

Optimization from Fundamentals
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Lecture - 14A
Complementary Slackness

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Complementary slackness

Primal: $\text{Max}_{x \in \mathbb{R}^n} C^T x \quad \text{s.t.} \quad Ax \leq b, x \geq 0$

Dual: $\text{Min}_{\lambda \in \mathbb{R}^m} b^T \lambda \quad \text{s.t.} \quad A^T \lambda \geq c, \lambda \geq 0$

$A \in \mathbb{R}^{m \times n}, c \in \mathbb{R}^n, b \in \mathbb{R}^m, \lambda \in \mathbb{R}^m$

"Every constraint in the primal LP has a corresponding variable in the dual"

$\& \text{ vice versa}$

$S_p = \{x \mid Ax \leq b, x \geq 0\}$

$S_d = \{\lambda \mid A^T \lambda \geq c, \lambda \geq 0\}$

Weak duality:

$$C^T x \leq \lambda^T A x \leq b^T \lambda \quad \forall x \in S_p, \lambda \in S_d$$

Thus $x^* \in S_p$ is optimal for the primal LP if and only if $\exists \lambda^* \in S_d$ s.t.

$$\sum_{j=1}^n a_{ij} x_j^* < b_i \Rightarrow \lambda_i^* = 0$$

$$\sum_{i=1}^m \lambda_i^* a_{ij} > c_j \Rightarrow x_j^* = 0$$

(Complementary slackness)

$A = [a_{ij}]$
 $\text{row } i \rightarrow i=1, \dots, m$
 $\text{column } j \rightarrow j=1, \dots, n$

Ok. Welcome everyone. So, today, I will talk about an first to begin with I will talk about an important property called an important condition you can say called Complementary Slackness. And this is the condition that comes up because we whenever we consider optimization problems which have inequality constraints.

So, I will first illustrate this today in the context of linear programs, and then from there then we will take off to a more general problems. And hopefully, we will you will see either today

or in the next lecture complementary slackness coming up as a condition in more general optimization problems.

So, let us look at this linear program. So, this is called let us say we are maximizing $c^T x$ subject to $Ax \leq b$ and $x \geq 0$. Now, this is not in standard form, but and moreover it is also a maximization problem, but you can convert it to standard form, and then from the standard form derive it is dual.

And after you simplify the dual you will find that the dual takes this form. It is a min it is a minimization. So, here the maximization is over x . Your minimization, I will just use the variable λ here. Minimization is over λ of the objective $b^T \lambda$ subject to the constraints that $A^T \lambda \geq c$ and $\lambda \geq 0$, ok.

So, now, let us repeat the observations that we had made about linear programs and their duals before as well. So, if my matrix A is in $\mathbb{R}^{m \times n}$, c is in \mathbb{R}^n and b is in \mathbb{R}^m , so in that case the number of inequality constraints that we have here these inequality constraints, apart from the constraint $x \geq 0$, the number of inequality constraints that we have here this is equal to; this is equal to m which also happens to be the number of variables in this, in the dual problem, right.

The dual problem has m variables because λ is a m length variable, is an m length vector, λ is in \mathbb{R}^m . So, the number of inequality constraints that we have in the primal problem is equal to the number of variables of the dual problem. And if you look at the number of inequality constraints in the dual problem, that is equal to the number of variables in the primal problem.

And I had mentioned to you before that there is a close correspondence between these. So, what one can think of is that for every constraint in the primal, you actually have a variable in the dual and vice versa. So, every constraint in the primal LP has, so this is I have not written

here, this is primal and this one is this is the dual. Every constraint in the primal has a corresponding variable in the dual and vice versa.

Vice versa means that every constraint in the primal has a corresponding variable in the dual, right. So, what I will do today is through this condition of complementary slackness I will actually make this more precise, and I will tell you how this which variable is actually corresponding to which constraint and so on, ok.

So, let us define a few quantities. So, let us define ω_P as all x such that $Ax \leq b$, and $x \geq 0$. So, ω_P is simply the feasible region of the primal and ω_D is all λ such that $A^T \lambda \geq c$ and $\lambda \geq 0$.

Now, because these are duals to each other these two problems, then we can easily verify that we already have weak duality. Weak duality between them, what does this mean? If I take any x in that is feasible for the primal and look at $c^T x$, and that has its value is less than equal to, ok. So, what have I done here? What I have taken? I have, so this is true for all x in ω_P and all λ in ω_D .

So, what have I done to get to this relation? I have $c^T x$. So, and I know that $c^T x$ is less than equal to $\lambda^T A x$ or $c^T x \leq \lambda^T A x$ in other words $c^T x$ is less than equal to $\lambda^T A x$. So, I am multiplying both sides by the vector x and x being greater than equal to 0; because x belongs to ω_P , $x \geq 0$, then that ensures that the inequality is not flipped.

So, in short, I am taking the dual, I am taking the dual constraint and then multiplying both sides by x that gives me $\lambda^T A x \geq c^T x$. But then, $\lambda^T A x$ is actually the same as it can be it can be further bounded because $Ax \leq b$.

So, that can be further bounded and then you get that it is bounded by $b^T \lambda$, ok. And again, $\lambda \geq 0$, let me make sure that my inequality is

preserved. So, this is like we did in the standard form, you can get you have weak duality here as well, right.

Now, the important thing here is your the complementary slackness condition and, so let me write the theorem now. So, x^* in ΩP is optimal for the primal LP if and only if there exist a λ^* in dual in ΩD , I should write capital ΩD such that now, such that let me write it like this.

So, suppose let me on the side let me introduce a bit of notation. So, let the if the matrix A that is represented as a matrix of numbers a_{ij} , where i runs from 1 to m and j runs from 1 to n . So, i corresponds to rows, and j corresponds to columns, ok. So, x^* in ΩP is optimal for the primal LP if and only if there exists an λ^* in ΩD .

That means, it is a variable that is feasible for the dual LP such that you have the following two conditions hold. If I look at a_{ij} , x^*_j and I sum this from j equals 1 to n , this quantity is less than b_i and this implies the condition that this is the condition that this inequality holds means that $\sum_{j=1}^n a_{ij} x^*_j$ from j equal to 1 to n is less than b_i , this should this can this implies λ^*_i equal 0, ok.

And the other way around as well. The other condition is that if I do a again do is a_{ij} and write it this way. So, they consider the summation $\lambda^*_i a_{ij}$, i running from 1 to m , that is less than c_j implies x^*_j equals 0. So, when so what this means is, so, if the first inequality if this inequality here the way you should understand this is it says that if this inequality here is strict. So, then you must have that λ^*_i corresponding to that inequality is 0, ok.

So, for every so, what is this inequality? This inequality is the i th constraint of the primal LP. This is the i th constraint of the primal LP. So, if the i th constraint of the primal LP holds strictly, ok means it does not hold with equality then the λ^*_i corresponding to that must be 0. Likewise, if you look at the j th constraint in the dual LP, if that holds strictly, ok. Sorry,

this there is a, there is slight mistake here in the direction of the inequality. So, sorry there is a mistake in the direction of the inequality I just corrected it.

So, if likewise, if this inequality holds strictly, the j th inequality in the dual if that holds strictly then the corresponding primal variable x_j must equal 0, ok. So, what you should; then the way to think about primal and dual variables is that what you have. So, your lambdas are actually the lambda, the variable λ_i which multiplies with b_i in the objective is the one that corresponds to the i th constraint here, for the i th constraint here you have a variable λ_i .

And likewise the variable $c_j x_j$ that multiplies with c_j in the objective of the primal is the variable that corresponds to is the variable that corresponds to the j th constraint in the dual. So, what you have here are actually there are from i equal to 1 till all the way till m , there are m of these constraints, and then for each of these constraints you have a you have a dual variable which is λ_1 till λ_m .

The, and likewise in the dual you have constraints now going from j equal to 1 all the way till j equal to n and corresponding to each of those variables you have dual variables of the dual which are actually the primal variables. So, those are then x_1 till x_n , ok and these variables when you have when you are at optimality, they end up satisfying these constraint, these conditions. This is equivalent to being optimal.

That means, whenever the i th constraint in the primal LP holds with strict inequality the corresponding dual variable must be 0 and whenever the j th constraint in the dual LP holds with strict inequality the corresponding dual variable of the dual which means the primal variable $x_{\text{star } j}$ must be equal to 0, ok. So, this; so we will, this is what is called Complementary slackness.

So, what this is referring to is that whenever there is whenever there is the word complementary slackness only says this that whenever there is slack in one of these constraints, then there can be no slack for the dual variable corresponding to them. Means

the dual variable must be at its least value. Likewise, if there is a slack in this constraint then this one must be at its (Refer Time: 15:47) well, ok.

Student: Sir.

Yes.

Student: Is λ_i also (Refer Time: 15:53) value?

Yes. So, it will turn out that moreover it will turn out that λ^* is; so, that is a that is a good point. So, x here this statement only says that x^* is optimal for the primal LP if and only if there exist a λ^* like this. It will turn out that λ^* itself is actually optimal for the dual LP, ok. So, in fact, x^* and λ^* end up being optimal for their respective problems through these conditions.