A piecewise linear approximation of C(f) leads also to an approximation of the success probability P(f) of [3]

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March 13, 2022

Abstract

Solving reliable payment flows on the Lightning network with the methods proposed in [3] involves maximizing the success probability P(f) at best optimal. In order to solve the optimization problem it is reformulated to a minimization problem with convex but non-linear cost function C(f). When for example optimal piecewise linear approximation (PWL) with N linear segments [2] is applied to C(f), it can be solved more efficiently with established methods that require linearity¹. However, the introduced approximation error ϵ can lead to sub-optimality in C(f)and P(f). We show, how such an approximation error for C(f) reflects on the original objective P(f) (in the worst case) and that (in theory) the approximation of C(f) leads also to an approximation of P(f) that can be improved by improving the PWL of C(f).

1 Notation

Lets use the following notation:

- $C(f) := \sum_{e \in E} -\log \left(P_e(X_e \ge f_e) \right) \dots$ cost function of the min-cost flow problem of [3]
- $c_e(f_e) := -\log(P_e(X_e \ge f_e)) \dots$ (convex) summand of the cost function for a given channel $e \in E$ of [3]
- $g_e(f_e) \dots$ minimax solution that minimizes the error $\epsilon := \log(\delta), \delta \ge 1$ of the piecewise linear approximation of $c_e(f_e)$ with N elements as proposed in [2], i.e. $\log(\delta) = \max_{0 \le P_e \le 1} |g_e(f_e) c_e(f_e)|$
- $\tilde{C}(f) := \sum_{e \in E} g_e(f_e) \dots$ approximation of C(f) with lower and upper bounds on approximation error
- $P(f) := \prod_{e \in E} P_e(X_e \ge f_e) \dots$ success probability of entire flow of [3].
- $\tilde{P}(f) := \exp(-\tilde{C}(f)) \dots$ approximation of P(f) with lower and upper bounds on approximation error

2 Application of PWL to $c_e(f_e), \forall e \in E$

2.1 Deduce bounds for $\tilde{C}(f)$

By the definition of the minimax solution, i.e. $log(\delta) = \max_{0 \le P_e \le 1} |g_e(f_e) - c_e(f_e)|$, the following condition holds true:

$$c_e(f_e) - \log(\delta) \le g_e(f_e) \le c_e(f_e) + \log(\delta)$$

Applying these inequalities to C(f) we can establish the following approximation bounds for $\tilde{C}(f)$:

$$\sum_{e \in E} \left(-\log\left(P_e(X_e \ge f_e)\right) - \log(\delta) \right) \le \tilde{C}(f) \le \sum_{e \in E} \left(-\log\left(P_e(X_e \ge f_e)\right) + \log(\delta) \right)$$

¹See for example the implementations developed for [3]: https://github.com/renepickhardt/mpp-splitter/blob/master/ MinimalLinearizedmincostflowexampleforMPP.ipynb

2.2 Upper bound for $\tilde{P}(f)$

We start with the lower bound of $\tilde{C}(f)$:

$$\sum_{e \in E} \left(-\log \left(P_e(X_e \ge f_e) \right) - \log(\delta) \right) \le \tilde{C}(f)$$

This can be reformulated to:

$$\sum_{e \in E} \left(-\log \left(\delta P_e(X_e \ge f_e) \right) \right) \le \tilde{C}(f)$$

Multiplying the inequality with (-1) leads to:

$$\sum_{e \in E} \left(\log \left(\delta P_e(X_e \ge f_e) \right) \right) \ge -\tilde{C}(f)$$

Multiplying the inequality with exp() leads to:

$$\delta^{|E|} P(f) = \delta^{|E|} \prod_{e \in E} P_e \left(X_e \ge f_e \right) \ge \tilde{P}(f)$$

2.3 Lower bound for $\tilde{P}(f)$

We proceed with the upper bound of $\tilde{C}(f)$:

$$\tilde{C}(f) \le \sum_{e \in E} \left(-\log\left(P_e(X_e \ge f_e)\right) + \log(\delta) \right)$$

Multiplying the inequality with (-1) leads to:

$$-\tilde{C}(f) \ge \sum_{e \in E} \left(\log \left(P_e(X_e \ge f_e) \right) - \log(\delta) \right)$$

Multiplying the inequality with exp() leads to:

$$\tilde{P}(f) \ge \frac{\prod_{e \in E} P_e \left(X_e \ge f_e \right)}{\delta^{|E|}} = \frac{P(f)}{\delta^{|E|}}$$

2.4 Deduce bounds for P(f)

The previous bounds can be reformulated to:

$$\frac{\tilde{P}(f)}{\delta^{|E|}} \le P(f) \le \delta^{|E|} \tilde{P}(f)$$

3 Application of PWL to C(f) directly

In [3] it is shown, that C(f) is convex on the entire domain. Hence, the same arguments of previous sections can be applied to C(f) directly. For an PWL $\hat{C}(f)$ of C(f) the following condition holds true:

$$C(f) - \log(\delta) \le \hat{C}(f) \le C(f) + \log(\delta)$$

Multiplying the inequality with $-\exp()$ leads to:

$$\delta P(f) \ge \hat{P}(f) \ge \frac{P(f)}{\delta}$$

This can be reformulated to:

$$\frac{\hat{P}(f)}{\delta} \le P(f) \le \delta \hat{P}(f)$$

2 Preprint of preliminary work

4 Conclusions

- For $\delta \to 1^+$, $\tilde{P}(f)$ approximates P(f) (and vice versa).
- For $\delta \to 1^+$, $\tilde{C}(f)$ approximates C(f) (and vice versa).

5 Future work

- Explore [1] further to find **unknown** optimal or near-optimal N for a desired approximation error ϵ .
- Explore further literature besides [2] on piecewise linear approximation.
- Explore optimization literature on min-cost flow problems with uncertain capacities in more detail.
- An optimal solution f_C^* to $\tilde{C}(f)$ should also lead to a near-optimal solution of P(f) with some deducible error. Our intuition says, this should be the case given the problem properties. However, it should be argued properly.
- Is the approach with **optimal** piecewise linear approximation for a desired approximation quality for P(f) even practical and allows decent run-times?
- Finding a decent N and a corresponding piecewise linear approximation with desired approximation error can be calculated offline / cached.

6 Acknowledgements

We thank Rene Pickhardt for reviewing this preliminary work.

References

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