

SOLACE Seminars

Prediction-based Coflow Scheduling in Datacenter Networks

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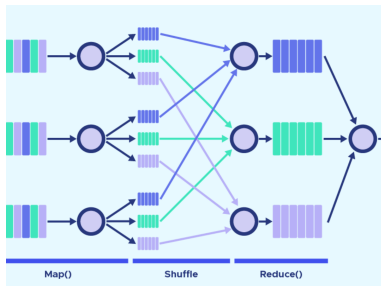
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INTRODUCTION

Context

- ▶ Distributed computing frameworks: [Hadoop MapReduce](#), [Apache Spark](#)
- ▶ Massive [data transfers](#) in datacenter networks (e.g., shuffle phase)
 - ▶ For some workloads, they can account for more than 50% of job completion times



- ▶ **Coflow:** set of concurrent flows related to a common task

Coflow scheduling

- ▶ Minimization of average **Coflow Completion Time** (CCT)
- ▶ **Clairvoyant** setting
 - ✓ Source and destination ports as well as the precise volume of each flow are revealed upon the arrival of a coflow.
 - ✓ NP-hard, inapproximable below a factor 2
 - ✓ Efficient approximation algorithms, e.g., **Varys** or **Sincronia**¹
- ▶ **Non-clairvoyant** setting
 - ✓ Flow sizes remains unknown
 - ✓ Scheduling schemes generalizing the *LAS* (e.g., **Aalo**) or *RR* (e.g., **BlindFlow**) scheduling disciplines.

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☞ M. Shafiee et al., [An improved bound for minimizing the total weighted completion time of coflows in datacenters](#), IEEE/ACM Trans. Netw., vol. 26, no. 4, 2018.

☞ S. Agarwal et al., [Sincronia: Near-optimal network design for coflows](#). in Proc. ACM SIGCOMM, 2018.

☞ M. Chowdhury et al., [Near optimal coflow scheduling in networks](#), in Proc. ACM SPAA, 2019.

Contributions

- ▶ **ML predictions** are revealed to the coflow scheduler
 - ✓ Actual flow sizes remain unknown and predictions are **unreliable**
 - ✓ How to exploit predictions for coflow scheduling? Is it even advisable to do so?
- ▶ Approximation ratio of **Sincronia** as a function of the **prediction error**
- ▶ A **Consistent** and **robust** prediction-based coflow scheduling algorithm.

PROBLEM FORMULATION AND EXISTING WORKS

System model and notations

- ▶ **Big-Switch model**: capacity b_ℓ for port ℓ .
- ▶ **Offline** setting.
- ▶ Set $\mathcal{C} = \{1, 2, \dots, n\}$ of coflows
 - ✓ Coflow k is a collection F_k of flows, where flow j has size $v^{k,j}$
 - ✓ $F_{k,\ell}$ is the set of flows of coflow k which use port ℓ
 - ✓ C_k denotes the CCT of coflow k
- ▶ **Problem formulation**

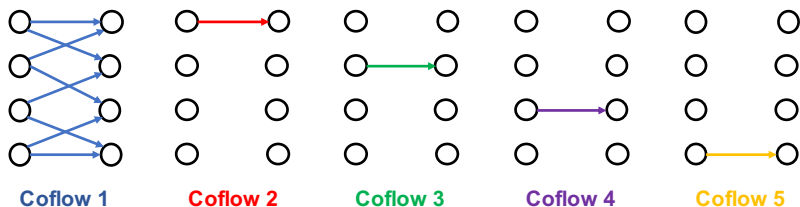
$$\min_r \sum_{k \in \mathcal{C}} C_k \quad (\text{P1})$$

$$\text{s.t.} \quad \sum_{k \in \mathcal{C}} \sum_{j \in F_{k,\ell}} r^{k,j}(t) \leq b_\ell, \quad \forall \ell \in \mathcal{L}, \forall t \in \mathcal{T}, \quad (1)$$

$$\int_0^{C_k} r^{k,j}(t) dt \geq v^{k,j}, \quad \forall j \in F_k, \forall k \in \mathcal{C}, \quad (2)$$

Example

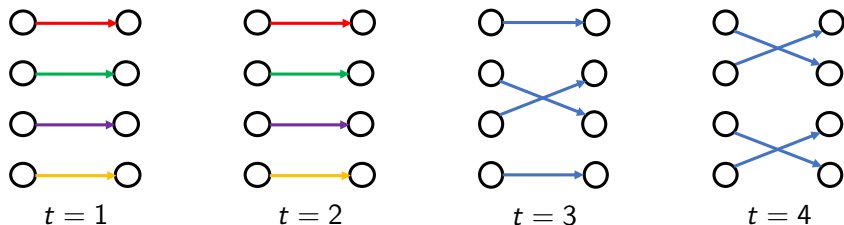
- ▶ All fabric ports have the same normalized bandwidth of 1
- ▶ All flows of coflow 1 have volume 1
- ▶ All other flows have volume $2 + \epsilon$



- ▶ The goal is to allocate flow rates so as to minimize $(C_1 + C_2 + C_3 + C_4 + C_5)/5$.

Example – Clairvoyant offline optimum

- ▶ Time-indexed MILP formulation for the clairvoyant setting²



- ▶ Average CCT is $OPT = (4 + 4 \times 2)/5 = 2.4$

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² Y. Magnouche et al., [Branch-and-benders-cut algorithm for the weighted coflow completion time minimization problem](#), INOC 2022.

Non-clairvoyant coflow scheduling – BlindFlow

- ▶ Round Robin allocation on port ℓ : $r_\ell(t) = b_\ell/n_\ell(t)$
- ▶ Generalized RR allocation:

$$r^{k,j}(t) = \min \{r_i(t), r_o(t)\} = \frac{1}{\max \{1/r_i(t), 1/r_o(t)\}}$$

for ongoing flow $j \in F_k$ with ingress/egress ports i and o .

- ▶ BlindFlow rate allocation³: $r^{k,j}(t) = \frac{1}{1/r_i(t)+1/r_o(t)}$

Theorem

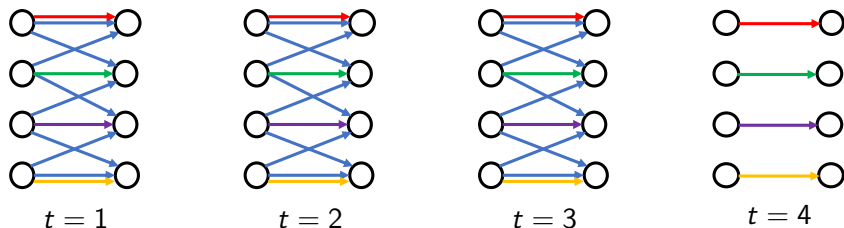
The rate allocation of BlindFlow is feasible and $8 \times p$ approximate, where $p = \max_{k \in \mathcal{C}} |F_k|$ is the maximum number of flows that any coflow can have.

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³ A. Bhimaraju, D. Nayak and R. Vaze, [Non-clairvoyant scheduling of coflows](#), WiOpt 2020, 2020.

Example – Generalized RR allocation

- ▶ All fabric ports have the same normalized bandwidth of 1
- ▶ Flows of coflow 1 have volume 1, all others have volume 2



- ▶ Average CCT is $(3 + 4 \times 4)/5 = 3.8 \approx 1.6 \times OPT$
($8 \times p = 64$)

Clairvoyant coflow scheduling – Sincronia

- ▶ Transport layer may not be able to enforce an arbitrary per-flow rate allocation.
- ▶ Sincronia **orders the coflows** in some appropriate order, and leverage **priority forwarding** mechanisms
 1. **σ -order**: coflow $\sigma(n)$ has priority over coflow $\sigma(n + 1)$
 2. **Greedy rate allocation**: a flow is blocked iff ingress/egress port is busy serving a higher-priority flow

Clairvoyant coflow scheduling – Sincronia σ -order

- ▶ CCT of coflow k at port ℓ in isolation: $p_{\ell,k} = \sum_{j \in F_{k,\ell}} v_{kj} / b_\ell$
- ▶ Method for computing the σ -order:

$$\text{Min } \sum_{k \in \mathcal{C}} C_k \quad (\text{P3-Primal})$$

s.t

$$\sum_{k \in S} p_{\ell,k} C_k \geq f_\ell(S), \quad \ell \in \mathcal{L}, S \subseteq \mathcal{C},$$

$$C_k \geq 0, \quad k \in \mathcal{C},$$

$$\text{Max } \sum_{\ell \in \mathcal{L}} \sum_{S \subseteq \mathcal{C}} f_\ell(S) y_{\ell,S} \quad (\text{P3-Dual})$$

s.t

$$\sum_{S: k \in S} \sum_{\ell \in \mathcal{L}} p_{\ell,k} y_{\ell,S} \leq 1, \quad k \in \mathcal{C},$$

$$y_{\ell,S} \geq 0, \quad \ell \in \mathcal{L}, S \subseteq \mathcal{C}.$$

$$\text{where } f_\ell(S) = \frac{1}{2} \sum_{k \in S} (p_{\ell,k})^2 + \frac{1}{2} \left(\sum_{k \in S} p_{\ell,k} \right)^2.$$

- ▶ Problem P3-Primal is a relaxation of the original coflow scheduling problem

Clairvoyant coflow scheduling – Sincronia σ -order

► Sincronia primal-dual algorithm

- 1: Initialize all dual variables $y_{\ell,S}$ to 0 and set $w_k = 1$ for all $k \in \mathcal{C}$
- 2: $S \leftarrow \mathcal{C}$
- 3: **for** $t = n \dots 1$ **do**
- 4: $b \leftarrow \operatorname{argmax}_{\ell \in \mathcal{L}} \sum_{k \in S} p_{\ell,k}$ ▷ Bottleneck port
- 5: $k^* \leftarrow \operatorname{argmin}_{k \in S} \left(\frac{w_k}{p_{b,k}} \right)$ ▷ Coflow with largest weighted proc. time
- 6: $C_{k^*} \leftarrow \sum_{k \in S} p_{b,k}$ and $y_{b,S} \leftarrow \frac{w_{k^*}}{p_{b,k^*}}$ ▷ Set primal and dual variables
- 7: $w_k \leftarrow w_k - w_{k^*} \frac{p_{b,k}}{p_{b,k^*}}$ for all $k \in S$ ▷ Update coflow weights
- 8: $\sigma(t) \leftarrow k^*$ ▷ Set priority of coflow k^*
- 9: $S \leftarrow S \setminus \{k^*\}$ ▷ Remove k^* from the set of unscheduled coflows
- 10: **end for**

Theorem

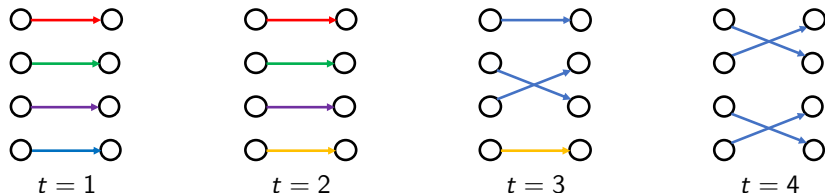
Sincronia provides a feasible solution to problem P3-Primal whose cost is at most $2 \times$ the optimal cost. As the Greedy rate allocation is 2-optimal, Sincronia achieves an average CCT within $4 \times$ of the optimal one.

Example – Sincronia

► σ -order

t	b	$\sigma(t)$	$\{w_1, w_2, w_3, w_4, w_5\}$	S
–	–	–	$\{1, 1, 1, 1, 1\}$	$\{1, 2, 3, 4, 5\}$
5	4	5	$\{\epsilon/(2 + \epsilon), 1, 1, 1, 0\}$	$\{1, 2, 3, 4\}$
4	3	1	$\{0, 1, 1, 1 - \epsilon/2, 0\}$	$\{2, 3, 4\}$
3	3	4	$\{0, 1, 1, 0, 0\}$	$\{2, 3\}$
2	2	3	$\{0, 1, 0, 0, 0\}$	$\{2\}$
1	1	2	$\{0, 0, 0, 0, 0\}$	\emptyset

► Greedy rate allocation with $\sigma = \{2, 3, 4, 1, 5\}$



► Average CCT is $(4 + 3 \times 2 + 3)/5 = 2.6 \approx 1.08 \times OPT$

COFLOW SCHEDULING WITH PREDICTIONS

Sincronia with predictions

- ▶ Sincronia is ran with **predictions** $\hat{v}^{k,j} = v^{k,j} + \Delta v^{k,j}$, where $\Delta v^{k,j}$ represents the **prediction error**
- ▶ Predicted transmission time of coflow $k \in \mathcal{C}$ on port $\ell \in \mathcal{L}$

$$\hat{p}_{\ell,k} = \sum_{j \in F_{k,\ell}} \frac{\hat{v}^{k,j}}{b_{\ell}} = p_{\ell,k} + \eta_{\ell,k},$$

- ▶ With $\mu_{min} = \min_{\ell,k} \left(\frac{\hat{p}_{\ell,k}}{p_{\ell,k}} \right)$ and $\mu_{max} = \max_{\ell,k} \left(\frac{\hat{p}_{\ell,k}}{p_{\ell,k}} \right)$,

$$\mu_{min} p_{\ell,k} \leq \hat{p}_{\ell,k} \leq \mu_{max} p_{\ell,k}, \quad \text{for all } \ell \text{ and } k.$$

Sincronia with predictions

Theorem

Scheduling coflows in the order determined by Sincronia with predictions as inputs yields an average CCT which is at most $\min \left\{ 4 \times \left(\frac{\mu_{max}}{\mu_{min}} \right)^2, 2n \right\}$ the optimal one.

- ▶ The first upper bound depends on the prediction error, but the second one not (robustness).
- ▶ **Example:** if the relative prediction error on flow sizes is at most 50%, then $\mu_{min} \geq \frac{1}{2}$ and $\mu_{max} \leq \frac{3}{2}$, so that the performance guarantee is $\min\{36, 2n\}$.

A consistent and robust prediction-based algorithm

- ▶ Run Sincronia and RR in parallel

- ▶ Sincronia uses predictions to schedule coflows in the fabric over a fraction λ of time,
- ▶ RR schedules the coflows the rest of the time
- ▶ The resulting rate allocation is

$$r^{k,j}(t) = \lambda \times r_{SP}^{k,j}(t) + (1 - \lambda) \times r_{RR}^{k,j}(t)$$

Theorem

Running in parallel Sincronia with predictions and RR yields an algorithm with *competitive ratio* $\min \left(\frac{4}{\lambda} \left(\frac{\mu_{max}}{\mu_{min}} \right)^2, \frac{2}{\lambda} n, \frac{8p}{1-\lambda} \right)$

- ▶ The algorithm is $\min \left\{ \frac{2}{\lambda} n, \frac{8p}{1-\lambda} \right\}$ -robust and $\frac{4}{\lambda}$ -consistent

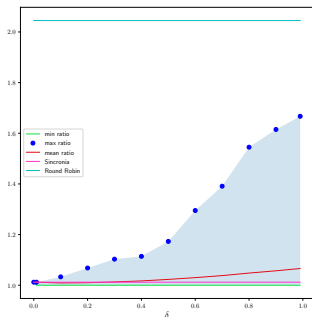
NUMERICAL RESULTS

Random Instances

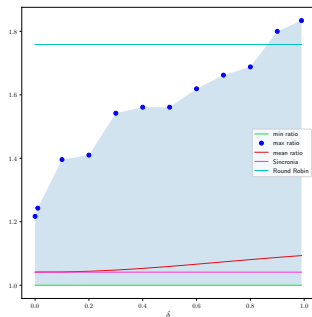
- ▶ **Random instance generation**
 - ▶ Number of coflows, number of ports and probability of a flow between two ingress/egress ports are given as inputs.
 - ▶ Flow volumes follow a (truncated) Gaussian distribution.
- ▶ **Predictions**
 - ▶ $\hat{v}^{k,j} = u^{k,j} \times v^{k,j}$ where $u^{k,j} \stackrel{iid}{\sim} U[1 - \delta, 1 + \delta]$.
 - ▶ 10,000 predictions for each instance and each value of $\delta \in \{0, 0.01, 0.1, \dots, 0.9, 0.99\}$.

Comparison against the clairvoyant optimum

- ▶ Instances with 6 coflows and 6 ports (10,000 predictions)



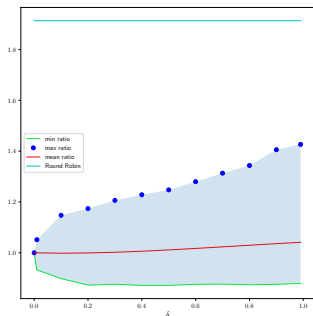
(a) One instance



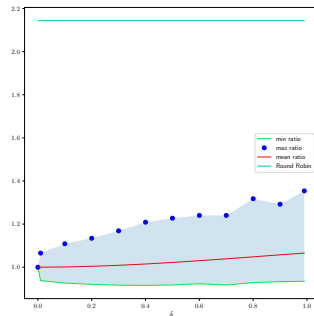
(b) 1,000 instances

Comparison against the clairvoyant Sincronia

- ▶ 100 instances with 10 ports and 15 or 30 coflows (10,000 predictions)



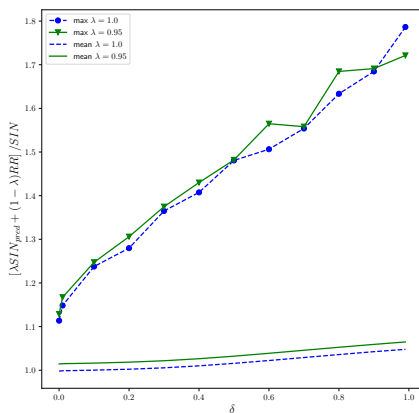
(a) 15 coflows



(b) 30 coflows

Combining Sincronia with predictions and RR

- ▶ 200 instances with 6 ports and 6 coflows (20,000 predictions)



Max and average values of $\frac{\lambda SIN_{pred} + (1-\lambda)RR}{SIN}$ for $\lambda = 0.95$ and $\lambda = 1.0$

CONCLUSION

Conclusion

- ▶ Coflow scheduling with **unreliable predictions** on flow sizes
- ▶ **Sincronia with predictions as inputs**
 - ✓ Approximation ratio
 - ✓ Sincronia performs well even when feed with terrible predictions
- ▶ No clear benefits in combining Sincronia with predictions and a RR rate allocation
- ▶ Operating Sincronia with ML predictions could be an efficient solution in practical scenarios

Questions?