Decomposition Applications

- rate control
- single commodity network flow
Rate control setup

• $n$ flows, with fixed routes, in a network with $m$ links

• variable $f_j \geq 0$ denotes the rate of flow $j$

• flow utility is $U_j : \mathbb{R} \rightarrow \mathbb{R}$, strictly concave, increasing

• traffic $t_i$ on link $i$ is sum of flows passing through it

• $t = Rf$, where $R$ is the routing matrix

\[
R_{ij} = \begin{cases} 
1 & \text{flow } j \text{ passes over link } i \\
0 & \text{otherwise}
\end{cases}
\]

• link capacity constraint: $t \leq c$
Rate control problem

maximize \[ U(f) = \sum_{j=1}^{n} U_j(f_j) \]
subject to \[ Rf \preceq c \]

- convex problem
- dual decomposition gives decentralized method
Rate control Lagrangian

Lagrangian (for minimizing $-U$) is

$$L(f, \lambda) = -U(f) + \lambda^T(Rf - c)$$

$$= -\lambda^T c + \sum_{j=1}^{n} (-U_j(f_j) + (r^T_j \lambda)f_j)$$

- $\lambda_i$ is price (per unit flow) for using link $i$
- $r^T_j \lambda$ is the sum of prices along route $j$
Rate control dual

dual function is

\[ g(\lambda) = -\lambda^T c + \sum_{j=1}^{n} \inf_{f_j} (-U_j(f_j) + (r_j^T \lambda) f_j) \]

\[ = -\lambda^T c - \sum_{j=1}^{n} (-U_j)^*(-r_j^T \lambda), \]

dual rate control problem:

maximize \[ -\lambda^T c - \sum_{j=1}^{n} (-U_j)^*(-r_j^T \lambda) \]
subject to \[ \lambda \succeq 0 \]
subgradient of negative dual:

\[ R\bar{f} - c \in \partial(-g)(\lambda) \]

where \( \bar{f}_j = \arg\max \left( U_j(f_j) - (r_j^T \lambda) f_j \right) \)
Dual decomposition rate control algorithm

given initial link price vector $\lambda \succeq 0$ \(e.g., \lambda = 1\).

repeat

1. Sum link prices along each route.
   Calculate $\Lambda_j = r_j^T \lambda$.

2. Optimize flows (separately) using flow prices.
   $f_j := \arg\max \left( U_j(f_j) - \Lambda_j f_j \right)$.

3. Calculate link capacity margins.
   $s := c - Rf$.

4. Update link prices.
   $\lambda := (\lambda - \alpha_k s)_+$.
Dual decomposition rate control algorithm

- decentralized:
  - links only need to know the flows that pass through them
  - flows only need to know prices on links they pass through

- prices converge to optimal; so do flows (since $U$ is strictly concave)

- iterates can be (and often are) infeasible, i.e., $R_f \nleq c$
  (but we do have $R_f \leq c$ in the limit)

- have upper bound $-g(\lambda)$ on optimal utility $U^*$
Generating feasible flows

• define \( \eta_i = \frac{t_i}{c_i} = \frac{(Rf)_i}{c_i} \)
  
  – \( \eta_i < 1 \) means link \( i \) is under capacity
  – \( \eta_i > 1 \) means link \( i \) is over capacity

• define \( f^{\text{feas}} \) as

\[
 f_{j,\text{feas}} = \frac{f_j}{\max\{\eta_i \mid \text{flow } j \text{ passes over link } i\}}
\]

• \( f^{\text{feas}} \) will be feasible, even if \( f \) is not

• finding \( f^{\text{feas}} \) is also decentralized
  (in fact this is a step in primal decomposition)
Example

- $n = 10$ flows, $m = 12$ links; 3 or 4 links per flow
- link capacities chosen randomly, uniform on $[0.1, 1]$
- $U_j(f_j) = \log f_j$ (can be argued to give proportionally fair flows)
- optimal flow as a function of price:
  $$\bar{f}_j = \arg\max(U_j(f_j) - \Lambda_j f_j) = 1/\Lambda_j$$
- initial prices: $\lambda = 1$
- constant stepsize $\alpha_k = 3$
Convergence of primal and dual objectives

\[ U(f^{\text{feas}}) \quad -g(\lambda) \]
Maximum capacity violation

\[ \max_i (R_f - c)_i \]

\[ k \]
Single commodity network flow setup

- connected, directed graph with \( n \) links, \( p \) nodes
- variable \( x_j \) denotes flow (traffic) on arc \( j \)
- given external source (or sink) flow \( s_i \) at node \( i \), \( 1^T s = 0 \)
- node incidence matrix \( A \in \mathbb{R}^{p \times n} \) is

\[
A_{ij} = \begin{cases} 
1 & \text{arc } j \text{ enters } i \\
-1 & \text{arc } j \text{ leaves node } i \\
0 & \text{otherwise}
\end{cases}
\]

- flow conservation: \( Ax + s = 0 \)
- \( \phi(x) = \sum_{j=1}^{n} \phi_j(x_j) \) is separable convex flow cost function
Network flow problem

optimal single commodity network flow problem:

\[
\text{minimize } \sum_{j=1}^{n} \phi_j(x_j)
\]

subject to \( Ax + s = 0 \)

• convex, readily solved with standard methods

• dual decomposition yields decentralized solution method
Network flow Lagrangian

Lagrangian is

\[ L(x, \nu) = \phi(x) + \nu^T(Ax + s) \]

\[ = \nu^T s + \sum_{j=1}^{n} (\phi_j(x_j) + (a_j^T \nu)x_j) \]

- \( a_j \) is \( j \)th column of \( A \)
- we'll interpret \( \nu_i \) as potential at node \( i \)
- we use \( \Delta \nu_j \) to denote \( a_j^T \nu \), which is potential difference across edge \( j \)
Network flow dual

dual function:

\[
g(\nu) = \inf_x L(x, \nu) \\
= \nu^T s + \sum_{j=1}^n \inf_{x_j} (\phi_j(x_j) + (\Delta \nu_j)x_j) \\
= \nu^T s - \sum_{j=1}^n \phi_j^*(-\Delta \nu_j)
\]

dual problem: maximize \( g(\nu) \)
Recovering primal from dual

- strictly convex $\phi_j$ means unique minimizer $x_j^*(y)$ of $\phi_j(x_j) - yx_j$

- if $\phi_j$ is differentiable, $x_j^*(y) = (\phi_j')^{-1}(y)$ (inverse of derivative function)

- optimal flows, from optimal potentials: $x_j^* = x_j^*(-\Delta \nu_j^*)$

- subgradient of negative dual function:

  $$-(Ax^*(\Delta \nu) + s) \in \partial(-g)(\nu)$$

  (negative of flow conservation residual)
Dual decomposition network flow algorithm

given initial potential vector $\nu$.

repeat

1. Determine link flows from potential differences.
   \[ x_j := x_j^* (-\Delta \nu_j), \quad j = 1, \ldots, n. \]

2. Compute flow surplus at each node.
   \[ S_i := a_i^T x + s_i, \quad i = 1, \ldots, p. \]

3. Update node potentials.
   \[ \nu_i := \nu_i + \alpha_k S_i, \quad i = 1, \ldots, p. \]

$\alpha_k$ is an appropriate step size
Dual decomposition network flow algorithm

- decentralized:
  - flow calculated from potential difference across edge
  - node potential updated from its own flow surplus

- $g(\nu)$ gives lower bound on $p^*$

- flow conservation $Ax + s = 0$ only holds in limit
Electrical network analogy

- electrical network with node incidence matrix $A$, nonlinear resistors in branches
- variable $x_j$ is the current flow in branch $j$
- source $s_i$ is external current injected at node $i$ (must sum to zero)
- flow conservation equation $Ax + s = 0$ is Kirkhoff Current Law (KCL)
- dual variables are node potentials; $\Delta \nu_j$ is $j$th branch voltage
- branch current-voltage characteristic is $x_j = x_j^*(-\Delta \nu_j)$

then, current and potentials in circuit are optimal flows and dual variables
Example: Minimum queueing delay

flow cost function

\[ \phi_j(x_j) = \frac{x_j}{c_j - x_j}, \quad \text{dom } \phi_j = [0, c_j) \]

where \( c_j > 0 \) are given link capacities

\( (\phi_j(x_j) \) gives expected waiting time in queue with exponential arrivals at rate \( x_j \), exponential service at rate \( c_j \)\)

conjugate is

\[ \phi_j^*(y) = \begin{cases} (\sqrt{c_j y} - 1)^2 & y > 1/c_j \\ 0 & y \leq 1/c_j \end{cases} \]
cost function $\phi(x)$ (left) and its conjugate $\phi^*(y)$ (right), $c = 1$

(note that conjugate is differentiable)
\[ x_j^*(-\Delta \nu_j), \text{ for } c_j = 1 \]
gives flow as function of potential difference across link
A specific example

network with 5 nodes, 7 links, capacities \( c_j = 1 \)
Optimal flow

optimal flows shown as width of arrows; optimal dual variables shown in nodes; potential differences shown on links
Convergence of dual function

fixed step size rules, $\alpha = 0.3, 1, 3$

for $\alpha = 1$, converges to $p^* = 2.48$ in around 40 iterations
Convergence of primal residual

\[ \| A \mathbf{x}(k) + s \|_2 = 0 \]

\[ \alpha = 0.3 \]
\[ \alpha = 1 \]
\[ \alpha = 3 \]
Convergence of dual variables

$\nu^{(k)}$ versus iteration number $k$, fixed step size rule $\alpha = 1$

($\nu_5$ is fixed as zero)