

An Efficient Algorithm for Optimal Routing Through Constant Function Market Makers

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Financial Cryptography 2023

tl;dr: It's all convex optimization

Routing (multi-DEX swaps, etc.) is a convex¹ optimization problem, so it can be *very efficiently* solved to *verifiable* global optimality.

¹when we ignore gas

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This talk: the 'very efficiently' part

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Outline

Background: Constant Function Market Makers

Formalizing Routing

When in Doubt, Take the Dual

Numerical Results

Wrap Up

Review: Constant Function Market Makers

- ▶ Most DEXs are implemented as *constant function market makers* (CFMMs)
- ▶ CFMMs are defined by their trading function $\varphi : \mathbb{R}_+^n \rightarrow \mathbb{R}$

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- ▶ Is concave and increasing
- ▶ Accepts trade $\Delta \rightarrow \Lambda$ if $\varphi(R + \gamma\Delta - \Lambda) \geq \varphi(R)$.

Most DEXs are CFMMs

- ▶ Geometric mean trading function (Balancer, Uniswap, etc...):

$$\varphi(R) = \left(\prod_{i=1}^n R_i^{w_i} \right)^{1/n}$$

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- ▶ Curve:

$$\varphi(R) = 1^T R - \alpha \prod_{i=1}^n R_i^{-1}$$

where $\alpha > 0$.

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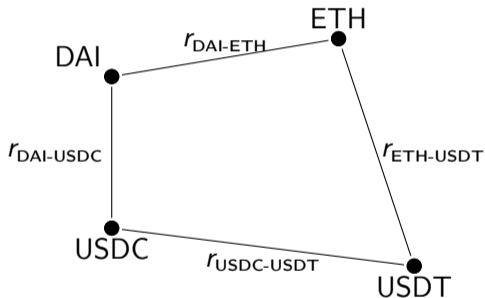
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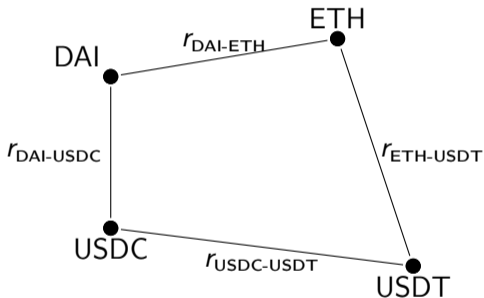
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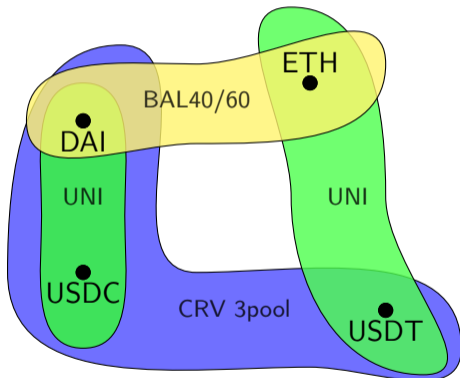
- ▶ Common representation: undirected graph with exchange rates



- ▶ But how to handle three pools? Multiple CFMMs?

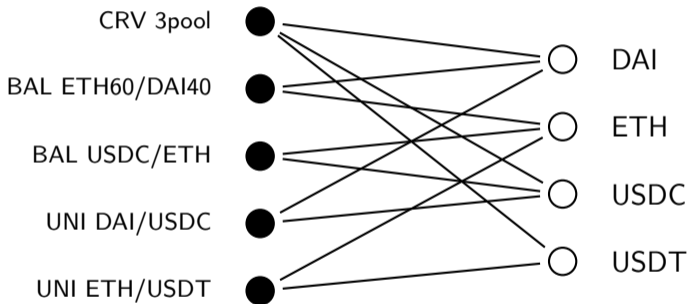
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- ▶ Good bookkeeping is essential!

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- ▶ Trade accepted if $\varphi_i(R_i + \gamma_i \Delta_i - \Lambda_i) \geq \varphi_i(R_i)$

Networks of CFMMs

- ▶ Matrices A_i map token's *local* index in CFMM i to global index, e.g., ,

Token	Local Index	Global Index
DAI	1	3
ETH	2	1

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- ▶ The overall net trade with the network is

$$\Psi = \sum_{i=1}^m A_i (\Lambda_i - \Delta_i)$$

Simplifying the Model

- ▶ We ignore gas fees
- ▶ We don't worry about transaction execution ordering
- ▶ We can return to these later...

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- ▶ Each individual CFMM is defined by trading constraints

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- ▶ Utility function U gives our satisfaction with the net trade
- ▶ We can also use U to encode constraints
- ▶ **Arbitrage:** Find the most profitable nonnegative net trade

$$U(\Psi) = c^T \Psi - \mathbb{I}(\Psi \geq 0)$$

- The vector c is a positive price vector
- Indicator function $\mathbb{I}(\Psi \geq 0) = 0$ if $\Psi \geq 0$ and $+\infty$ otherwise

Swaps: trade token i for j

- ▶ Goal: maximize **output of token j** given **fixed input of token i**
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- ▶ More generally, we can optimally purchase or liquidate a basket of tokens
- ▶ Capturing “arbitrage” opportunities as part of the swap

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- ▶ Strong duality \implies certificate of optimality (very cheap to check)

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- ▶ $\text{arb}_i(A_i^T \nu)$ is the **optimal arb** on CFMM i with global token prices ν
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- ▶ To add a DEX, **only need to define this arbitrage function**

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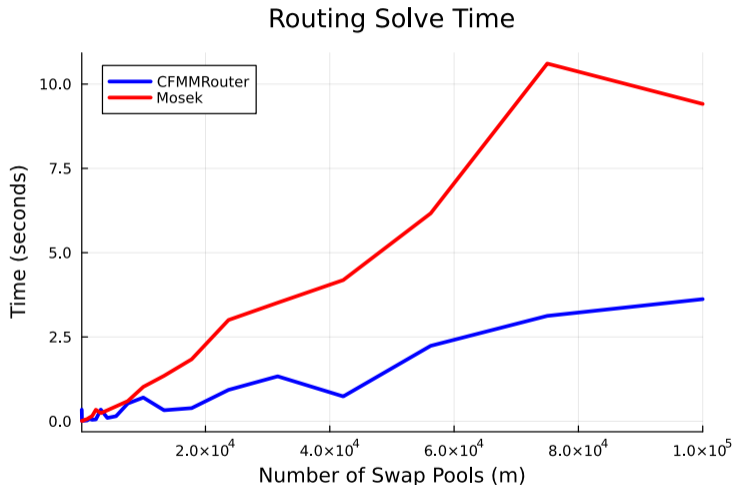
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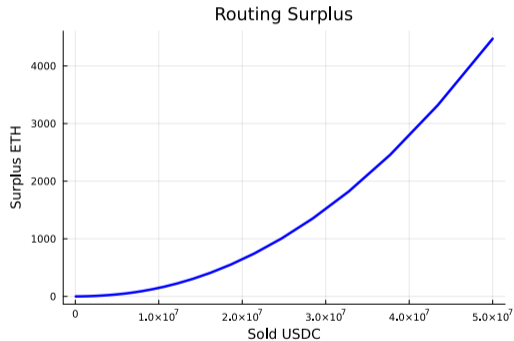
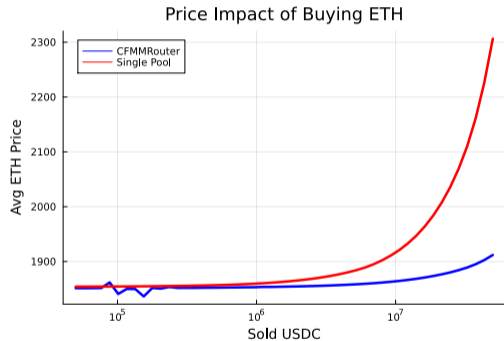
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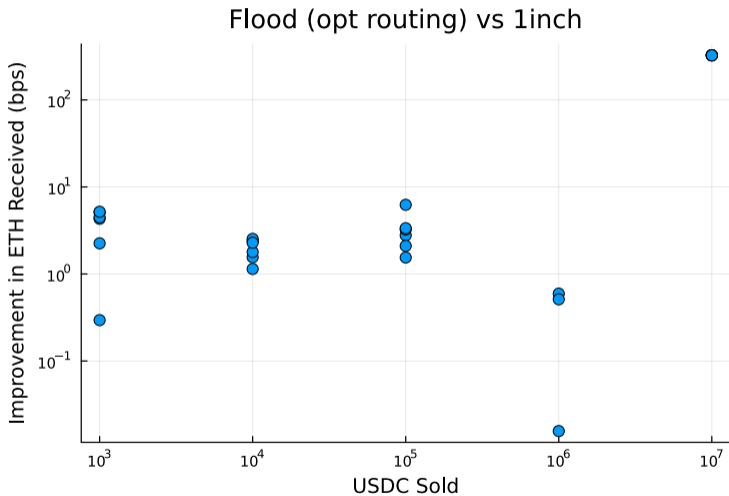
Our solver **CFMMRouter** is faster than commercial convex solvers



We see way less price impact for large txns



And it beats 1inch in production on Arbitrum (flood.bid)



Routing package on Github: `CFMMRouter.jl`

Flood in beta on Arbitrum: `flood.bid`

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- ▶ This means it can be solved quickly to global optimality
- ▶ And we can prove a feasible point is optimal
- ▶ We construct an efficient algorithm using convex duality
- ▶ This algorithm is implemented in `CFMMRouter.jl`

Future work includes expanding this framework

- ▶ Routing with gas fees (nonconvex—need good heuristics)
- ▶ Routing through liquidations
- ▶ Routing with probabilistic constraints when TXs may fail (e.g., cross-chain)

For more info, check out our paper & `CFMMRouter.jl`



Paper

Thank you!

Theo Diamandis

`tdiamand@mit.edu`

Appendix

Optimality conditions

For the primal problem

$$\begin{aligned} & \text{maximize} && U(\Psi) \\ & \text{subject to} && \Psi = \sum_{i=1}^m A_i(\Lambda_i - \Delta_i) \\ & && \varphi_i(R_i + \gamma_i \Delta_i - \Lambda_i) \geq \varphi_i(R_i), \quad i = 1, \dots, m \\ & && \Delta_i \geq 0, \quad \Lambda_i \geq 0, \quad i = 1, \dots, m \end{aligned}$$

The optimality conditions are

$$\lambda_i \gamma_i \nabla \varphi_i(R_i + \gamma_i \Delta_i^* - \Lambda_i^*) \leq A_i^T \nu^* \leq \lambda_i \nabla \varphi_i(R_i + \gamma_i \Delta_i^* - \Lambda_i^*), \quad i = 1, \dots, m$$

Routing with gas fees

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- ▶ **Issue:** this problem is nonconvex...
- ▶ ...but we have good heuristics for this type of problem

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- ▶ This is relatively easy: simple algorithm & closed form solution within a tick
- ▶ **Answer 2:** The φ constraint is a bit of a lie...
- ▶ Only need a convex reachable reserve set (or, equivalently, trading set):

$$\varphi(R + \gamma\Delta - \Lambda) \geq \varphi(R) \iff R + \gamma\Delta - \Lambda \in S(R)$$