without revealing their real identities



#### **Finance**

Enable confidential credit scoring, dark pools and more

## We are open-source

#### Libraries

Everything is available on Zama's Github repo: zama-ai

#### Free for research and prototype

Our libraries are free for research and prototype. It's only when used in commercial products that licenses change

#### **Bounties**

We encourage people to showcase some use-cases with our Bounty Program: github.com/zama-ai/bounty-and-grant-program

#### **Demos**

We show our own examples, including on our Hugging Face: <u>zama-fhe</u>

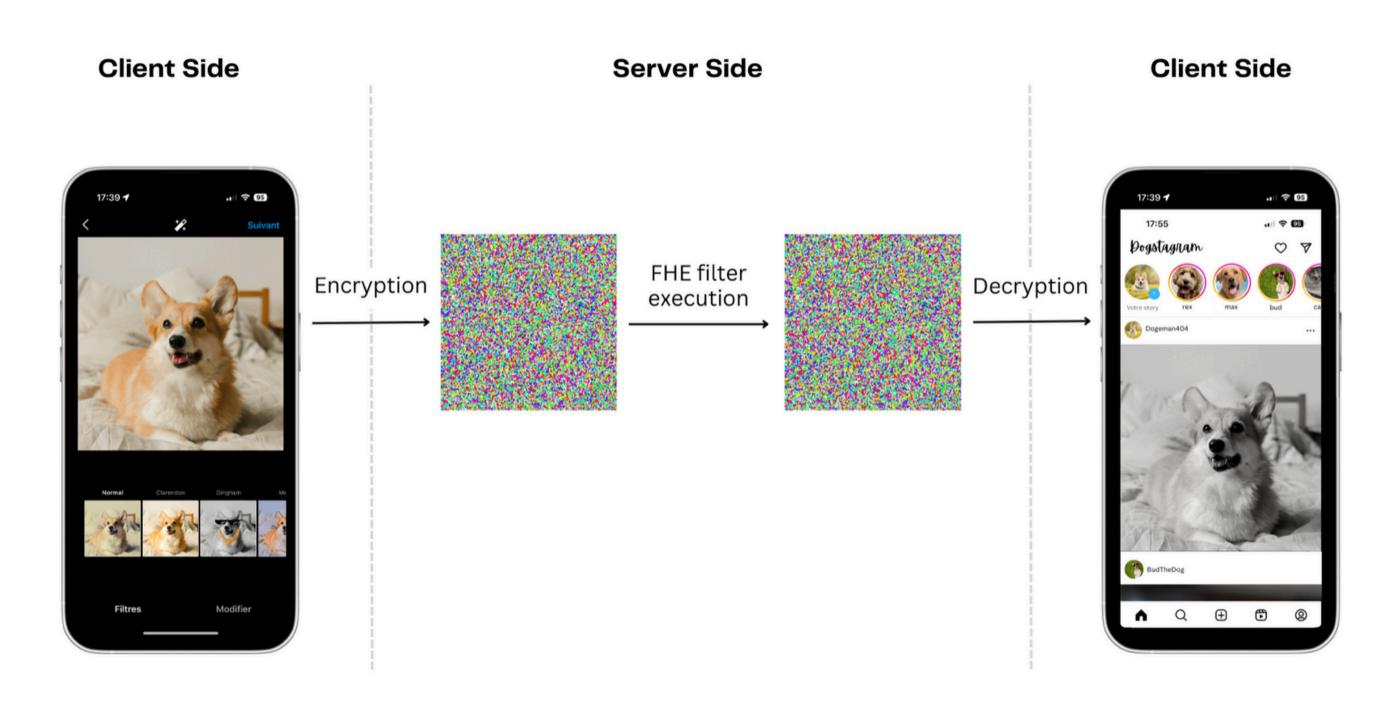
#### **Ecosystem**

We build an ecosystem around FHE, by helping companies and granting them. Also we co-build <u>fhe.org</u>

#### **Community support**

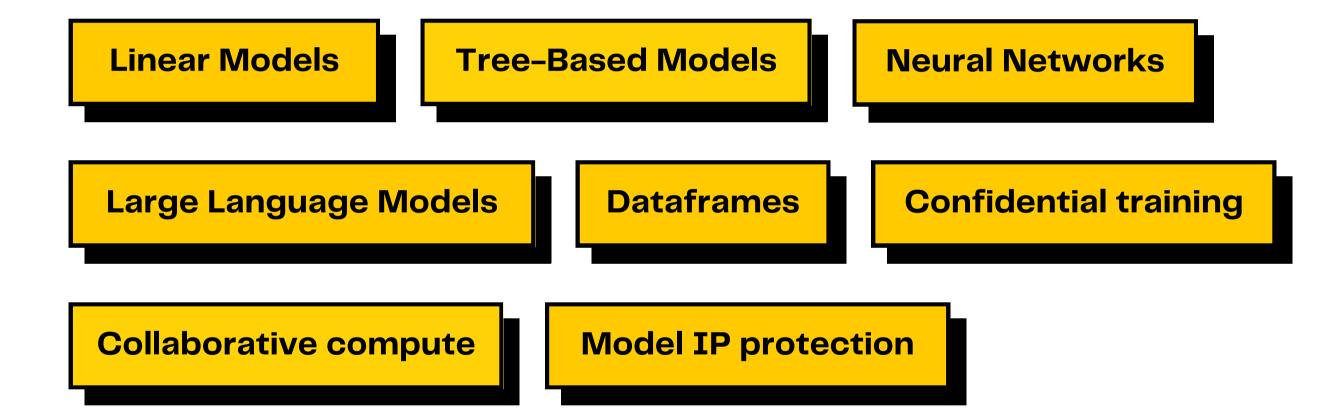
We offer free support to users on Discord: <a href="mailto:discord.com/invite/fhe-org">discord.com/invite/fhe-org</a>

## Image filtering as a demo



https://huggingface.co/spaces/zama-fhe/encrypted\_image\_filtering

### **Concrete ML**





## Our APIs are already familiar

```
from concrete.ml.sklearn import LogisticRegression

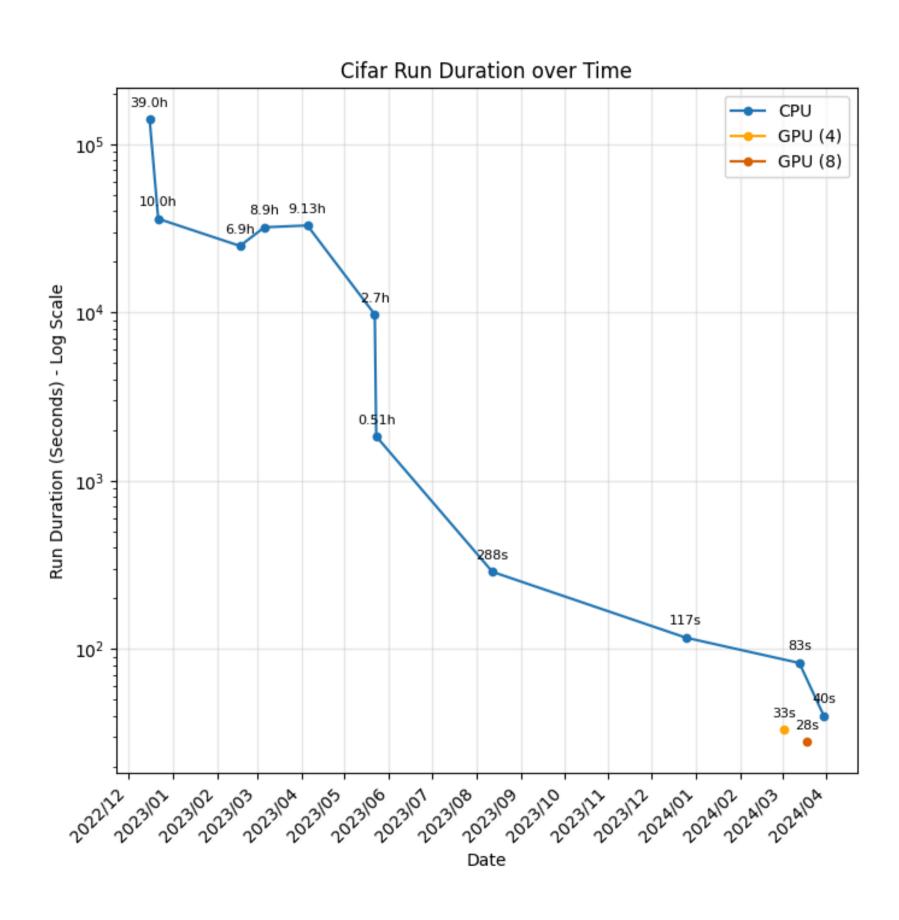
model = LogisticRegression(n_bits=12)
model.fit(X_train, y_train)
model.predict(X_test)
model.compile(X_train)
model.predict(X_test, fhe="simulate")
model.predict(X_test, fhe="execute")
```

```
from concrete.ml.sklearn import XGBClassifier

model = XGBClassifier(n_bits=8)
model.fit(X_train, y_train)
model.predict(X_test)
model.compile(X_train)
model.predict(X_test, fhe="simulate")
model.predict(X_test, fhe="execute")
```

```
import torch
import torch.nn as nn
import torch.nn.functional as F
from concrete.ml.torch.compile import compile_torch_model
class SimpleNet(nn.Module):
   def __init__(self):
       super(). init ()
       self.fc1 = nn.Linear(784, 30)
       self.fc2 = nn.Linear(30, 30)
       self.fc3 = nn.Linear(30, 2)
   def forward(self, x):
       x = F.relu(self.fc1(x))
       x = F.relu(self.fc2(x))
       x = self.fc3(x)
        return x
model = SimpleNet()
input_data = torch.randn(100, 784)
quantized_fhe_module = compile_torch_model(model, input_data, n_bits=8)
```

### FHE is getting faster and faster



	Concrete ML	Other FHE	MPC (multi party computation)	TEES (trusted execution environment)
Models supported				
Layers supported				
Performance				
Computation result				
Hardware acceleration				
Developer experience				
Security				

	Concrete ML	Other FHE	MPC (multi party computation)	TEES (trusted execution environment)
Models supported				
Layers supported				Anything
Performance				Fast
Computation result				Exact
Hardware acceleration				Yes
Developer experience				Medium
Security				Prone to side channel attacks

	Concrete ML	Other FHE	MPC (multi party computation)	TEES (trusted execution environment)
Models supported			Limited due to	
Layers supported			large communication	Anything
Performance			Fast	Fast
Computation result			Exact	Exact
Hardware acceleration			No	Yes
Developer experience			Hard	Medium
Security			Nodes can collude to reveal the data	Prone to side channel attacks

	Concrete ML	Other FHE	MPC (multi party computation)	TEES (trusted execution environment)
Models supported		Limited depth	Limited due to	
Layers supported		Basic support for non-linear layers	large communication	Anything
Performance		Medium to fast depending on the model	Fast	Fast
Computation result		Approximate	Exact	Exact
Hardware acceleration		Yes	No	Yes
Developer experience		Hard	Hard	Medium
Security		No known attack	Nodes can collude to reveal the data	Prone to side channel attacks

	Concrete ML	Other FHE	MPC (multi party computation)	TEEs (trusted execution environment)	
Models supported		Limited depth	Limited due to	Anything	
Layers supported	Anything	Basic support for non-linear layers	large communication		
Performance	Medium to fast depending on the model*	Medium to fast depending on the model	Fast	Fast	
Computation result	Exact and Approximate	Approximate	Exact	Exact	
Hardware acceleration	Yes	Yes	No	Yes	
Developer experience	Simple	Hard	Hard	Medium	
Security	No known attack	No known attack	Nodes can collude to reveal the data	Prone to side channel attacks	

<sup>\*</sup>ASIC acceleration for Concrete ML will be available in 2025 and offer up to 1000x speedup

## 

## Thank you.

## Contact and Links

