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Gen AI in Payments: Secure Synthetic Data & More

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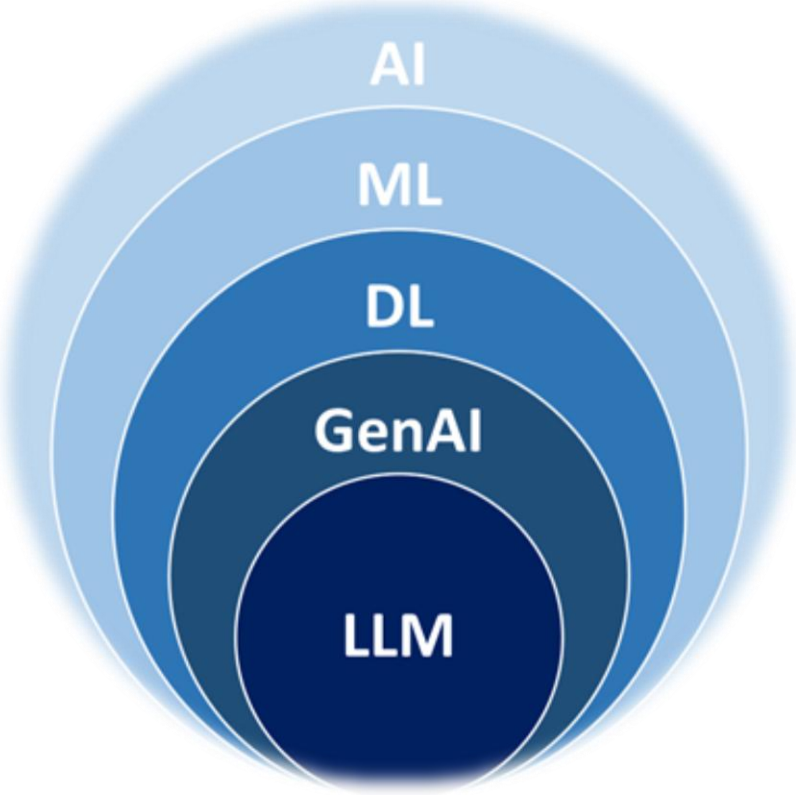
Gen AI in Payments



Motivation

- **Gen AI** is class of machine learning models designed to learn from extensive datasets and generate new, human-like content (or data)

- **LLM** is a type of Gen AI model trained to predict the “**next word** in a sentence"

- Can these model be trained or tuned to predict the "**next payment** in a sequence"?

Opportunities in payment

- AI agents trained on historical transactions can learn payment **patterns**; with additional personalized data, can they **automate tasks** for financial institutions?

  - Alternative way to **generate synthetic** payment generation
  - Counterfactual transaction examples for **anomaly** detection models
  - Generative **payment agents** to study behavior and strategies of cash managers
  - Artificial intelligent payment system simulator (a **sandbox**) for policy analysis

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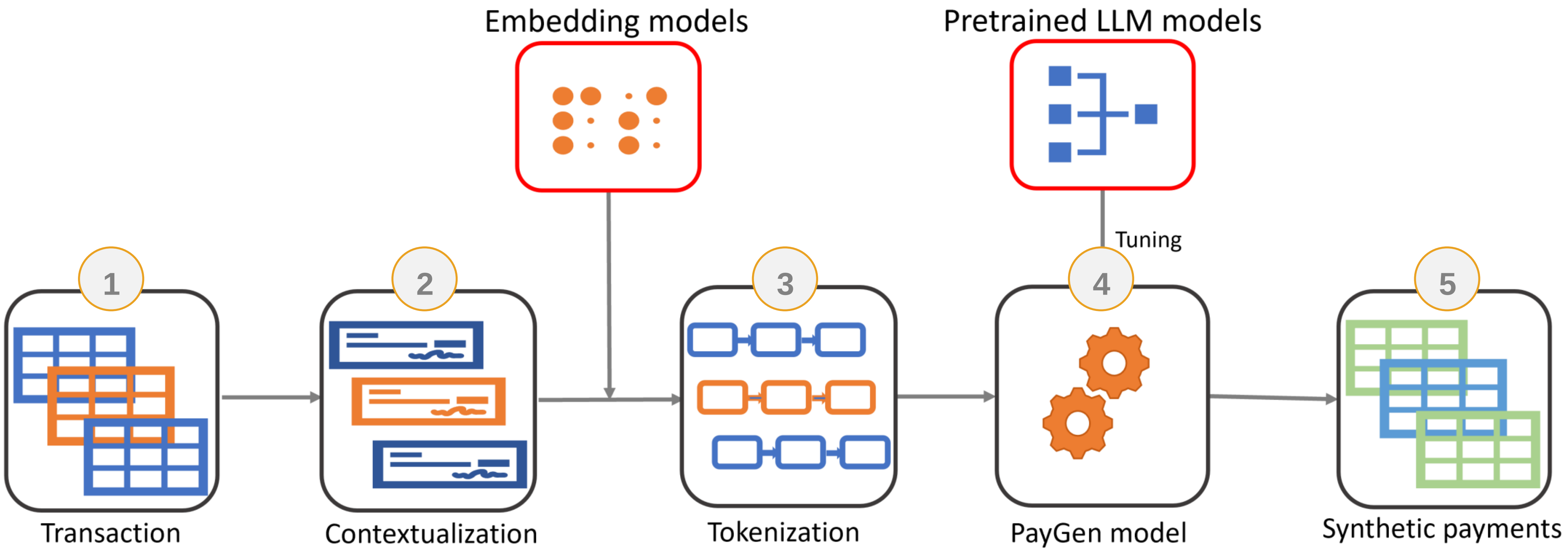
Gen AI for synthetic payments data

Why?

- **Captures Complex Patterns**: Can learns intricate nonlinear relationships in payment data and help identifying rare and emerging patterns
- **Sensitivity & Scarcity**: Data is generated from learned patterns, which can help preserve privacy, and it is easy to produce ample synthetic transactions
- **Customizability**: Enable the creation of data tailored to specific scenarios, both realistic or counterfactuals

Workflow using LLM



Using LLM

1. **Transactions**: Extract transaction features (sender, receiver, amount, type, etc.)

2. **Contextualization**: Add relevant contextual information (when, where, why, etc.)

3. **Tokenization**: Convert contextualized transactions into set of LLM tokens

4. **PayGen** model: Fine-tuning version of pre-trained LLM on payments data

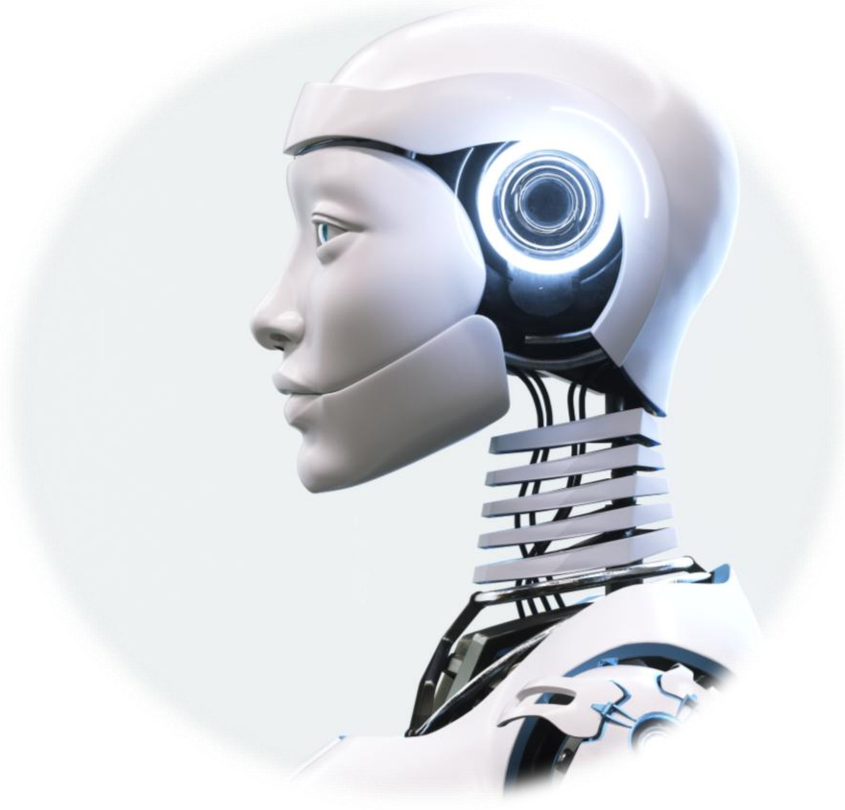
5. **Synthetic** data: Use PayGen model to generate synthetic transactions

Preliminary findings

LLM-based approach: preparing training data is hard but model training is easy

- **Data anonymization**: using anonymization techniques for protecting payments data
- **Data augmentation**: limited contextual information available for high-value payments
- **Tools testing**: both **Llama** and **Mistral** in a secure environment
- **Preliminary results**: encouraging outcomes observed on a **dummy sample** based on Canada's payment system

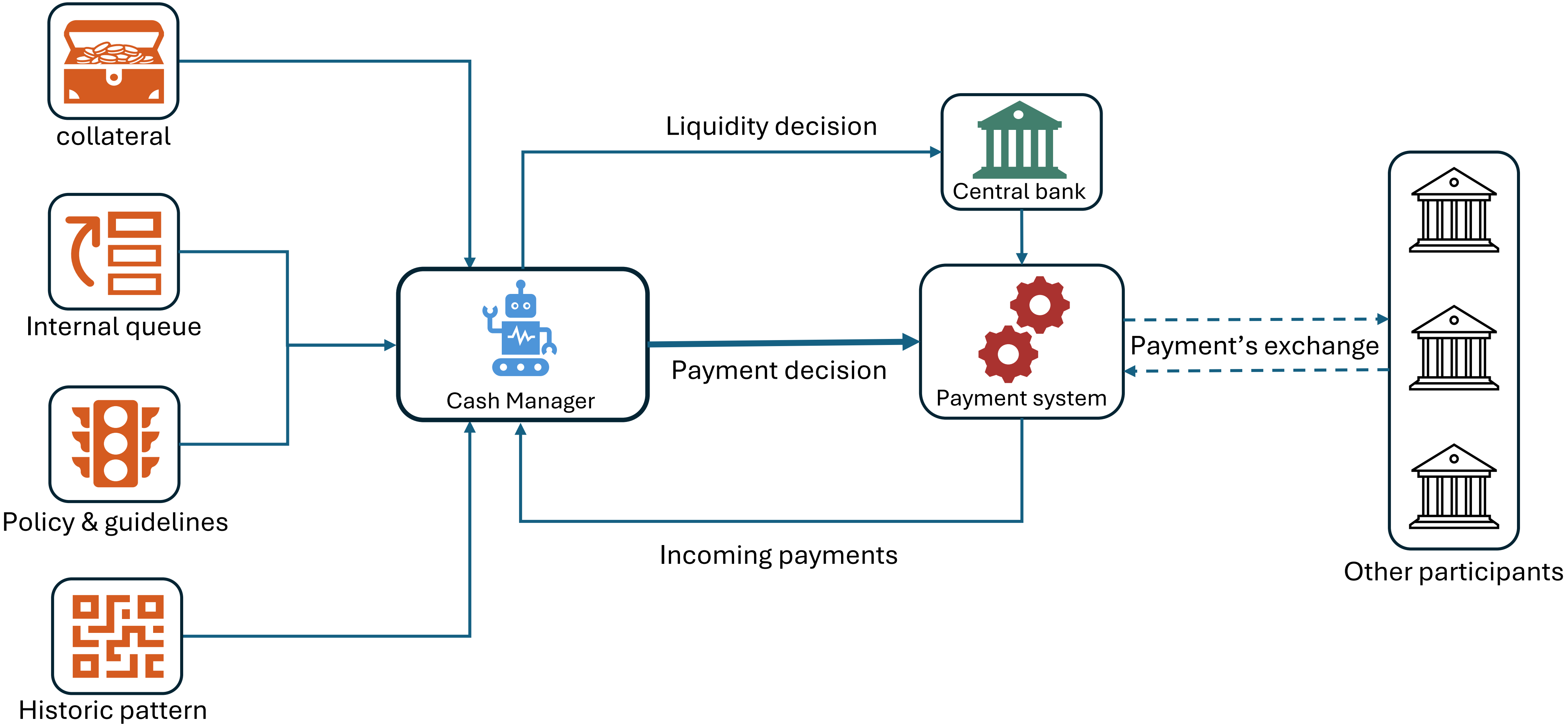
Gen AI agent as a cash manager



Why?

- **Cost reduction:** AI agents can automate routine processes such as payment scheduling and liquidity management, which can help lower operational cost
- **Safety & efficiency**: AI agents can adapt to higher transaction volumes without compromising accuracy, and they can help detect anomalous payments
- **Innovation:** AI agents can help continuously refine algorithms to explore new payment and liquidity management strategies

Workflow using ChatGPT 'reasoning' model



Objective

- Evaluates the **cash manager-like** decision-making capabilities of an **AI agent** using series of **prompt-driven experiments** with ChatGPT's "*4o1*" model
  - Can agents demonstrate **precautionary** payment decisions?
  - Can agents navigate payment **priority** situations?
  - Can agents mitigate liquidity and delay **trade-offs**?

Precautionary decision

Test 1: Model reason for 5 seconds [drop-down menu summarizing reasoning steps]

Context: Pretend you are a cash manager at a bank, tasked with managing payments in a high-value payment system. You currently have a liquidity limit of $10.

In the first period, you have two pending payments of $1 each in the queue. However, there is a possibility of an urgent $10 payment arising in the next period.

Prompt: What you would do in the first period? Answer briefly.

Response: I would delay the two $1 payments in period 1 to preserve liquidity for the potential $10 urgent payment in period 2.

Navigating priorities

Test 2: Model reason for 15 seconds [drop-down menu summarizing reasoning steps]

Context: Pretend you're a cash manager at a bank responsible for managing payments in high-value payment systems.

You have current liquidity limit of $10. You have two $1 payments in the queue in the first period, but there is a 50% probability of an urgent $10 payment in period 2. Additionally, there is a 75% probability that you might receive a $1 payment from another participant in the first period.

Prompt: What you would do in the first period, answer briefly?

Response: In the first period, I would **process one of the $1 payments** and hold the other. This strategy balances the need to fulfill current obligations while preserving enough liquidity to handle the potential urgent $10 payment in the second period.

Mitigating liquidity-delay trade-off

Test 3: model reason for 55 seconds [drop-down menu summarizing reasoning steps]

Context: Pretend you're a cash manager at a bank responsible for managing payments in HVPS. Before the first period you need to allocate certain liquidity at cost of 2%, subsequently, in the first period you need to send or delay a payment of 1$ at delay cost of 1%, and you might receive $1 with 95% probability.

In the second period you might have to send a payment of $2 with 90% probability with delay cost of 1%, and might receive 2$ payment with 99% probability.

In the third period if anything is left in the queue and if you don't have enough liquidity then you have to borrow at higher interest rate than the initial liquidity cost.

Prompt: How much initial liquidity you will allocate, answer briefly?

Response: I would allocate **zero initial liquidity** to minimize costs, relying on the high probabilities of incoming payments to cover outgoing obligations and accepting minimal delay or borrowing costs if necessary.

Takeaways

- **Potential for AI-driven solutions?**
  - General-purpose AI models show the capability to automate simple payments and liquidity management decisions
- **Opportunities for financial institutions?**
  - Higher chances for purpose-built AI solutions to use for payment and liquidity management to reduce operational costs, and enhance safety and efficiency
- **Additional policy considerations?**
  - Policymakers need to evaluate the feasibility, adoption and regulatory requirements to ensure the safe and responsible use of Gen AI in critical financial infrastructures

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Thank you!

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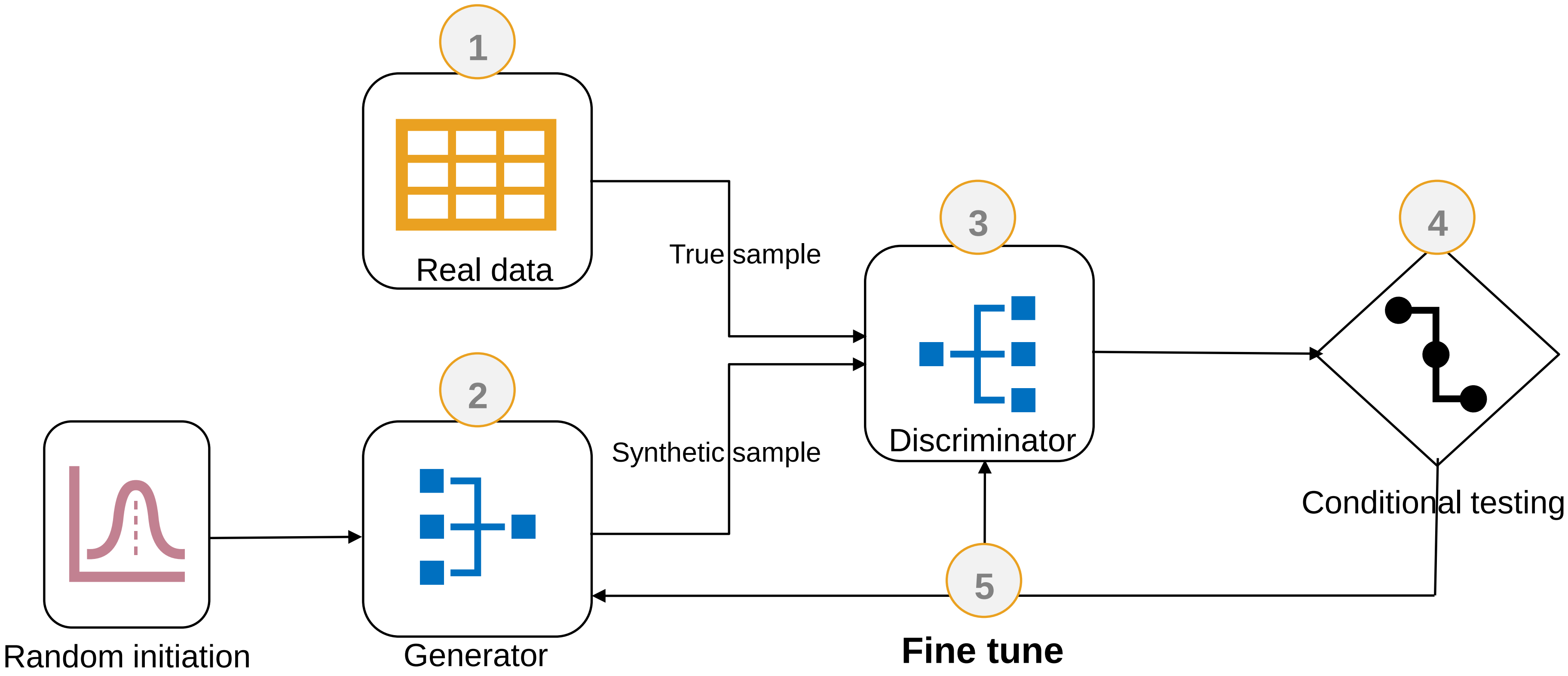
Approach 2: Using GAN



Approach 2: Using GAN

1. **Real data**: Sample a sequence of transactions from the real dataset
2. **Generator**: Model generates a synthetic sequency of transactions
3. **Discriminator**: Model tries to identify if generated sequency is synthetic or real
4. **Condition**: Check if discriminator able to identify the generated sequency is synthetic
5. **Finetuning**: Both models are trained/tunned until the discriminator consistently fails to recognize if generated sequency is synthetic or real

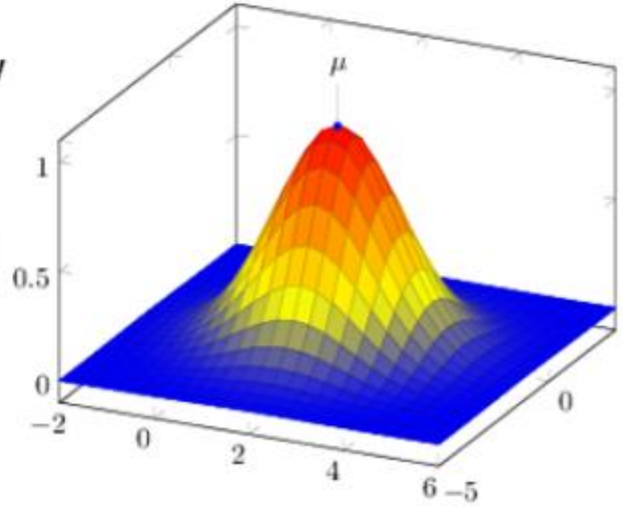
Benchmark: using normalizing flows model

Real Payments data

Normalizing flow T^{-1}

Probabilistic

Model



Normalizing flow T

Sample from

distribution

Synthetic Payments data