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Today, I basically worked on some mathematical tools mentioned in the reference paper, most of them are about optimizations like KKT, dual problems and so on.

Math language

- **subject to:**

It is a way to specify constraints. To put it very simply, the problem "do 'X' subject to 'Y'" means that, you have to do "X" (whatever X is), but you have to do it such that "Y" is also satisfied in the process.

- **objective function:**

The objective function in a mathematical optimization problem is the real-valued function whose value is to be either minimized or maximized over the set of feasible alternatives. In problem P above, the function f is the objective function.

- **Two different types of constraints:**

- Inequality constraints: $g_i(x) \leq 0, 1 \leq i \leq p$
- equality constraints: $h_j(x) = 0, 1 \leq j \leq q$

- $R^n \rightarrow R^m$:

A linear transformation T between two vector spaces R^n and R^m , written $T: R^n \rightarrow R^m$ just means that T is a function that takes as input n -dimensional vectors and gives you m -dimensional vectors. These properties are:

$$\begin{aligned} 1. T(v + w) &= T(v) + T(w) \\ 2. T(av) &= aT(v) \end{aligned}$$

for all $v, w \in R^n$ and a real number.

- **Lagrange dual problems:**

For an optimization problems:

minimize $f_0(x)$

subject to $f_i(x) \leq 0 \quad i = 1,$

$h_i(x) = 0 \quad i = 1,$

with variable $x \in R^n$, domain D , and optimal value p^* .

The Lagrangian is a function L :

$$L(x, \lambda, \mu) = f_0(x) + \sum_{i=1}^m \lambda_i f_i(x) + \sum_{i=1}^p v_i h_i(x)$$

where λ_i is the Lagrange multiplier associated with $f_i(x) \leq 0$ and v_i is the Lagrange multiplier associated with $h_i(x) = 0$, **while they are all greater than 0**

Then the Lagrange dual function can be defined as:

$$\begin{aligned} g(\lambda, \mu) &= \inf_{x \in D} L(x, \lambda, \mu) \\ &= \inf_{x \in D} (L(x, \lambda, \mu) = f_0(x) + \sum_{i=1}^m \lambda_i f_i(x) + \sum_{i=1}^p v_i h_i(x)) \end{aligned}$$

The original primal problem is to find the minimum then we can obtain that by find the maximum of this dual problem to find the best lower bound.

- **Affine functions:**

An affine function is a function composed of a linear function + a constant and its graph is a straight line.

- **KKT conditions:**

if we have an optimization problems:

$$\begin{aligned} \min f(x) \\ \text{s.t. } g_i(x) &\leq 0 (i = 1, 2, \dots, m) \\ h_k(x) &= 0 (k = 1, 2, \dots, l) \end{aligned}$$

If have an optimal value x^* , and we want to determine it is an optimal value for our optimization, then we can use KKT conditions to check

$$\left\{ \begin{array}{l} \frac{\delta f}{\delta x_i} + \sum_{j=1}^m \mu_j \frac{\delta g_j}{\delta x_i} + \sum_{k=1}^l \lambda_k \frac{\delta h_k}{\delta x_i} = 0, (i = 1, 2, \dots, n) \\ h_k(x) = 0, (k = 1, 2, \dots, l) \\ \mu_j g_j(x) = 0, (j = 1, 2, \dots, m) \\ \mu_j \geq 0 \end{array} \right.$$

Optimization

We are trying to maximize the target energy efficiency which belongs to SWIPT-Enabled D2D links.

$$\begin{aligned} P1 : \max \quad & EE_i^D \\ \text{s.t.} \quad & C1 : 0 < P_i^D \leq P_{max} \\ & C2 : 0 \leq \lambda_i^e \leq 1 \\ & C3 : T_i^D \geq T_{min}^D \\ & C4 : T_c^k \geq T_c^{min} \\ & C5 : P_i^R \geq P_{th}^1 \\ & C6 : P_{th}^j \leq P_i^R \leq P_{th}^{j+1}, j \in 0, \dots, L \end{aligned}$$

And for Constraints C1-C5, we have the Lagrange functions:

$$\begin{aligned} L(P_i^D, \lambda_i^e, \alpha, \beta, \gamma, \delta, \epsilon) = & T_i^D - Q_i^D EE_i^D - \alpha(P_i^D - P_{max}) - \beta(\lambda_i^e - 1) + \gamma(T_i^D - T_{min}^D) + \\ & \delta(T_i^C - T_c^{min}) + \epsilon(P_i^R - P_{th}^1) \end{aligned}$$

So for the original problem, we have the following optimization problems:

$$\begin{aligned} P1 : \max \quad & EE_i^D \\ \text{s.t.} \quad & C1 : 0 < P_i^D \leq P_{max} \\ & C2 : 0 \leq \lambda_i^e \leq 1 \\ & C3 : T_i^D \geq T_{min}^D \\ & C4 : T_c^k \geq T_c^{min} \\ & C5 : P_i^R \geq P_{th}^1 \\ & C6 : P_{th}^j \leq P_i^R \leq P_{th}^{j+1}, j \in 0, \dots, L \end{aligned}$$

So the original optimization problem which need to be found the maximum can be obtained to find its dual problem which needs to find the minimum:

$$\min_{\{\alpha, \beta, \gamma, \delta, \epsilon \geq 0\}} \quad \max_{P_i^D, \lambda_i^e} \quad L(P_i^D, \lambda_i^e, \alpha, \beta, \gamma, \delta, \epsilon), i \in Eha^D$$

which subjects to constraint 6 C6.