Overcoming Data-Sharing Challenges in Central Banking: Federated Learning of Diffusion Models for Synthetic Data Generation

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3rd IFC Workshop on Data Science in Central Banking
„Data Sharing and Data Access“
17-19 October 2023, Rome, Bank of Italy

Agenda

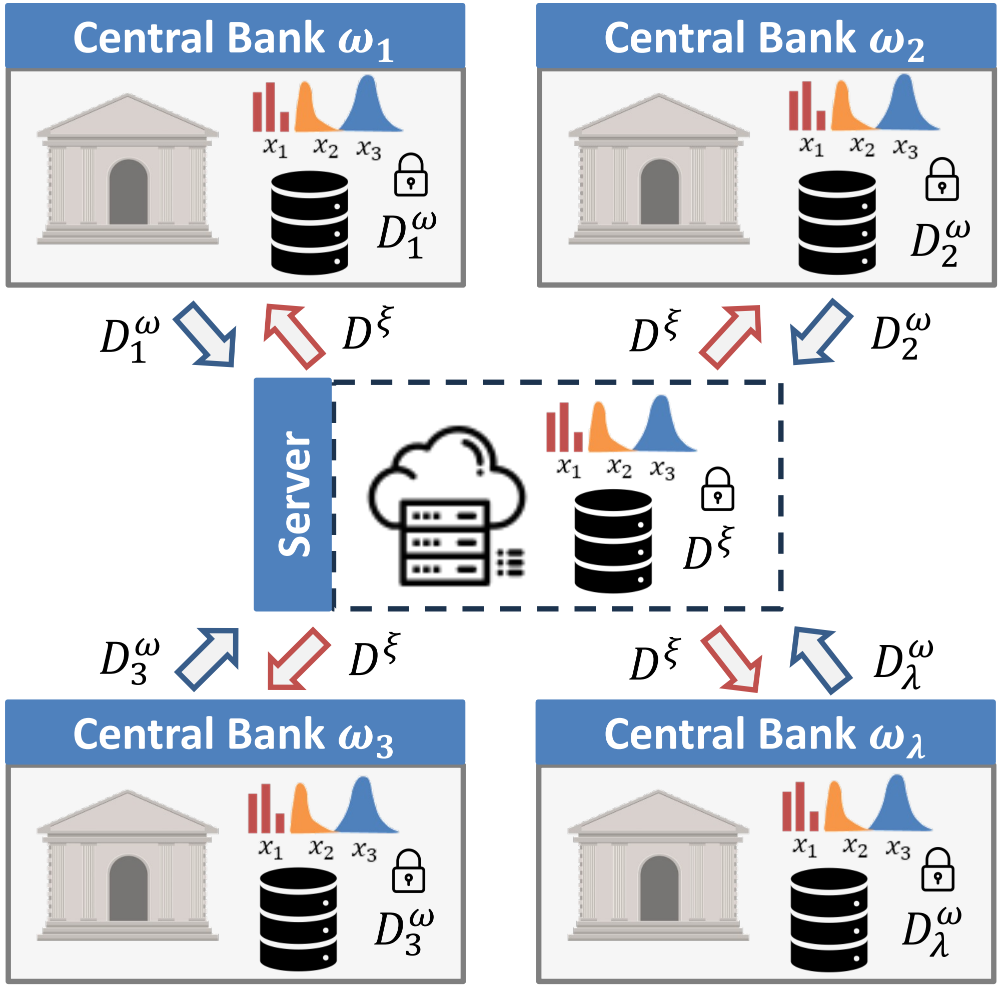
- Motivation
- Federated Learning
- Diffusion Models
- FedTabDiff
- Experimental Results
- Conclusion

Motivation

The sharing of financial data between central banks is crucial for managing economic policy and financial sector supervision.

Key advantages:

- **Improved economic policy**: Informed responses to global trends and risks.
- **Boosted financial stability**: Identifies risks and strengthens systems proactively.
- **Better cross-border regulation**: Enables consistent standards and detects misconduct.



Motivation

Challenges:

- **Legal and Regulator Constraints**: varying laws and data protection regulations in different countries can be cumbersome for data sharing.
- **Data Privacy and Security Concerns**: any breaches of confidential information can have severe consequences.
- **Data Transmission**: moving extensive datasets between central banks can become bandwidth-intensive and expensive.

Motivation

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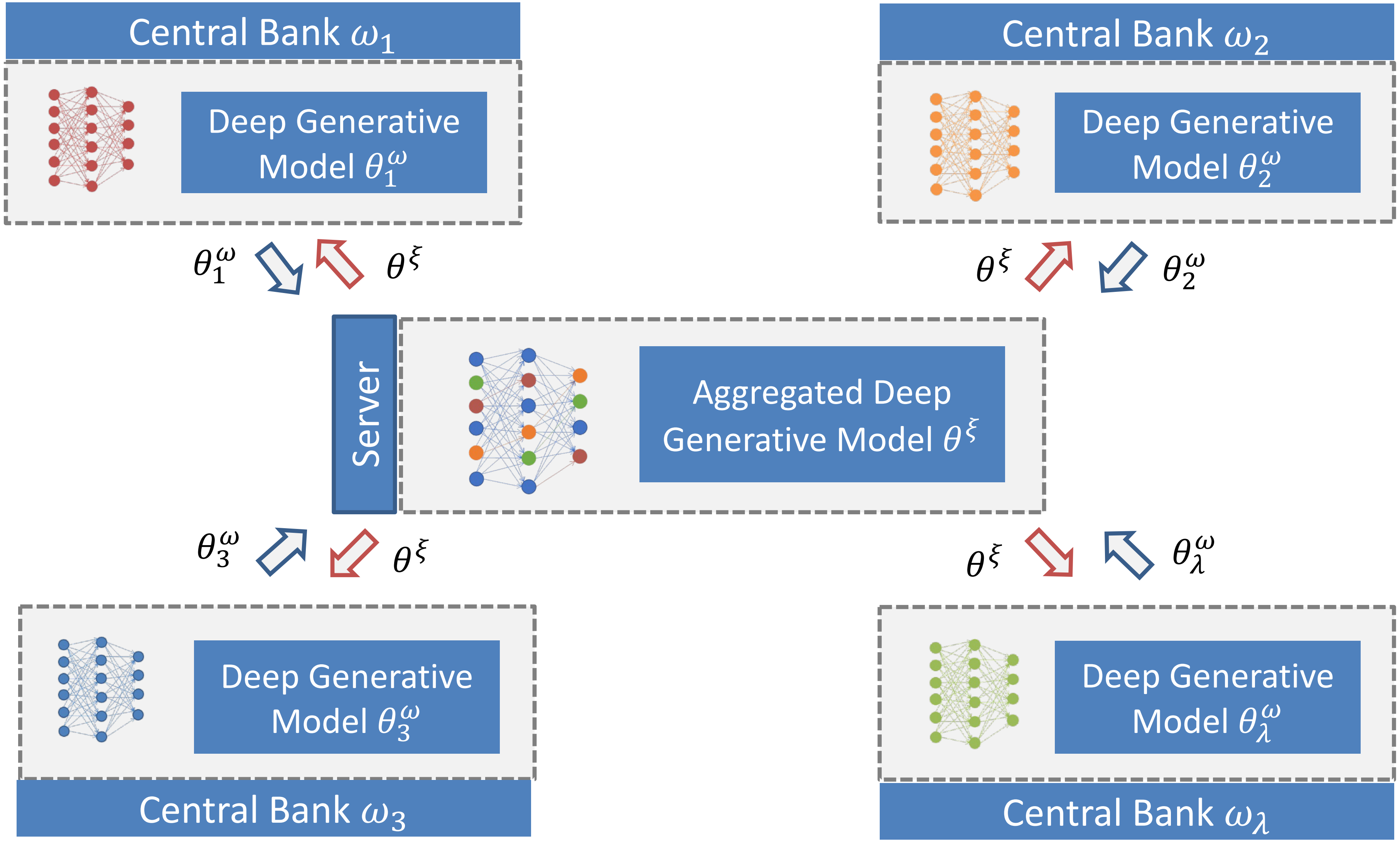
Idea: “Federated Learning + Diffusion Models”

- Use **Federated Learning** for decentralized node training without data exchange.
- Utilize **Diffusion Models** to synthesize central bank’s local data; then share the trained synthesizer model as part of the federated training.
- The **global model aggregates** knowledge from central banks to produce high-quality synthetic data.

Data Sharing with Federated Learning



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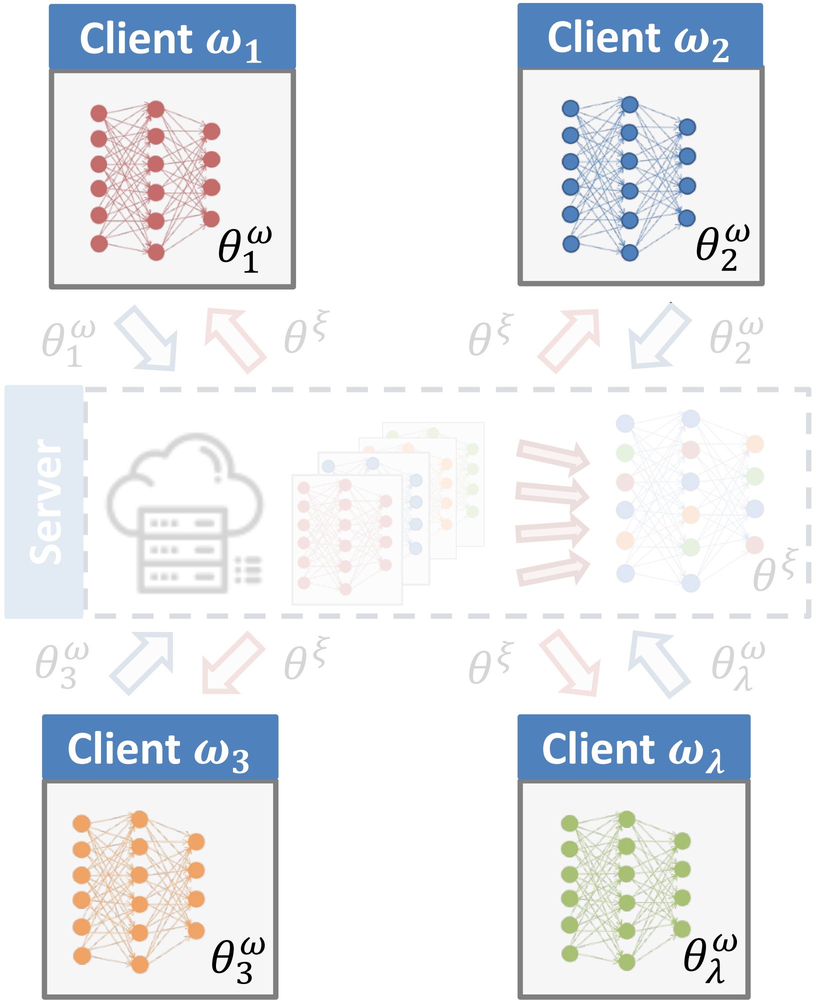
Main ingredients:

1. **Training on the Client**: the initial model θ_i^ω is trained locally on each client ω_i using the local data D_i, ensuring data privacy and security.



Federated Learning: the mechanics

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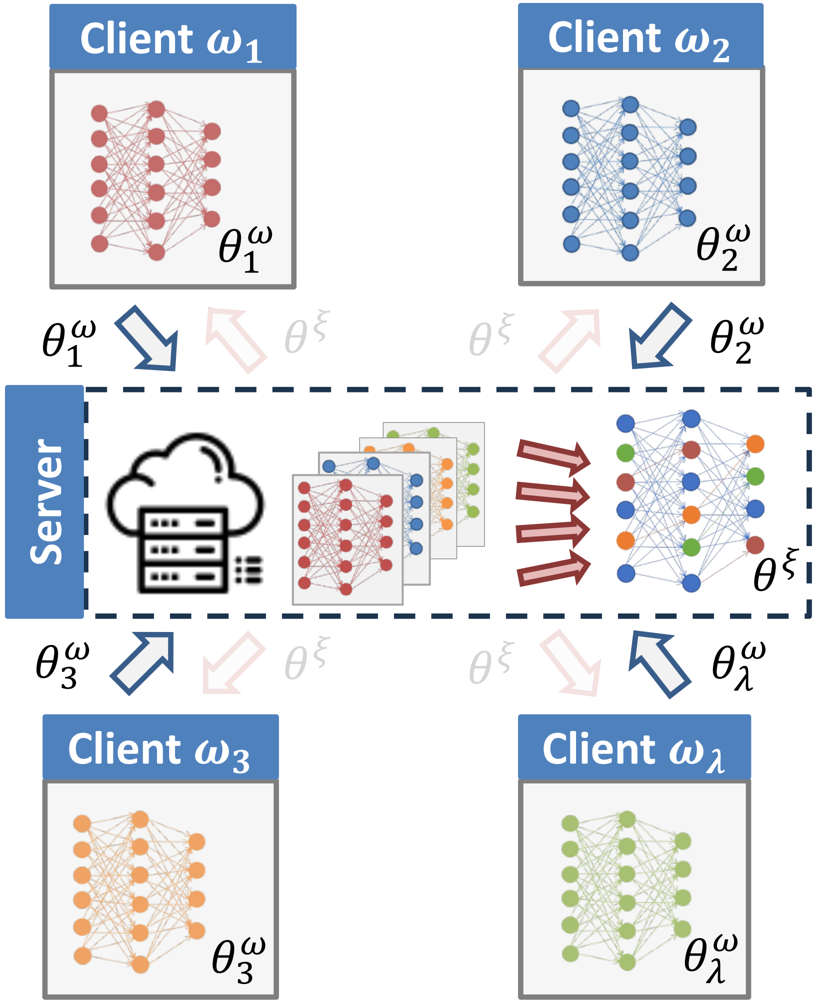
1. **Training on the Client**: the initial model θ_i^ω is trained locally on each client ω_i using the local data D_i, ensuring data privacy and security.
2. **Model Aggregation at the Server**: after each communication round $r = 1, \ldots, R$ only the model parameters are sent to a centralized server, where they are aggregated into a "global" model θ^ξ.



Main ingredients:

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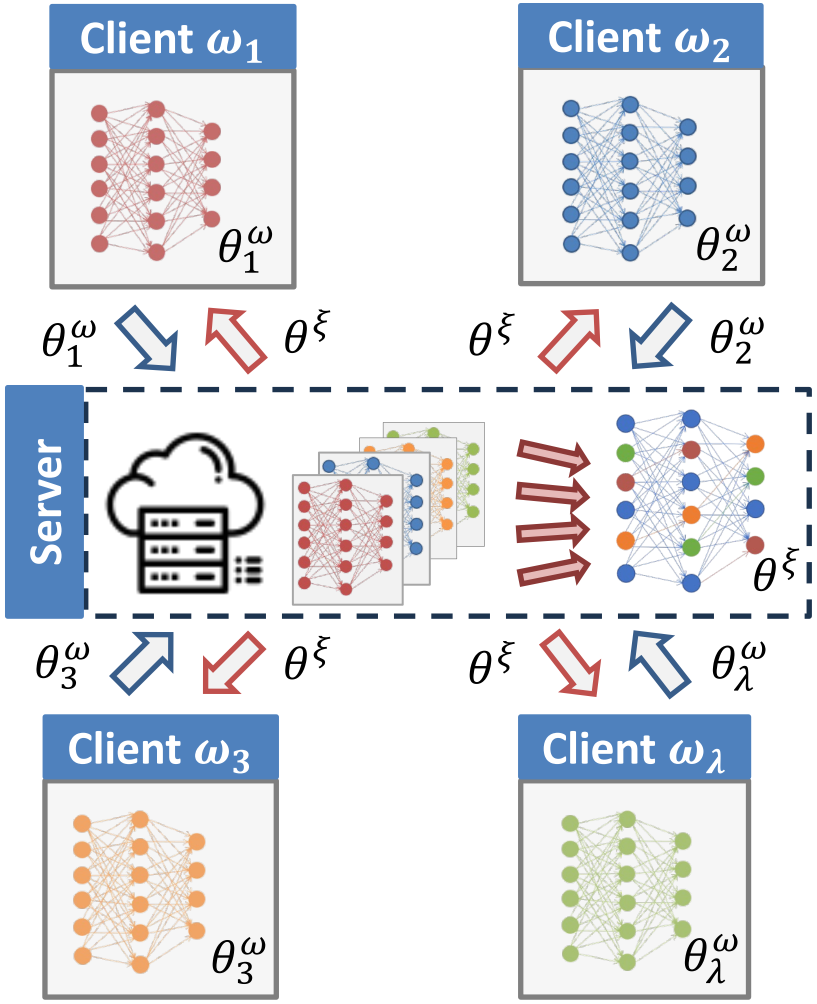
3. **Continuous Learning Cycle**: The updated global model is sent back to the clients for further local training, creating a continuous cycle of learning and improvement.



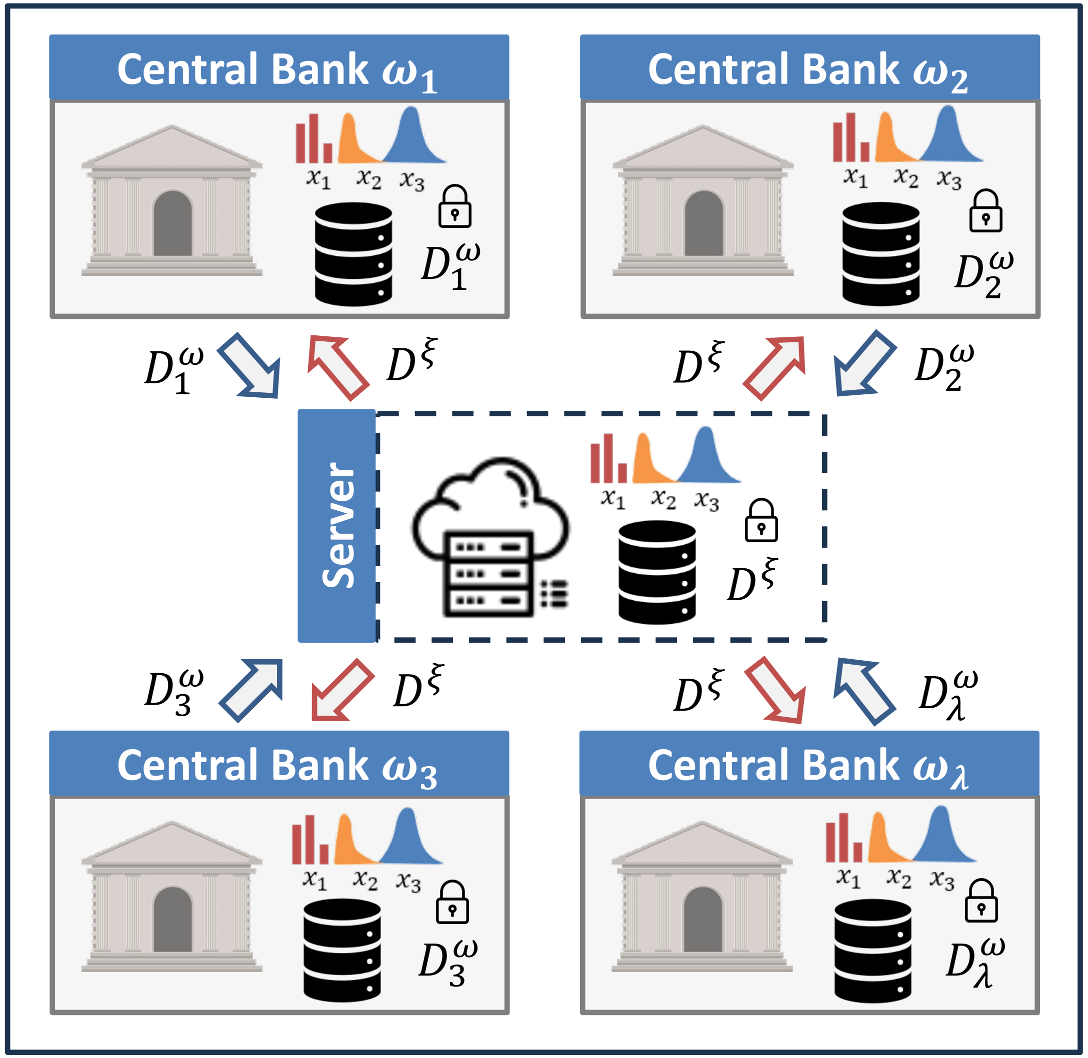
Federated Learning: Benefits

Privacy Preserving: Federated Learning enhances user privacy by keeping all the sensitive data on the local device, never sending raw data to the central server.

Reduced Data Transfer Costs: in the Federated Learning setup only the model parameters are being exchanged therefore avoiding transmission of large data volumes.

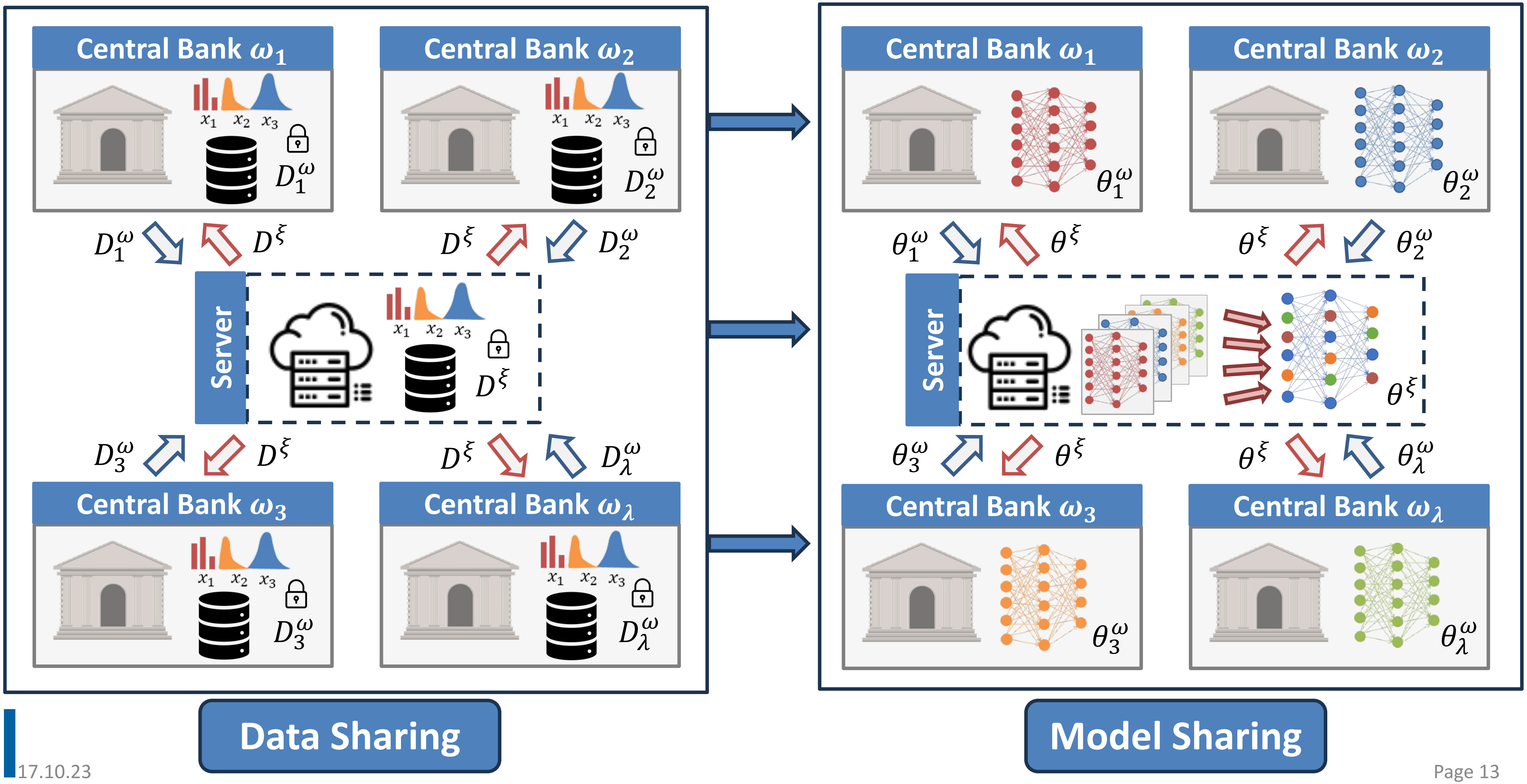
Global Insights: financial institutions can benefit from insights gathered globally across different markets and segments, but applied in a way that is tailored to local market conditions and regulations.

From Data Sharing to Model Sharing



Data Sharing

From Data Sharing to Model Sharing



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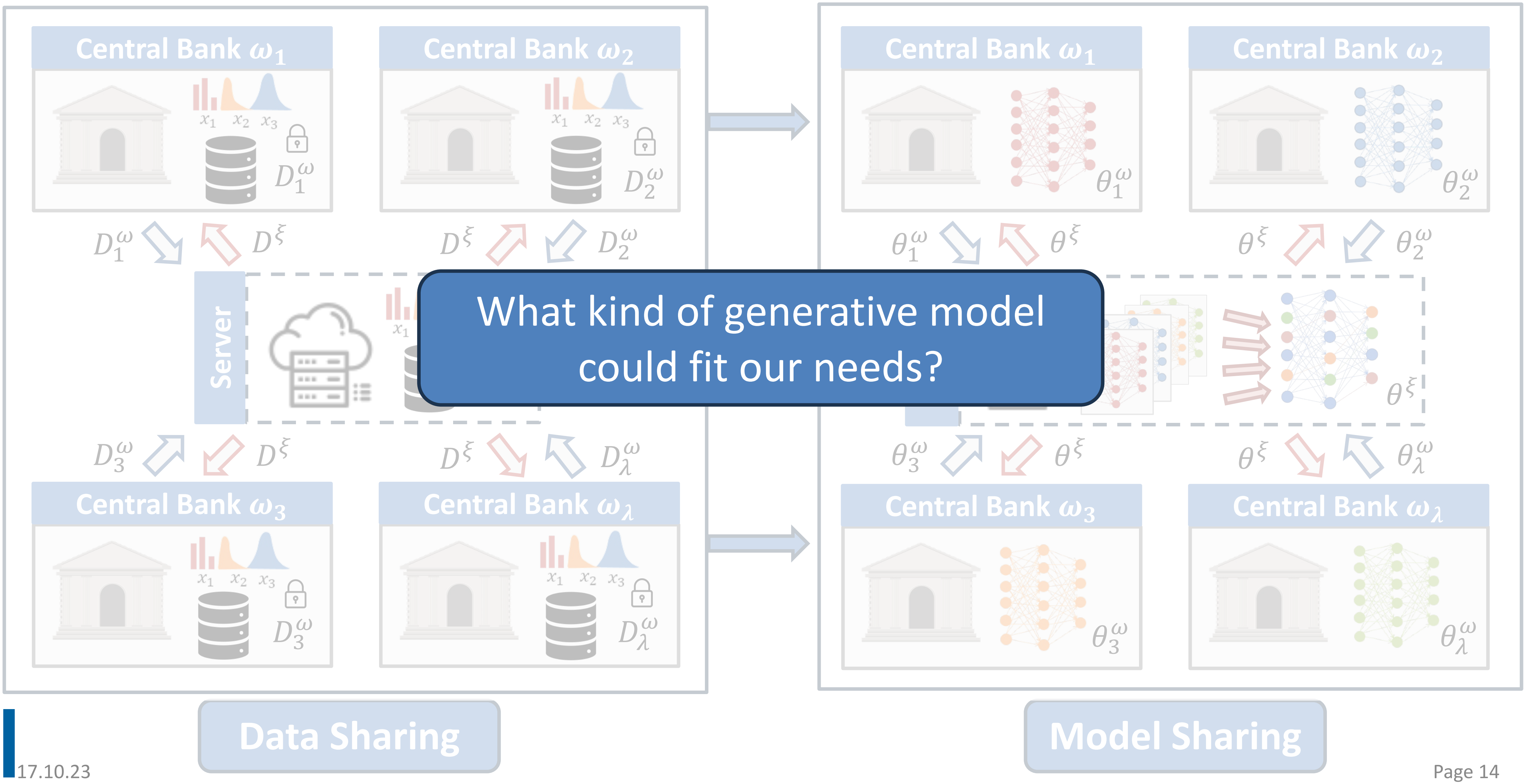

What kind of generative model could fit our needs?

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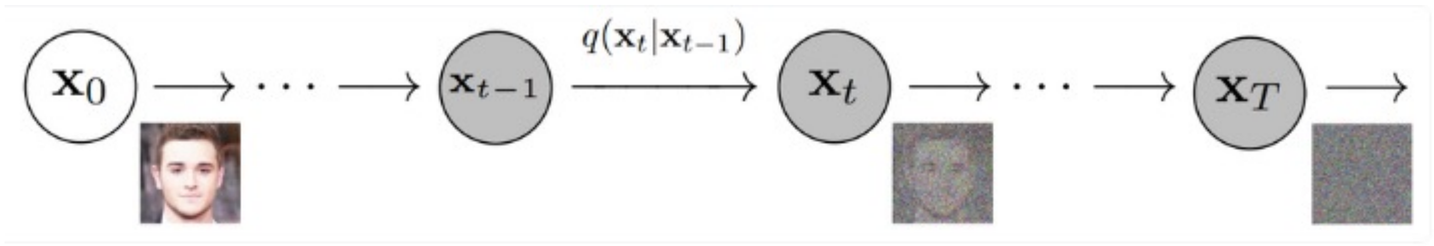
Diffusion Models

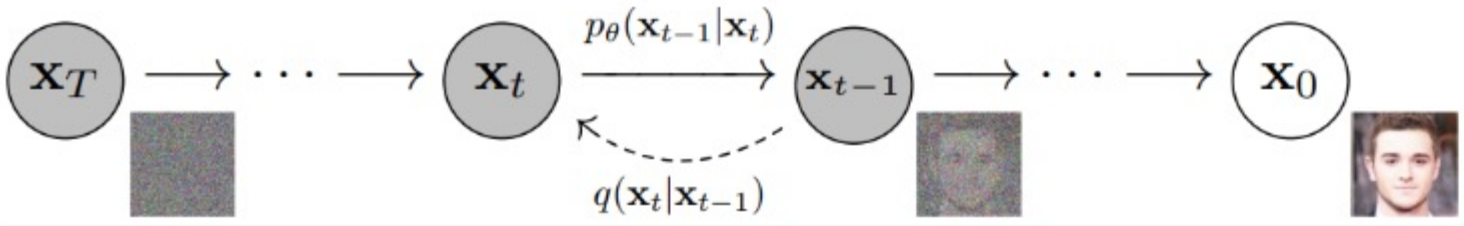
- Diffusion Models – are **generative models** trained with the objective of noise removal and subsequently constructing the desired **data samples from pure noise**.
- First introduced by Jascha Sohl-Dickstein et al. in 2015 with motivation from non-equilibrium thermodynamics. They can be thought as a **sequence of denoising autoencoders**.

Forward Diffusion Process



- Markov chain of diffusion steps.
- Add Gaussian noise in *T* steps.
- When $T \to \infty$, x_t is equivalent to an isotropic Gaussian.
- No learning at this step.

Reverse Diffusion Process



- Reverse process of *T* steps.
- Data generation from Isotropic Gaussian noise.
- Usually is called sampling.
- Learning is required.

Figure is taken from „Denoising Diffusion Probabilistic Models " by Ho et al. https://arxiv.org/pdf/2006.11239.pdf

Diffusion Models for Financial Tabular Data

FinDiff: Diffusion Models for Financial Tabular Data Generation

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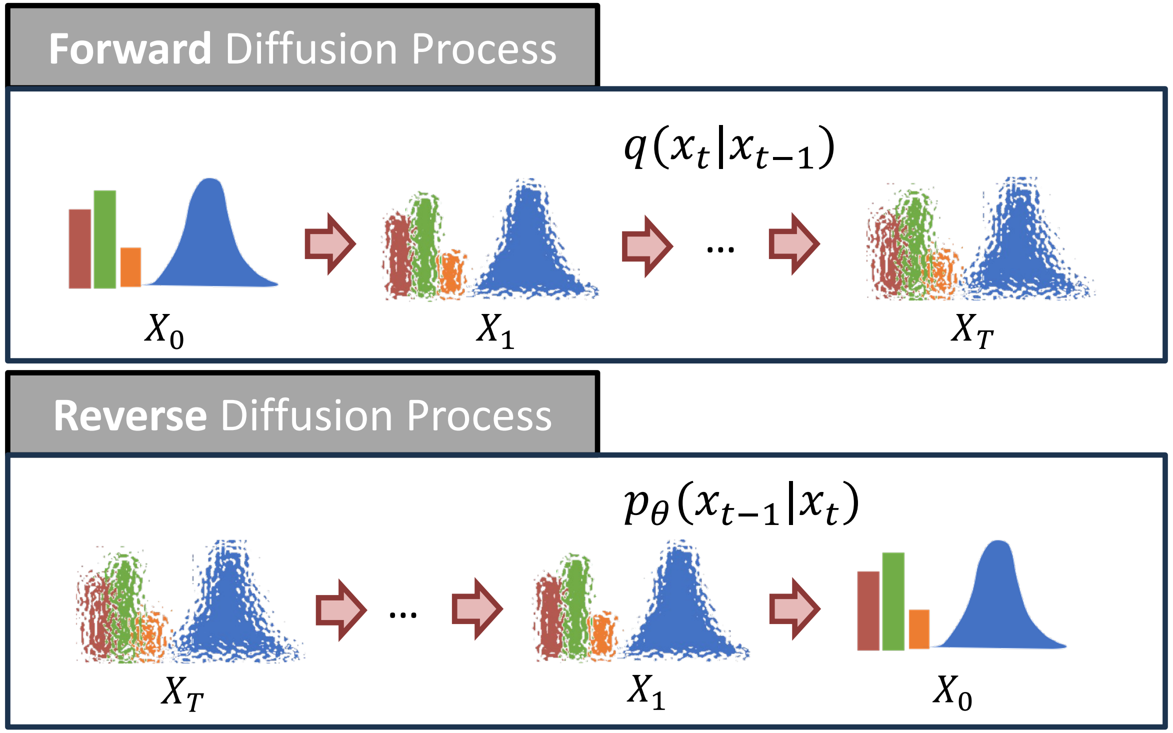

https://arxiv.org/abs/2309.01472

- FinDiff is a diffusion based generative model, that synthesizes financial tabular data for **regulatory downstream tasks**.
- It uses **embeddings** for mixed modality financial data, comprising both **categorical and numeric** attributes.
- Empirical results demonstrate **high fidelity, privacy, and utility** using FinDiff.

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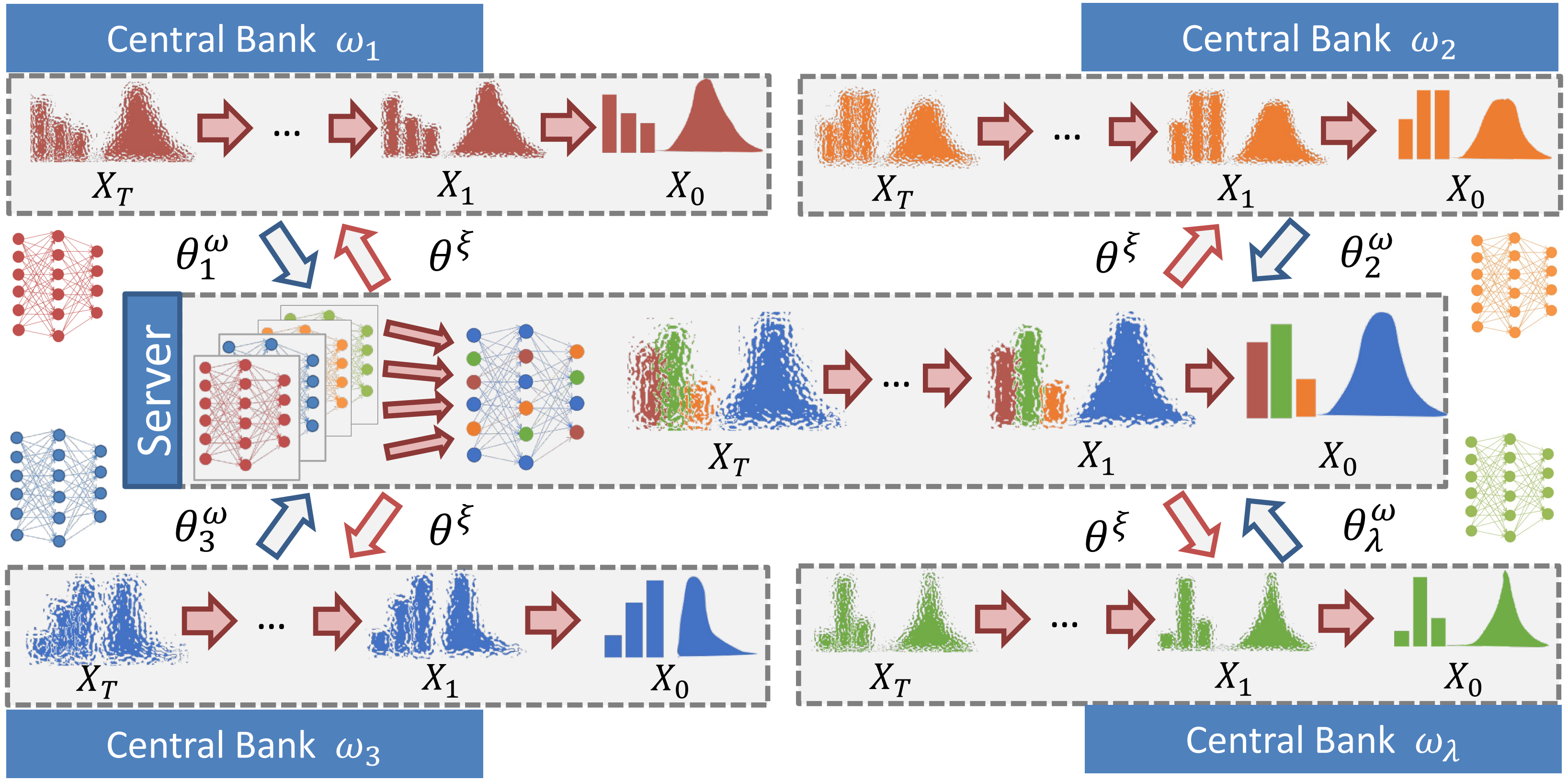
FedTabDiff schematic overview

1. Each central bank trains a **local generative model $\boldsymbol{\theta_i^\omega}$.**
2. The Server aggregates all models into a **global generative model $\boldsymbol{\theta^\xi}$** accumulating knowledge from local datasets D_i^ω.
3. The global model θ^ξ is used to **generate high quality tabular data** without sharing the actual data.



Experimental Setup

- Mixed-type tabular datasets:
  City of Philadelphia Payments – 215,302 payments generated by 58 city departments in 2017. Contains 10 categorical and 1 numeric attributes.
  Diabetes Hospital Data – 92,689 clinical care records collected by 130 US hospitals between 1999-2008. Each record has 40 categorical and 8 numeric attributes.
- The dataset was **non-iid partitioned** $D_i \subseteq D$ across 5 clients ω_i.
- Evaluation **metrics**: fidelity, utility, privacy, and coverage.
- **Federated learning hyperparameters**
  total communication rounds: $R = 1000$
  client model θ_i^ω updates: $R_c = 20$
- **Diffusion model hyperparameters:**
  MLP layers: 1024 -> 1024 -> 1024 -> 1024
  activation: leakyRelu
  total diffusion steps: $T = 500$

Dataset	Client	# samples $\mathcal{D}_i$
Philadelphia	ω_1	40,038
	ω_2	28,521
	ω_3	16,831
	ω_4	93,119
	ω_5	36,793
	all	215,302
Diabetes	ω_1	9,685
	ω_2	17,256
	ω_3	22,483
	ω_4	26,068
	ω_5	17,197
	all	92,689

Experimental Results

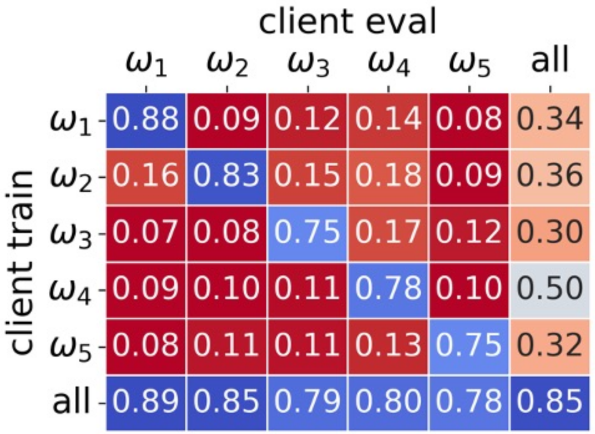
- Comparative analysis of the **Federated** (FedTabDiff) versus **Non-Federated** (FinDiff) models, evaluated using the full dataset D.
- Non-Federated diffusion models are trained individually at each client ω_i with subset $D_i \subseteq D$ (column "Split") and evaluated against the entire dataset D.

			Evaluation Measures			
Dataset	**Client**	**Split $\mathcal{D}_i$**	**Fidelity [5, 32] ↑**	**Utility [50] ↑**	**Coverage [7] ↑**	**Privacy [55] ↓**
Philadelphia	ω_1	19%	0.267 ± 0.03	0.263 ± 0.04	0.689 ± 0.03	3.162 ± 0.19
	ω_2	13%	0.264 ± 0.03	0.325 ± 0.06	0.681 ± 0.02	3.103 ± 0.13
	ω_3	8%	0.207 ± 0.03	0.118 ± 0.04	0.847 ± 0.04	3.178 ± 0.03
	ω_4	43%	0.394 ± 0.01	0.430 ± 0.01	0.863 ± 0.02	2.919 ± 0.14
	ω_5	17%	0.238 ± 0.03	0.197 ± 0.03	0.898 ± 0.01	3.359 ± 0.33
	FedTabDiff		$\mathbf{0.590 \pm 0.01}$	$\mathbf{0.837 \pm 0.03}$	$\mathbf{0.944 \pm 0.03}$	$\mathbf{2.607 \pm 0.18}$
Diabetes	ω_1	10%	0.217 ± 0.01	0.104 ± 0.03	0.944 ± 0.02	10.261 ± 0.25
	ω_2	18%	0.269 ± 0.01	0.186 ± 0.01	0.943 ± 0.03	10.091 ± 0.38
	ω_3	24%	0.314 ± 0.01	0.242 ± 0.01	$\mathbf{0.946 \pm 0.01}$	9.895 ± 0.31
	ω_4	28%	0.331 ± 0.01	0.281 ± 0.01	0.939 ± 0.01	9.941 ± 0.21
	ω_5	18%	0.269 ± 0.01	0.185 ± 0.01	0.943 ± 0.02	10.139 ± 0.19
	FedTabDiff		$\mathbf{0.720 \pm 0.01}$	$\mathbf{0.265 \pm 0.01}$	0.906 ± 0.01	$\mathbf{3.120 \pm 0.09}$

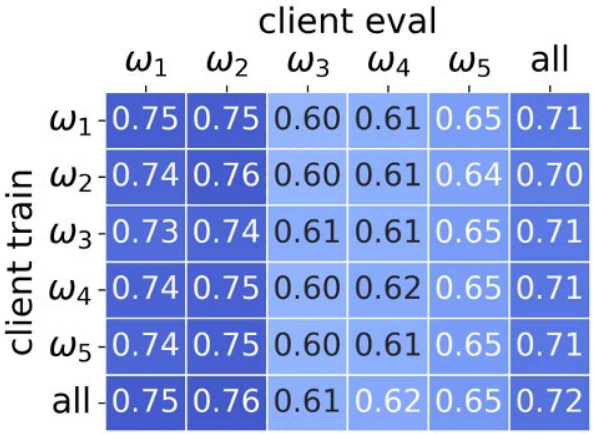
*Scores are derived from the averaged results and standard deviations of five experiments, each initiated with distinct random seeds

Experimental Results

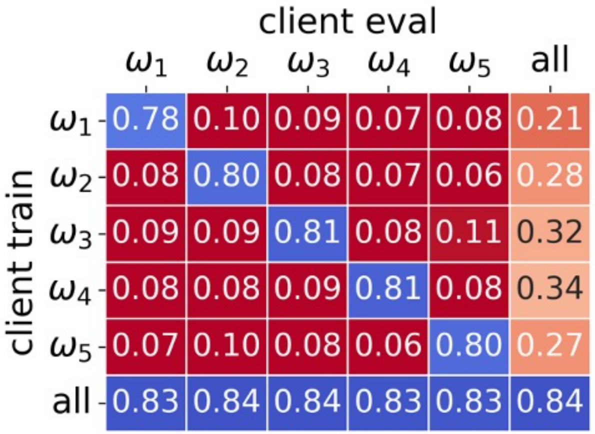
- Fidelity - **similarity of every column** in the synthetic dataset against the real dataset.
- Fidelity score comparison between **Federated** (FedTabDiff) and **Non-Federated** (FinDiff).
- In the Non-Federated model, each client is trained on its data subset $D_i \subseteq D$ and evaluated across all subsets.



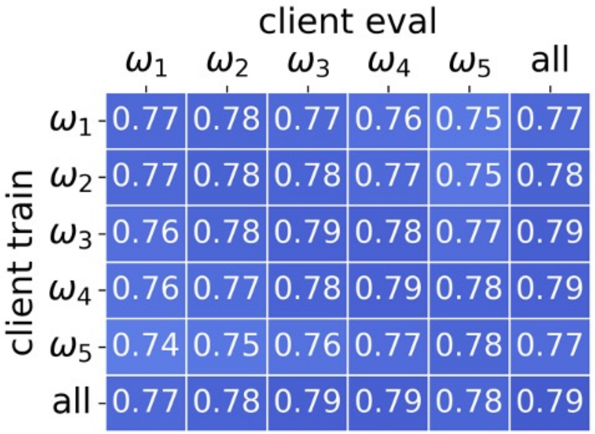
Non-Federated (FinDiff)
Philadelphia



Federated (FedTabDiff)
Philadelphia



Non-Federated (FinDiff)
Diabetes



Federated (FedTabDiff)
Diabetes

Conclusion and Future Work

- Through the adoption of federated learning methodologies central banks may transition **from data sharing to model sharing.**
- FedTabDiff is a **federated diffusion-based generative model** for high-fidelity synthesis of mixed-type tabular data.
- The model **avoids sharing of sensitive information** by training a generative model and sharing it across different authorities without distributing the underlying data.
- Generated tabular data can be used for a variety of **downstream tasks,** such as regulatory compliance, anti-money laundering, fraud detection, risk management and many others.
- Future trajectories: advancement of **privacy-preserving** techniques, mitigation of **information dissemination** risks and evaluation on the **proprietary regulatory financial statistics**.

Thank you

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