# Optimisation and Operations Research <br> Lecture 9: Duality and Complementary Slackness 

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## Section 1

## Duality

## Problem Recap

We will start with a problem in standard equality form.

$$
\begin{aligned}
\max & =\mathbf{c}^{T} \mathbf{x}+z_{0} \\
\text { such that } A \mathbf{x} & =\mathbf{b} \\
\text { and } \mathbf{x} & \geq 0
\end{aligned}
$$

We call this the primal LP

## Dual

Primal (P)

$$
\begin{aligned}
\max & =\mathbf{c}^{T} \mathbf{x}+z_{0} \\
\text { such that } A \mathbf{x} & =\mathbf{b} \\
\text { and } \mathbf{x} & \geq 0
\end{aligned}
$$

Consider a new LP called the dual problem (D)

$$
\begin{aligned}
\min & =\mathbf{b}^{T} \mathbf{y}+z_{0} \\
\text { such that } & A^{T} \mathbf{y}
\end{aligned} \frac{\geq \mathbf{c}}{\text { and }} \begin{aligned}
\mathbf{y} & \text { free }
\end{aligned}
$$

## Origin of the dual

Suppose there is an optimal solution $\left(\mathbf{x}^{*}, z^{*}\right)$ to the primal LP

$$
\begin{aligned}
\max \quad z & =\mathbf{c}^{T} \mathbf{x}+z_{0} \\
\text { such that } A \mathbf{x} & =\mathbf{b} \\
\text { and } \mathbf{x} & \geq 0
\end{aligned}
$$

with $z^{*}=\mathbf{c}^{\top} \mathbf{x}^{*}+z_{0}$.
We might have obtained this via Simplex

Initial Tableau
Simplex

| $A$ | $\mathbf{b}$ |
| :---: | :---: |
| $-\mathbf{c}^{T}$ | $z_{0}$ |

Final Tableau

where $z^{*}=\hat{z}_{0}$

## Origin of the dual

The final tableau comes from pivots, so there are some numbers $y_{1}^{*}, \ldots, y_{m}^{*}$ such that

$$
\begin{aligned}
-\hat{c}_{j} & =\sum_{i=1}^{m} y_{i}^{*} a_{i j}-c_{j}, \quad j=1, \ldots, n \\
\hat{z}_{0} & =\sum_{i=1}^{m} y_{i}^{*} b_{i}+z_{0}
\end{aligned}
$$

At the end of Simplex $-\hat{c}_{j} \geq 0$ so

$$
\sum_{i=1}^{m} y_{i}^{*} a_{i j} \geq c_{j} \quad \text { for } j=1, \ldots, n
$$

So let's consider any variables $y_{1}, \ldots, y_{m}$ which satisfy

$$
\sum_{i=1}^{m} y_{i} a_{i j} \geq c_{j}, \text { for } j=1, \ldots, n
$$

We could look for an optimisation to find the $\mathbf{y}^{*}$

## Origin of the dual

Let's build a new objective function with

$$
w=\sum_{i=1}^{m} y_{i} b_{i}+z_{0}
$$

From the Primal, $b_{i}=\sum_{j=1}^{n} a_{i j} x_{j}$ so

$$
\begin{aligned}
w & =\sum_{i=1}^{m} y_{i}\left(\sum_{j=1}^{n} a_{i j} x_{j}\right)+z_{0} \\
& =\sum_{j=1}^{n}\left(\sum_{i=1}^{m} y_{i} a_{i j}\right) x_{j}+z_{0} \\
& \geq \sum_{j=1}^{n} c_{j} x_{j}+z_{0}
\end{aligned}
$$

Hence $w \geq z$, but also the above is true for any feasible $\mathbf{x}$, so $w \geq \hat{z}_{0}$, the optimal value of the primal. But we defined $w$ so that $w\left(\mathbf{y}^{*}\right)=\hat{z}_{0}$, so $\hat{z}_{0}$ is the minimum of $w$.

## The Dual of an LP (Summary)

In the dual, variables become constraints, and visa versa

$$
\begin{gathered}
(P) \quad \max z=\sum_{j=1}^{n} c_{j} x_{j}+z_{0} \\
\sum_{j=1}^{n} a_{i j} x_{j}=b_{i}, \quad i=1, \ldots, m \\
\hline x_{j} \geq 0, \quad j=1, \ldots, n \\
\text { or } \\
\max \quad z=\mathbf{c}^{T} \mathbf{x}+z_{0} \\
A \mathbf{x}=\mathbf{b} \\
\mathbf{x} \geq 0
\end{gathered}
$$

| (D) $\quad \min w=\sum_{i=1}^{m} y_{i} b_{i}+z_{0}$ |
| :---: |
| $\frac{y_{i} \text { free, } \quad i=1, \ldots, m}{\sum_{i=1}^{m} y_{i} a_{i j} \geq c_{j}, \quad j=1, \ldots, n}$ |
| or |
| $\min \quad w=\mathbf{y}^{T} \mathbf{b}+z_{0}$, |
| $\mathbf{y}^{T} A \geq \mathbf{c}^{T}$, |
| $\mathbf{y}$ free. |

Note how the lines are paired up

## Dual Example

## Example (Dual)

$$
\begin{aligned}
&(P) \quad \max z=\begin{array}{c}
3 x_{1}
\end{array}-x_{2}+x_{3} \\
& x_{1}+2 x_{2} \\
& \text { s.t. } x_{1}-x_{2}+x_{3}=7 \\
& x_{2}+6 x_{3}=11 \\
& x_{1} \geq 0, x_{2} \geq 0, x_{3} \geq 0 .
\end{aligned}
$$

(D) $\quad \min w=5 y_{1}+7 y_{2}+11 y_{3}$
st.

| $y_{1}+y_{2}$ |  |
| ---: | :--- |
| $2 y_{1}-y_{2}+y_{3}$ | $\geq-1$ |
| $y_{2}+6 y_{3}$ | $\geq 1$ |

$y_{1}, y_{2}$ and $y_{3}$ are all free variables.

## Why do we call it the dual?

## Theorem

The Dual of the Dual is the Primal.
Proof: The dual is

$$
\begin{array}{rll}
\min & w & =\mathbf{b}^{T} \mathbf{y}+z_{0} \\
\text { such that } & A^{T} \mathbf{y} & \geq \mathbf{c} \\
\text { and } & \mathbf{y} & \text { free }
\end{array}
$$

We convert to standard equality form by

- multiplying the objective by -1 (to make it a max)
- multiplying the constraints by -1
- adding slack variables
- replacing free variables $y_{i}$ with non-negative variables $y_{i}^{+} \geq 0$ and $y_{i}^{-} \geq 0$ such that $y_{i}=y_{i}^{+}-y_{i}^{-}$,


## Why do we call it the dual?

Proof: (continued) The dual, written in standard equality form is (D')

$$
\begin{aligned}
\max & -w & =\mathbf{b}^{T} \mathbf{y}^{-}-\mathbf{b}^{T} \mathbf{y}^{+}-z_{0} \\
\text { such that } & A^{T} \mathbf{y}^{-}-A^{T} \mathbf{y}^{+}+\mathbf{s} & =-\mathbf{c} \\
\text { and } & \mathbf{y}^{+}, \mathbf{y}^{-}, \mathbf{s} & \geq 0
\end{aligned}
$$

Now we can take the dual of (D') which we denote (DD) by creating a variable $x_{i}$ for each constraint, and a constraint for each variable $y_{j}$ and $s_{j}$.

| $\min$ | $u$ | $=-\mathbf{c}^{T} \mathbf{x}-z_{0}$ |  |
| ---: | :--- | ---: | :--- |
| such that |  |  |  |
| and $-A \mathbf{x}$ | $\geq \mathbf{b}^{T}$ |  | from $\mathbf{y}^{-}$ |
| and | $\geq-\mathbf{b}^{T}$ |  | from $\mathbf{y}^{+}$ |
| $\mathbf{x}$ | $\geq 0$ |  | from $\mathbf{s}$ |

## Why do we call it the dual?

Proof: (continued) We have (DD)

| min | $=-\mathbf{c}^{T} \mathbf{x}-z_{0}$ |  |  |
| ---: | :--- | ---: | :--- |
| such that |  |  |  |
| and | $\geq \mathbf{b}^{T}$ |  | from $\mathbf{y}^{-}$ |
| and | $\geq-\mathbf{b}^{T}$ |  | from $\mathbf{y}^{+}$ |
| $\mathbf{x}$ | $\geq 0$ |  | from $\mathbf{s}$ |

Note that

- we can multiply the objective by -1 (to have a max)
- The constraints $A \mathbf{x} \geq \mathbf{b}^{T}$ and $A \mathbf{x} \leq \mathbf{b}^{T}$ together imply that $A \mathbf{x}=\mathbf{b}$.

So (DD) $\equiv(\mathrm{P})$.
Q.E.D.

## Weak Duality

$$
\begin{array}{rlrl}
\text { Primal } & \text { Dual } \\
\max z & =\mathbf{c}^{T} \mathbf{x}+z_{0} & \min w & =\mathbf{b}^{T} \mathbf{y}+z_{0} \\
A \mathbf{x} & =\mathbf{b} & A^{T} \mathbf{y} & \geq \mathbf{c} \\
\mathbf{x} & \geq 0 & \mathbf{y} & \text { free }
\end{array}
$$

Theorem
Given primal and dual problems as above have feasible solutions $\mathbf{x}$ and $\mathbf{y}$, then $z \leq w$.

## Weak Duality Proof

Proof: We essentially showed this earlier:

$$
\begin{array}{rlr}
w & =\sum_{i=1}^{m} y_{i} b_{i}+z_{0} & \\
& =\sum_{i=1}^{m} y_{i}\left(\sum_{j=1}^{n} a_{i j} x_{j}\right)+z_{0} & \text { because (P) requires } b_{i}=\sum_{j=1}^{n} a_{i j} x_{j} \\
& =\sum_{j=1}^{n}\left(\sum_{i=1}^{m} y_{i} a_{i j}\right) x_{j}+z_{0} & \\
\text { swapping order of summation } \\
& \geq \sum_{j=1}^{n} c_{j} x_{j}+z_{0} & \\
& =z & \text { from constraints of (D) }
\end{array}
$$

Hence $w \geq z$

## Weak Duality Consequences

## Corollary

If we have feasible solutions $\mathbf{x}$ and $\mathbf{y}$ to the primal and dual respectively and $w=z$, then these are optimal solutions to their respective problems.

Proof: $w$ is an upper bound on $z$ (and visa versa), so if $z=w$ for a feasible solution, it has achieved its upper bound, and hence we have an optimal solution.
Q.E.D.

## Boundedness v Feasibility

## Corollary <br> If the primal (dual) problem is unbounded then the dual (primal) problem is infeasible.

Proof: If the primal were feasible and unbounded, then that means there can be no upper bound on $z$, so we cannot have a feasible solution the dual.
Similarly if the dual is unbounded.
Q.E.D.

## Strong Duality

## Theorem

If the primal (dual) problem has a finite optimal solution, then so does the dual (primal) problem, and these two values are equal.

Proof: see later as a result of complementary slackness.

## The Dual of an LP - 12

Summary of Results for Primal/Dual pair $(P)$ and $(D)$
(1) For a feasible solution $x_{1}, \ldots, x_{n}$ of $(P)$, with value $z$, and a feasible solution $y_{1}, \ldots, y_{m}$ of $(D)$, with value $w$, we have $w \geq z$ (Weak Duality)
(2) If $(P)$ has an optimal solution then $(D)$ has an optimal solution and $\max z=\min w$ (Strong Duality)
(3) Because the dual of the dual is the primal, if $(D)$ has an optimal solution then $(P)$ has an optimal solution and $\max z=\min w$ (Strong Duality)
(1) If $(P)$ has no optimal solution $(z \rightarrow \infty)$ then $(D)$ cannot have a feasible solution (as $w \geq \max z$ ), and if $(D)$ has no optimal solution $(w \rightarrow-\infty)$ then $(P)$ cannot have a feasible solution (as $z \leq \min w)$.

## The Dual of an LP - 13

Summary of Results for Primal/Dual pair $(P)$ and $(D)$

|  |  | Primal ( $P$ ) |  |  |
| :---: | :---: | :---: | :---: | :---: |
|  |  | stop 1 optimal solution | stop 2 <br> feasible sol ${ }^{n}$, no opt. sol ${ }^{n}$ | stop 3 no feasible solution |
|  | stop 1 optimal solution | possible $\ddagger$ | impossible | impossible |
| Dual (D) | stop 2 <br> feas. sol ${ }^{n}$, no opt. sol ${ }^{n}$ | impossible | impossible | possible |
|  | stop 3 no feasible solution | impossible | possible | possible |

$\ddagger(\max z=\min w)$

## Section 2

## Complementary Slackness

## Complementary slackness

## Theorem (Complementary slackness)

Given primal problem $P$ and dual problem $D$ with feasible solutions $\mathbf{x}$ and $\mathbf{y}$, respectively, then $\mathbf{x}$ is an optimal solution of $(P)$ and $\mathbf{y}$ an optimal solution of $(D)$ if and only if

$$
x_{j}\left(\sum_{i=1}^{m} y_{i} a_{i j}-c_{j}\right)=0, \quad \text { for } j=1, \ldots, n
$$

Implicit in this theorem is the Strong Duality Theorem, which we prove now, and the second part is called the complementary slackness relations.

## Definition (Complementary Slackness Relations)

The relations $x_{j}\left(\sum_{i=1}^{m} y_{i} a_{i j}-c_{j}\right)=0$, for each $j=1, \ldots, n$ are called the
Complementary Slackness Relations (CSR).

## Complementary slackness proof

Proof: We have already seen the argument:

$$
\begin{aligned}
z=\sum_{j=1}^{n} c_{j} x_{j}+z_{0} & \leq \sum_{j=1}^{n} \sum_{i=1}^{m} y_{i} a_{i j} x_{j}+z_{0} \quad\left(\text { as } \sum_{i=1}^{m} y_{i} a_{i j} \geq c_{j}, x_{j} \geq 0\right) \\
& =\sum_{i=1}^{m} \sum_{j=1}^{n} a_{i j} x_{j} y_{i}+z_{0} \quad \\
& =\sum_{i=1}^{m} y_{i} b_{i}+z_{0}=w \quad\left(\text { as } \sum_{j=1}^{n} a_{i j} x_{j}=b_{i}\right)
\end{aligned}
$$

So $z \leq w$ for all feasible solutions

## Complementary slackness proof

## Proof : (cont)

From Strong Duality, if we have an optimal solution, then $z^{*}=w^{*}$. Reversing the above logic, we get

$$
\sum_{j=1}^{n} c_{j} x_{j}+z_{0}=\sum_{j=1}^{n}\left(\sum_{i=1}^{m} y_{i} a_{i j} x_{j}\right)+z_{0}
$$

which, when we group the $x_{i}$ terms together gives

$$
\sum_{j=1}^{n}\left(\sum_{i=1}^{m} y_{i} a_{i j}-c_{j}\right) x_{j}=0
$$

## Complementary slackness proof

## Proof : (cont)

If we know that $n_{j} \geq 0$, and we have

$$
\sum_{j} n_{j}=0
$$

then we must have $n_{j}=0$.
This applies here because we know from the LP dual and primals that

$$
\sum_{i=1}^{m} y_{i} a_{i j}-c_{j} \geq 0 \text { and } x_{j} \geq 0
$$

Hence

$$
\left(\sum_{i=1}^{m} y_{i} a_{i j}-c_{j}\right) x_{j}=0, \text { for each } j=1, \ldots, n .
$$

## Complementary Slackness: Example

| Primal Tableax (P) |  |  |  |  |  |
| ---: | ---: | ---: | ---: | ---: | ---: |
| $x_{1}$ | $x_{2}$ | $x_{3}$ | $x_{4}$ | $x_{5}$ | $b$ |
| 2 | -1 | -1 | 1 | 0 | 1 |
| 2 | 2 | 1 | -2 | 0 | 3 |
| 1 | 1 | 1 | 1 | 1 | 2 |
| -1 | 1 | 1 | 1 | 0 | 0 |

Simplex Phase I and II

| 1 | 0 | $-\frac{1}{6}$ | 0 | 0 | $\frac{5}{6}$ |
| ---: | ---: | ---: | ---: | ---: | ---: |
| 0 | 1 | $\frac{2}{3}$ | -1 | 0 | $\frac{2}{3}$ |
| 0 | 0 | $\frac{1}{2}$ | 2 | 1 | $\frac{1}{2}$ |
| 0 | 0 | $\frac{1}{6}$ | 2 | 0 | $\frac{1}{6}$ |

Resulting solution $\mathbf{x}^{*}=(5 / 6,2 / 3,0,0,1 / 2)$, with $z^{*}=1 / 6$.

## Complementary Slackness: Example

Primal Tableax (P)

| $x_{1}$ | $x_{2}$ | $x_{3}$ | $x_{4}$ | $x_{5}$ | $b$ |
| ---: | ---: | ---: | ---: | ---: | ---: |
| 2 | -1 | -1 | 1 | 0 | 1 |
| 2 | 2 | 1 | -2 | 0 | 3 |
| 1 | 1 | 1 | 1 | 1 | 2 |
| -1 | 1 | 1 | 1 | 0 | 0 |

## Dual Tableax (D)

(note that these represent $\geq$ )

$\Rightarrow$| $y_{1}$ | $y_{2}$ | $y_{3}$ | $c$ |
| ---: | ---: | ---: | ---: |
| 2 | 2 | 1 | 1 |
| -1 | 2 | 1 | -1 |
| -1 | 1 | 1 | -1 |
| 1 | -2 | 1 | -1 |
| 0 | 0 | 1 | 0 |
| -1 | -3 | -2 | 0 |

## Complementary slackness

Write down the dual ( $D$ ) of ( $P$ ).
(D) $\min w=y_{1}+3 y_{2}+2 y_{3}$

$$
\begin{align*}
2 y_{1}+2 y_{2}+y_{3} & \geq 1  \tag{iv}\\
-y_{1}+2 y_{2}+y_{3} & \geq-1  \tag{v}\\
-y_{1}+y_{2}+y_{3} & \geq-1  \tag{vi}\\
y_{1}-2 y_{2}+y_{3} & \geq-1  \tag{vii}\\
y_{3} & \geq 0
\end{align*}
$$

$y_{1}, y_{2}$ and $y_{3}$ are all free variables ${ }^{1}$.

Writing down the CSR, we see that

- From (iv), we get $\left(2 y_{1}^{*}+2 y_{2}^{*}+y_{3}^{*}-1\right) x_{1}^{*}=0$ and since $x_{1}^{*}>0$, we have $2 y_{1}^{*}+2 y_{2}^{*}+y_{3}^{*}=1$.
- From (v), since $x_{2}^{*}>0$, we have $-y_{1}^{*}+2 y_{2}^{*}+y_{3}^{*}=-1$.
- Similarly, from (viii), since $x_{5}^{*}>0$, we have $y_{3}^{*}=0$.

[^0]
## Complementary slackness

Thus from the CSR for (iv),(v) and (viii) we see that

$$
\begin{aligned}
2 y_{1}^{*}+2 y_{2}^{*}+y_{3}^{*} & =1 \\
-y_{1}^{*}+2 y_{2}^{*}+y_{3}^{*} & =-1 \\
y_{3}^{*} & =0
\end{aligned}
$$

Solving these equalities for $y_{1}^{*}, y_{2}^{*}, y_{3}^{*}$, we get $y_{1}^{*}=\frac{2}{3}, y_{2}^{*}=-\frac{1}{6}, y_{3}^{*}=0$, which need to be checked for feasibility in the other constraints:
That is,

$$
\begin{array}{lrl}
\text { (vi) } & -\frac{2}{3}-\frac{1}{6}+0>-1 \\
\text { (vii) } & \frac{2}{3}+\frac{1}{3}+0>-1 .
\end{array}
$$

Also note that $z^{*}=\frac{5}{6}-\frac{2}{3}=\frac{1}{6}=w^{*}=\frac{2}{3}-3 \times \frac{1}{6}=\frac{2}{3}-\frac{1}{2}=\frac{1}{6}$.

## Takeaways

- Optimisation problems have a Dual
- this is a very general concept, and holds beyond LPs
- Complementary slackness relates dual solutions to primal
- these give us an edge in knowing when we have found optimal solutions
- we'll use these later!


## Further reading I


[^0]:    ${ }^{1}$ Note the last constraint tightens $y_{3}$, but this is OK.

