

# **ELE539A: Optimization of Communication Systems**

## **Lecture 13: Network Utility Maximization**

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## Lecture Outline

- Resource allocation problems
- Network utility maximization
- Dual decomposition and canonical distributed algorithm
- Kelly's decomposition and primal algorithm

## Well-Known: Network Flow Problem

Minimize a **linear cost** subject to **linear flow constraints**

Classical **linear programming** based methods

Includes many special cases:

- Multicommodity flow problems (max flow, min cut...)
- Transportation and assignment problems
- Shortest path and spanning tree problems

**Limitations** in modelling nonlinearity in Internet and wireless networks

## Rate Allocation Problem

**Elastic traffic:** applications modify their data transfer rates according to available bandwidth in communication networks

- TCP traffic over Internet TCP/IP suite
- ABR traffic over ATM networks

Q: How to **share available bandwidth among competing flows** of elastic traffic?

Mathematical model of **rate control** and **distributed algorithms** to understand

- Equilibrium properties: efficiency and fairness
- Dynamic properties: local and global stability

## Resource Allocation Problem

Application-level view: what's user **utility**?

Utility as function of QoS parameters: throughput, latency, jittering, distortion, energy efficiency...

**Objective:** maximize sum of user utilities

Network **constraints:**

- Link capacity, total power...
- Medium access possibilities
- Routing possibilities

Constrained nonlinear optimization problem formulations

## Basic Model

Communication networks with  $L$  links, each with capacity  $c_l$

Sources (end user):  $S$  of them, each emitting a flow with transmission rate  $x_s$

Fixed single-path routing: source  $s$  uses links  $l \in L(s)$

Routing matrix  $\mathbf{R}$ : 0 – 1 matrix with  $R_{ls} = 1$  iff  $l \in L(s)$

Linear flow constraint on rates:  $\mathbf{R}\mathbf{x} \preceq \mathbf{c}$

Each source has utility  $U_s(x_s)$ , an increasing, strictly concave, twice differentiable function of  $x_s \geq 0$

Objective: maximize network utility (sum of source utilities)

Economics interpretation: Dual variables as feedback congestion price

## NUM Framework

Basic version (A monotropic program):

$$\begin{aligned} & \text{maximize} && \sum_s U_s(x_s) \\ & \text{subject to} && \sum_{s:l \in L(s)} x_s \leq c_l, \quad \forall l, \\ & && \mathbf{x} \succeq 0 \end{aligned}$$

Current applications:

- **Reverse engineering**: TCP congestion control and Internet rate allocation
- **Forward engineering**: Network resource allocation, e.g., power control
- **Layering as optimization decomposition**: TCP/IP/MAC/PHY interactions

Major approaches:

- **Optimization-theoretic**: distributed optimal solution algorithm
- **Game-theoretic**: Nash equilibrium characterization

## Fairness

Family of utility functions parameterized by  $\alpha \geq 0$ :

$$U^\alpha(x) = \begin{cases} (1 - \alpha)x^{1-\alpha}, & \text{if } \alpha \neq 1, \\ \log x, & \text{otherwise} \end{cases}$$

$\alpha = 1$ : proportional fair

$\alpha = 2$ : harmonic-mean fair

$\alpha = \infty$ : maxmin fair

Feasible  $\mathbf{x}$  is **proportionally fair** (per unit charge) if for any other feasible  $\mathbf{x}'$ ,

$$\sum_s w_s \frac{x'_s - x_s}{x_s} \leq 0$$



## Lecture 15: TCP Congestion Control Solving NUM

Different **source algorithms** update **primal variables** (source rates) for different utilities:

- TCP Vegas: log utilities
- TCP Tahoe: arctan utilities

Different **queue management** update **dual variables** (link prices):

- FIFO
- RED

Rigorous and significant **implications** to **equilibrium** properties of efficiency, fairness, stability, delay of rate allocation

## NUM Extensions

### Utility function:

- Nonconcave
- Coupled
- Not a function of rate
- Nonsmooth

### Constraint:

- Nonlinear constraints
- Integer constraints

### Pricing:

- Per-user differential pricing

## G.NUM

Generalized NUM:

Minimizing **additive** objective over **additive** constraints

- Compared to NFP: **nonlinear** objectives
- Compared to MP (Basic NUM): **nonlinear** constraints
- Compared to separable convex optimization: **coupling, nonconvexity**
- Compared to general market equilibrium theory: new questions on **distributed solution and dynamic behavior**

A special case of Generalized NUM: **Geometric Programming**

## Lecture 16: Layering as Optimization Decomposition

- Network
- Generalized NUM
- Layers
- Decomposed subproblems
- Interfaces
- Functions of primal or dual variables
- Layering
- Decompositions

## Lecture 16: Layering as Optimization Decomposition

- How to layer? How not to layer?
- Separation theorem?
- Both reverse engineering and forward engineering
- Systematic study of architectural principles and tradeoffs of layering
- Vertical and horizontal decomposition

How many different ways to decompose?

- Infinite!
- How you write down the problem constraints decomposition possibilities!

## Lecture 19: Wireless NUM

Rate allocation constraint set **depends** on

- Time-varying channel condition
- Adaptive resource allocation, e.g., power control

**Joint** rate allocation and power control in:

- Cellular: single cell downlink
- Cellular: single cell uplink
- Cellular: multiple cells
- Ad hoc wireless multi-hop networks
- End-to-end hybrid networks

Many other **variations**: scheduling, beamforming, base station assignment...

## Dual Decomposition

Basic NUM:

Convex optimization with zero duality gap

Lagrangian decomposition:

$$\begin{aligned} L(\mathbf{x}, \boldsymbol{\lambda}) &= \sum_s U_s(x_s) + \sum_l \lambda_l \left( c_l - \sum_{s:l \in L(s)} x_s \right) \\ &= \sum_s \left[ U_s(x_s) - \left( \sum_{l \in L(s)} \lambda_l \right) x_s \right] + \sum_l c_l \lambda_l \\ &= \sum_s L_s(x_s, \lambda^s) + \sum_l c_l \lambda_l \end{aligned}$$

Dual problem:

$$\begin{aligned} &\text{minimize} && g(\boldsymbol{\lambda}) = L(\mathbf{x}^*(\boldsymbol{\lambda}), \boldsymbol{\lambda}) \\ &\text{subject to} && \boldsymbol{\lambda} \succeq 0 \end{aligned}$$

## Canonical Distributed Algorithm

Source algorithm:

$$x_s^*(\lambda^s) = \operatorname{argmax} [U_s(x_s) - \lambda^s x_s], \quad \forall s$$

- Selfish **net utility maximization** locally at source  $s$

Link algorithm (gradient or subgradient based):

$$\lambda_l(t+1) = \left[ \lambda_l(t) - \alpha(t) \left( c_l - \sum_{s:l \in L(s)} x_s(\lambda^s(t)) \right) \right]^+, \quad \forall l$$

- Balancing supply and demand through **pricing**

Certain choices of step sizes of **distributed algorithm** guarantee convergence to **globally optimal**  $(\mathbf{x}^*, \boldsymbol{\lambda}^*)$



## Kelly's Decomposition

Problem  $USER_s(U_s; \lambda_s)$  with variables  $w_s$ , one for each source  $s$ :

$$\begin{aligned} &\text{maximize} && U_s \left( \frac{w_s}{\lambda_s} \right) - w_s \\ &\text{subject to} && w_s \geq 0 \end{aligned}$$

Source  $s$  chooses to pay  $w_s$  to maximize profit, where  $\lambda_s$  is charge per unit flow for source  $s$

Problem  $NETWORK(\mathbf{R}, \mathbf{c}; \mathbf{w})$  with variables  $\mathbf{x}$ :

$$\begin{aligned} &\text{maximize} && \sum_s w_s \log x_s \\ &\text{subject to} && \mathbf{R}\mathbf{x} \preceq \mathbf{c} \\ &&& \mathbf{x} \succeq 0 \end{aligned}$$

Network knows payments  $w_s$  from all sources  $r$  and chooses rate allocation to maximize log utility over linear flow constraints

Network does **not** need to know  $\{U_s\}$ , but still needs to be distributively solved

## Kelly's Decomposition

**Theorem:** there exist  $\lambda, \mathbf{w}$  and  $\mathbf{x}$  satisfying  $w_s = \lambda_s x_s$  such that

1.  $w_s$  solves  $USER_s(U_s; \lambda_s)$
2.  $\mathbf{x}$  solves  $NETWORK(\mathbf{R}, \mathbf{c}; \mathbf{w})$
3.  $\mathbf{x}$  is the unique solution to basic NUM

**Proof:** by Lagrange duality and complementary slackness

Economic interpretation:

- User's choice of charges and network's choice of allocated rates and price per unit share reaches equilibrium  $\Rightarrow$  System optimum
- Demand  $w_s$  equals price  $\lambda_s$  times quantity  $x_s$

## Dual NETWORK Problem

Primal problem  $NETWORK(\mathbf{R}, \mathbf{c}; \mathbf{w})$  with variables  $\mathbf{x}$ :

$$\begin{aligned} & \text{maximize} && \sum_s w_s \log x_s \\ & \text{subject to} && \mathbf{R}\mathbf{x} \preceq \mathbf{c} \\ & && \mathbf{x} \succeq 0 \end{aligned}$$

Lagrange dual problem  $DUAL(\mathbf{R}, \mathbf{c}; \mathbf{w})$  with variables  $\boldsymbol{\mu}$ :

$$\begin{aligned} & \text{maximize} && \sum_s w_s \log(\sum_{l \in L(s)} \mu_l) - \sum_l \mu_l c_l \\ & \text{subject to} && \boldsymbol{\mu} \succeq 0 \end{aligned}$$

Recover optimal primal variables from optimal dual variables:

$$x_s = \frac{w_s}{\sum_{l \in L(s)} \mu_l}$$

## Primal Algorithm

$$\begin{aligned}\frac{dx_s(t)}{dt} &= \kappa \left( w_s - x_s \sum_{l \in L(s)} \mu_l(t) \right) \\ \mu_l(t) &= p_l \left( \sum_{s: l \in L(s)} x_s(t) \right)\end{aligned}$$

- Link  $l$  charge  $p_l(y_l)$  per unit flow, when total flow on link  $l$  is  $y_l = \sum_{s: l \in L(s)} x_s$ . Each source tries to equalize the total cost with target value  $w_s$
- Link  $l$  generates feedback signal  $p_l(y_l)$  when total flow on link  $l$  is  $y_l$ . Each source **linearly increase** its rate (proportional to  $w_s$ ) and **multiplicatively decrease** its rate (proportional to total feedback)

Assume  $p_l(y_l)$  is nonnegative, continuous, and increasing function not identically zero

## Global Stability

**Theorem:** The following function is a **Lyapunov function** for the primal algorithm. The unique  $\mathbf{x}$  maximizing network utility is a stable point to which all trajectories converge

$$U(\mathbf{x}) = \sum_s w_s \log x_s - \sum_l \int_0^{\sum_{s:l \in L(s)} x_s} p_l(y) dy$$

Rates  $\mathbf{x}$  vary gradually as shadow prices  $\boldsymbol{\mu}$  change as functions of  $\mathbf{x}$

Let

$$p_l(y) = (y - c_l + \epsilon)^+ / \epsilon^2$$

As  $\epsilon \rightarrow 0$ , maximization of Lyapunov function approximates arbitrarily closely the primal problem  $NETWORK(\mathbf{R}, \mathbf{c}; \mathbf{w})$

Barrier function interpretation

## Lecture Summary

### Network Utility Maximization

- An **emerging, unifying** framework for analysis and design of communication systems
- Substantial theoretical advances in recent years
- Significant practical motivations and applications

Readings: F. P. Kelly, A. K. Maulloo, and D. K. H. Tan, "Rate control for communication networks: shadow prices, proportional fairness and stability," *J. Operations Research Society*, vol. 49, no. 3, pp. 237-252, March 1998.

F. P. Kelly, "Charging and rate control for elastic traffic," *Eur. Trans. on Telecomm.*, vol. 8, pp. 33-37, 1997.