# Optimization of a Distributed Storage Architecture under Uncertain Demand A Study in Fast Flow Algorithms

Paul Beaujean\*† Éric Gourdin†

\*ENSIIE-MPRO

†Orange Labs

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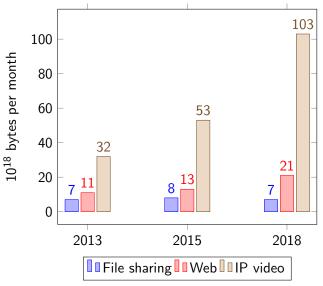
#### Context

The rise of IP video Content Delivery Network

### Multicommodity Flow

Column generation FPTAS

### Context: The rise of IP video



▶ IP video: 80% of all IP traffic by 2020.

Source: CISCO Visual Networking Index 2014

### Content Delivery Network

A Content Delivery Network is a distributed storage architecture. Provides content to users by caching it close to where it is requested.

Less upstream bandwidth consumption.

# Content Delivery = Multicommodity Flow

Insert a beautiful picture of multiple servers delivering contents to multiple clients.

### Fractional Multiflow is in P

No combinatorial algorithm known to solve multiflow.

### Polynomial-size LP with edge formulation

$$\begin{aligned} &\max \sum_{s,t \in K} \sum_{a \in \delta^+(s)} f_a^{s,t} \\ &\text{s.t.} \sum_{s,t \in K} f_a^{s,t} \leq c_a, \ \forall a \in A \\ &\sum_{s,t \in K} \sum_{a \in \delta^-(v)} f_a^{s,t} = \sum_{s,t \in K} \sum_{a \in \delta^+(v)} f_a^{s,t}, \ \forall v \in V \setminus \{s,t\} \\ &\sum_{a \in \delta^-(s)} f_a^{s,t} = 0, \ \forall s \in S \\ &f \in \mathbb{R}_+^{|A \times K|} \end{aligned}$$

can be solved in polynomial time with an IPM  $\implies Multiplication \in P$ 

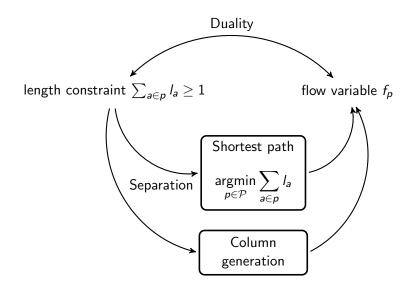
# Can it be solved on large instances?

### Implicit exponential-size path formulation

$$(\Pi) \begin{cases} \max & \sum_{p \in \mathcal{P}} f_p \\ \text{s.t.} & \sum_{p \ni a} f_p \le c_a, \ \forall a \in A \ (I_a) \\ & f \in \mathbb{R}_+^{|\mathcal{P}|} \end{cases}$$

$$(\Delta) \begin{cases} \min & \sum_{a \in A} c_a I_a \\ \text{s.t.} & \sum_{a \in p} I_a \ge 1, \ \forall p \in \mathcal{P} \ (f_p) \\ & I \in \mathbb{R}_+^{|\mathcal{A}|} \end{cases}$$

## Column generation



# Primal-dual approximation algorithm

### Fully Polynomial Time Approximation Scheme

An algorithm that returns a solution of value within  $\epsilon$  of the optimal value:

- ▶ in time bounded by a polynomial in the instance size,
- ▶ in time bounded by a polynomial in  $\epsilon^{-1}$ .

There exists combinatorial algorithms that achieve such guarantees.

### How to design one?

- based on the multiplicative weights algorithm
- reuse ideas from column generation

# Multiplicative weights

#### Background

Discovered several times:

- ▶ 1950's: machine learning
- ▶ 1970's: continuous optimization
- ▶ 2000's: design of competitive online algorithms
- ▶ 2010's: approximation algorithms for SDP

#### Definition

Given a finite set of actions with bounded gain

$$A = \{ a \mid g_a^t \in [-1, 1] \}$$

Associate weights

$$orall a \in \mathcal{A} \ egin{cases} \lambda_a^1 &= 1 \ \lambda_a^{t+1} &= \lambda_a^t (1 + \epsilon \ g_a^t) \end{cases}$$

# A surprising result

### The multiplicative weights algorithm

► At round t, choose action a with probability  $\frac{\lambda_a^t}{\sum_a \lambda_a^t}$ 

### has a guaranteed gain of

$$G \geq G_a - \epsilon |G_a| - \frac{\ln |A|}{\epsilon}, \forall a \in A$$

$$G = \sum_t \mathbb{E}(g^t)$$
 expected gain of the algorithm  $G_a = \sum_t g_a^t$  gain of action  $a$ 

# Mapping multiplicative weights concepts to multiflow

### Mapping concepts

### Iterative primal-dual algorithm

Successively adds flow to the graph

#### Choosing arcs by constraint separation

Instead of choosing arcs randomly:

- ightharpoonup compute shortest path w.r.t. the length  $I_a^t$
- all arcs on that path receive maximum feasible flow
- probabilities are set a posteriori

# Combining gain guarantee and properties of flows

### Using the gain guarantee

$$G \geq (1-\epsilon)G_* - rac{\log m}{\epsilon}$$

#### and simple flow considerations

- $G_*$   $G_*$
- ▶  $F/F^* \ge G$ : approximation ratio bounds the expected gain

#### results in

- ▶ If  $G_* = \log m \ \epsilon^{-2}$  then  $F/G_* \ge (1-2\epsilon)F^* \leftarrow \mathsf{AS}$
- ▶ Runtime:  $O(km^2 \log m \epsilon^{-2}) \leftarrow \text{FPT}$

# Numerical experiments

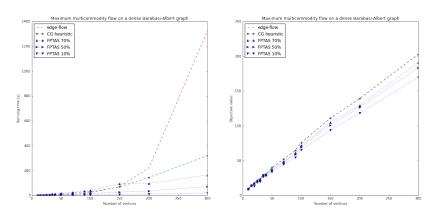


Figure: Performance of LP, column generation, and FPTAS

#### Conclusion

### Highlights

- CDN design naturally involves multiflows
- Approximation: an interesting alternative to exact algorithms

#### **Achievements**

- Studied in depth a theoretical problem
- Implemented a state-of-the-art algorithm
- Integrated it in an Operations Research library

#### Perspectives

- Studying the matrix multiplicative weights algorithm
- Application to solving SDP approximatively

during a PhD at Orange Labs and Université Paris-Dauphine