# TL system design

## **Summary:**

## Requirements:

- 1. Git, multiple commit, public accessible link 🗸
- 2. Test code 🗸
- 3. Dockerize with docker-compose V
- 4. README
  - a. Build
  - b. Test
  - c. Run
  - d. Mention Architectural Principles, why choose them
  - e. Design considerations
  - f. Coding styles, pep 8 for python 🗸 (pycharm plugin install)

#### **Exercise:**

- 1. Keep track of all transactions involved in the Uniswap V3 USDC/ETH pool
  - a. Transaction fee in USDT when Txn first confirmed on the blockchain
- 2. Real time data recording + Historical batch data recording
  - a. Continuously record live txn data
  - b. Process batch job requests to retrieve historical Txns for a given period of time
  - c. REST API:
    - i. Input: txn hash, Output: transaction fee
    - ii. State clearly Interface specifications (Follow Swagger UI standards)
- 3. Data Source:
  - a. All Historical Txns for Uniswap WETH-USDC
    - i. https://etherscan.io/address/0x88e6a0c2ddd26feeb64f039a2c41296fcb3f5640#tokentx

- b. Get historical Txns Programmatically: Etherscan API:
  - i. https://docs.etherscan.io/api-endpoints/accounts#get-a-list-of-erc20-token-transfer-events-by-address
- c. Eg. 0x8395927f2e5f97b2a31fd63063d12a51fa73438523305b5b30e7bec6afb26f48
- d. Base fee in ETH, to calculate Fee in USDT based on historical/live price for ETH/USDT
  - i. Use Binance SPOT API for price: Orderbook/kline
  - ii. https://binance-docs.github.io/apidocs/spot/en/#change-lo
- 4. Additional Requirement:
  - a. Availability, Scalability, Reliability considerations
  - b. Decode the actual Uniswap price exectuted for each Txn.
    - i. Single Txn may contain multiple swaps. You only need to decode and save the executed price from Uniswap event. Provide REST API.
      - 1. Infura, Web3 packages (web3Py)

## **Tech Stack:**

Python: Rich Library, data processing tools, SDK from Binance

DB: Redis, duplicate requests, rate limit implementation, binance api data caching, can be implemented as message queue if needed for real time streaming + fast processing.

Docker: As specified, for containerization

FastAPI (python framework): Pydantic, async support, auto generation of documentation (swagger), for high performance

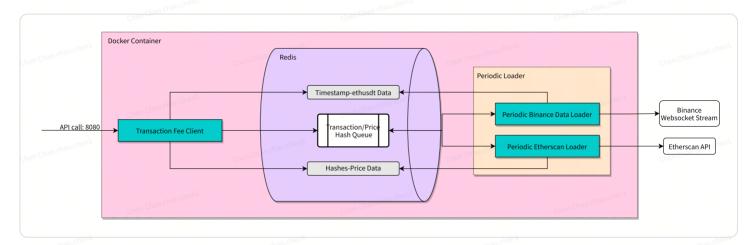
### POC:

- Etherscan API
  - a. Require API Key: (Store in .env file), to be replace
  - b. Rate Limit: 5 QPS, 100k Per Day
- 2. Binance Spot API (public) 🗸
  - a. Order Book (depth API)
  - b. Kline (kline API)

- c. Rate limit: 1,200 requests per minute, or up to 1,800 requests per minute in bursts (QPS 20)
- 3. FastAPI 🗸
  - a. Set up an app
- 4. Dockerize V
  - a. Setup Redis
  - b. Run App with redis as a dependency
  - c. Docker File
  - d. Docker compose

# **High Level TD**

## **Architectural Diagram**



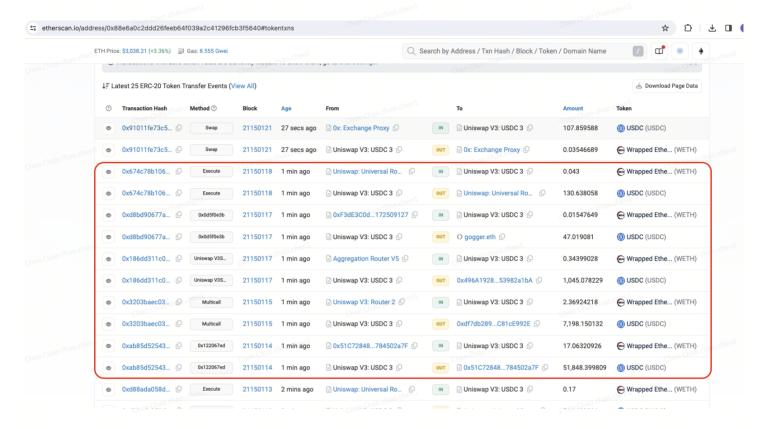
### Components

#### 1.1 Periodic Transaction Loaders

#### 1.1.1 Etherscan Transaction Loader

We will have a transaction loader that periodically loads data from etherscan by calling the etherscan API. This loader needs to adhere to the rate limit that etherscan imposes. Based on the 100k per day requirement, we can roughly call the api at 1qps to check for new transactions. This loader will start loading on app start up, polling the api at an interval of 1s. We can also cache the latest transaction block number for future calls. Based on transaction observation, we can roughly know that this part is non-data intensive as we barely hit 5 transactions in a minute. There is also an upper bound on the ethereum chain itself which comprises of the gas fee. Higher transactions lead to higher gas leads to lower transactions.

This recursive nature will lead to a theoretical upper bound to exist. Black swan can happen. For now, we can assume that data is rather small.



#### 1.1.2 Binance Spot API Loader

Note that we need to return the values stored as USDT, since what we retrieve is the ETH gas price, a conversion needs to be done. We can use the Binance spot API for that by looking at the ETH/USDT pair price. The product of the two would give the transaction price in USDT. This can be slightly data intensive. As from second to second, the price change can be quite drastic, we would want to reach second level data to achieve high precision. Since etherscan data can return epoch level timestamp, we can then use this data to retrieve the exact price of the Binance Spot pair ETH/USDT at that exact second.

The challenging part about this arises from retrieving the kline data in near real time manner, since second level data is streaming in, if we employ a rest api (pull model), the network overhead will cause a significant lag in data retrieval. We should instead use a push model by employing the binance websocket. We can, of course, do a rough estimation using minute level data, but the correctness of the price will be an issue, given the market can move very drastically within a minute.

Lets do a rough estimation. We would need to store the timestamp and the closing price, which will be two separate strings. In a single day we would have 24\*60\*60 = 86400 of data, each string stored in redis has roughly 80 bytes of overheads as well. We roughly assume it to be 200 bytes per two strings. Then, we will have about 17MB of data every day, which brings it to . In theory, we roughly want to have at most 25GB of data in a single redis node. Beyond that point, performance will start to degrade. For simplicity sake, we assume that our redis at

most holds about 1 year worth of data, and anything beyond that point expires and cleans up itself.

Everything beyond this point, if needed, we can just query the api and cache that data in the redis, in case some other people want to use it in the future.

Discussion point as a follow up: If we want to scale this up to store all this data in memory, we can potentially have two options.

- a. Redis cluster, we can horizontally scale the size by adding more redis nodes to form a redis cluster.
- b. Utilize big data technology, eg, flink, to achieve real time data pipelines.
- c. Just persist the data and query from harddisk works just fine. From there on, it is easy to scale with sharding based on dates.

#### 1.2 Transaction/Price Hash Queue

Note that it is not always the case that a transaction/price is going to be in our redis after we start running the app. For simplicity sake, we would want to query this data as a batch job and inform the API caller to come back later on if the data is missing. We can simply use a message queue for this. One safe assumption is that this is probably not a critical service, otherwise it's probably better to use a log and persist for this job request, in this case for easier tracing. The caller of the API should also have fallback logic anyways.

As for implementation, redis provides publishing-subscribe architecture for real time low latency event processing. This is one of the considerations being used when choosing redis as part of the tech stack, since we can use it both for event streaming queues and data persistence.

The periodic loaders will also contain implementations to retrieve the data from the message queue, depending on what kind of data is missing.

For simplicity, we can always decouple the message consumption and job to separate classes. For now, there is no need to do so, since they are just loading data from the two separate data sources.

#### 1.3 Transaction Fee Client

We will have a single API endpoint for this purpose. The API endpoint description is illustrated below. Calculation is done here directly

URL		PO	ST /transaction-fee	
Input	Туре	Description	Sample	
Chen Chila chao chen L		Chen Chao ch	an.chen1	<sup>su</sup> Chao chao chen <sup>1</sup>

transaction eRequest	nFe	TransactionF eeRequest	Request DTO transactionHashes: list[str] (Mandatory)	TransactionFeeRequest: {     transactionHashes: ["0x123",     "0x456",] }
Output		Туре	Description - Constitution	Sample Chen Chao chao chen L
transaction eResponse		TransactionF eeResponse	Response DTO transactionsList: list[TransactionsDTO]	TransactionFeeResponse: {  transactionsList: [
			TransactionsDTO transactionHash: str success: boolean	transactionHash: "0x123", success: true, fee: 0.123
			fee: float error_msg: string	error_msg: ""  },  Chen Chao Chao Chao Chao Chao Chao Chao Chao
			Chen Chao chao chen L	transactionHash: "0x456", success: false,
			Chen Chao chao chen 1	error_msg: "invalid hash"  },
			<sub>ako</sub> chao chen1	Chen Chao chao chao chao chao chao chao chao c

# Design considerations:

# 1. Scalability

 Horizontal Scaling of Redis: Redis is used to store price and transaction data temporarily, making it suitable for quick access. Redis can be scaled horizontally by deploying a Redis cluster, distributing the load across multiple nodes to handle an increased volume of transactions or data requests.

- Batch Processing for Historical Data: The system distinguishes between real-time
  transaction tracking and historical data retrieval. Batch processing jobs for historical data
  allow efficient handling of large data sets without affecting real-time processing capabilities,
  ensuring the system can handle both high transaction volumes and large historical queries.
- WebSocket for Real-Time Data: The Binance WebSocket is used for fetching real-time ETH/USDT prices, which minimizes the need for repetitive REST API calls and reduces network overhead. This setup enables the system to scale efficiently while maintaining real-time responsiveness. We can extend this idea to the evm clients and etherscan apis
- Event-Driven Architecture: Leveraging an event-driven approach (e.g., using Kafka or RabbitMQ) for processing transaction data and price updates would enable asynchronous processing. For example, the Etherscan transaction loader and Binance price loader could publish events when new data is fetched, and downstream services (e.g., a fee calculation service) could consume these events to perform necessary computations without blocking.

## 2. Availability

- **Docker and Docker Compose**: Using Docker for containerization ensures a consistent runtime environment and simplifies deployment across multiple servers. Docker Compose helps manage service dependencies like Redis and the API server, facilitating fast recovery and replication in case of a failure.
- API Rate Limiting and Caching: Given Etherscan and Binance have API rate limits, implementing caching with Redis and rate-limiting logic ensures that the system doesn't exceed limits and can handle request bursts by serving cached responses.

## 3. Reliability

- Data Redundancy in Redis and Message Queues: Redis provides low-latency data storage
  for transaction data and pricing, and using a message queue for asynchronous task
  processing ensures that transaction processing requests are not lost even if components go
  down temporarily.
- Fallback Logic for Missing Data: If transaction or price data is missing, the system can queue
  requests and notify the client to check back later. This approach allows the system to handle
  failures gracefully without dropping requests, enhancing reliability.
- Error Handling and Retry Mechanism: The system should include robust error handling for API interactions, especially with rate limits and connectivity issues. Implementing retry mechanisms and exponential backoff strategies ensures that temporary failures do not lead to permanent data loss or unhandled exceptions.

These design choices allow the system to handle large volumes of data reliably, adapt to demand variations, and maintain high availability for continuous operation.

## **Further Enhancements Possibilities**

## 1. Scalability

- **Database Partitioning and Sharding**: If the transaction or price data exceeds Redis's capacity or the overall storage requirements grow, database partitioning can help. Sharding based on transaction date or type would allow efficient distribution across multiple storage nodes, thus handling larger data volumes while maintaining query performance.
- Microservices Architecture: Dividing the system into smaller, focused microservices—such
  as one for transaction retrieval, another for fee calculation, and another for data
  transformation—enables independent scaling. Each microservice can then be scaled
  horizontally as required, allowing the system to handle increased loads without affecting
  overall performance.
- Auto-Scaling for API Instances: Setting up auto-scaling based on traffic allows the REST API
  to dynamically adjust to fluctuating workloads. During high-demand periods, more instances
  are deployed; during low-demand times, resources scale down to optimize costs.

## 2. Availability

- **Load Balancing**: The REST API endpoints can be scaled by deploying multiple instances behind a load balancer, ensuring that if one instance fails, the load balancer can redirect requests to healthy instances, enhancing availability.
- Failover and Replication in Redis: Configuring Redis with primary-replica replication
  ensures that if one instance fails, another replica can immediately take over. Redis Sentinel
  or Redis Cluster setups can further automate failover management to enhance the service's
  availability.

## 3. Reliability

- Data Persistence and Backups: While Redis offers quick access to recent data, for long-term reliability, essential data should also be stored in a persistent database (e.g., PostgreSQL, MongoDB). Routine backups of transaction data ensure that historical data is never lost and can be restored if the main storage fails.
- Monitoring and Alerting: Implementing robust monitoring and alerting is crucial. Tools like
  Prometheus and Grafana can track application metrics (e.g., request latency, error rates,
  memory usage). Automated alerts ensure rapid response to system issues, supporting
  reliability and proactive troubleshooting.