

Machine Learning II

Bjoern Andres

Machine Learning for Computer Vision
TU Dresden



<https://mlcv.cs.tu-dresden.de/courses/26-summer/ml2/>

Summer Term 2026

Definition 1. For any $A \in \mathbb{R}^{m \times n}$ and any $b \in \mathbb{R}^m$,

$$Ax = b \tag{1}$$

$$x \geq 0 \tag{2}$$

is called the **standard system** defined by A and b , and

$$X_{Ab} := \{x \in \mathbb{R}^n \mid Ax = b \wedge x \geq 0\} \tag{3}$$

is called its **feasible set**. The elements of X_{Ab} are called the **feasible solutions** to (1)–(2).

Remark 1. If the rows of A are linearly dependent, rows can be deleted without changing feasible set X_{Ab} . Thus, we may assume that $\text{rank}(A) = m$.

Remark 2. Assume $\text{rank}(A) = m$. If $n \leq m$ then $n = m$. In this case, the solution $x' := A^{-1}b$ to (1) is unique. If $x' \geq 0$, $X_{Ab} = \{x'\}$. Otherwise, $X_{Ab} = \emptyset$. More interesting is the case where $n > m$.

Definition 2. For any $m, n \in \mathbb{N}_0$ and any $A \in \mathbb{R}^{m \times n}$ with $\text{rank}(A) = m$, a **basis** of A is any $K \subseteq n$ with $|K| = m$ such that $A|_{\cdot K}$ is non-singular.

Definition 3. For any $m, n \in \mathbb{N}_0$, any $A \in \mathbb{R}^{m \times n}$ with $\text{rank}(A) = m$, any $b \in \mathbb{R}^m$, any $x \in X_{Ab}$ and any basis K of A , x is called a **basic feasible solution (BFS)** with basis K to the standard system defined by A and b iff

$$x|_K = A|_{\cdot K}^{-1}b \tag{4}$$

$$x|_{n \setminus K} = 0 \tag{5}$$

Lemma 1. For any $m, n \in \mathbb{N}_0$, any $A \in \mathbb{R}^{m \times n}$ with $\text{rank}(A) = m$ and any $b \in \mathbb{R}^m$, the standard system defined by A and b has at most $\binom{n}{m}$ BFSs.

Proof. Every BFS is related to a basis.

For any basis K , the $x \in \mathbb{R}^n$ defined by (4)–(5) is unique. x is a BFS iff $x \in X_{Ab}$. Thus, there is at most one BFS per basis.

Every basis K is, in particular, a set $K \subseteq n$ with $|K| = m$, of which there are $\binom{n}{m}$ many. □

Theorem 1. Let $m, n \in \mathbb{N}_0$, $A \in \mathbb{R}^{m \times n}$ with $\text{rank}(A) = m$ and $b \in \mathbb{R}^m$. If $X_{Ab} \neq \emptyset$, there exists a BFS $x \in X_{Ab}$.

Remark 3. By virtue of Theorem 1 and Lemma 1, the search for a feasible solution can be reduced to a finite set.

Linear optimization for machine learning

Proof. For any $y \in \mathbb{R}^n$, let $K_y := \{k \in n \mid y_k \neq 0\}$. Consider any $x \in X_{Ab}$.

a) If the columns of $A|_{.K_x}$ are l.i., $\text{rank}(A) = m$ implies $|K_x| \leq m$.

– If $|K_x| = m$, x is a BFS with the basis K_x .

– If $|K_x| < m$, choose $K \subseteq n$ such that $K_x \subseteq K$ and $|K| = m$ such that the columns of $A|_{.K}$ are l.i.. This is possible because $\text{rank}(A) = m$. Now, x is a BFS with the basis K .

b) If the columns of $A|_{.K_x}$ are l.d., there exists $d \in \mathbb{R}^n$ such that

$$A d = 0 \tag{6}$$

$$\emptyset \neq K_d \subseteq K_x \ . \tag{7}$$

For any $\lambda \in \mathbb{R}$, let $x' := x + \lambda d$. Now:

$$A x' = A x + \lambda A d \stackrel{(6)}{=} A x = b \ . \tag{8}$$

Choose $k' \in K_d$ so as to minimize $\frac{x_{k'}}{|d_{k'}|}$. Let $\lambda' := -\frac{x_{k'}}{d_{k'}}$. Now:

$$\forall k \in m \setminus K_x: \quad x'_k = x_k - \lambda' d_k \stackrel{(7)}{=} 0 \tag{9}$$

$$x'_{k'} = x_{k'} - \frac{x_{k'}}{d_{k'}} d_{k'} = 0 \tag{10}$$

$$\forall k \in K_x \setminus \{k'\}: \quad x'_k = x_k - \frac{x_{k'}}{d_{k'}} d_k = \begin{cases} x_k & \text{if } d_k = 0 \\ \left(\frac{x_k}{d_k} - \frac{x_{k'}}{d_{k'}}\right) d_k & \text{if } d_k \neq 0 \end{cases} \ . \tag{11}$$

Linear optimization for machine learning

Proof (contd.). We analyze (11): If $d_k > 0$ then

$$\left(\frac{x_k}{d_k} - \frac{x_{k'}}{d_{k'}}\right) d_k = \left(\frac{x_k}{|d_k|} - \frac{x_{k'}}{d_{k'}}\right) |d_k| \geq \left(\frac{x_k}{|d_k|} - \frac{x_{k'}}{|d_{k'}|}\right) |d_k| \geq 0 . \quad (12)$$

If $d_k < 0$ then

$$\begin{aligned} \left(\frac{x_k}{d_k} - \frac{x_{k'}}{d_{k'}}\right) d_k &= \left(-\frac{x_k}{d_k} + \frac{x_{k'}}{d_{k'}}\right) |d_k| = \left(\frac{x_k}{|d_k|} + \frac{x_{k'}}{d_{k'}}\right) |d_k| \\ &\geq \left(\frac{x_k}{|d_k|} - \frac{x_{k'}}{|d_{k'}|}\right) |d_k| \geq 0 . \end{aligned} \quad (13)$$

Thus, $x' \geq 0$. Together with (8) follows $x' \in X_{Ab}$. Moreover, $K_{x'} \subseteq K_x \setminus \{k'\}$.

If the columns of $A|_{\cdot, K_{x'}}$ are l.i., a BFS exists by Part (a).

Otherwise, Part (b) can be iterated until the columns of $A|_{\cdot, K_{x'}}$ are l.i..

Thus, a BFS always exists. □

Definition 4. Let $m, n \in \mathbb{N}_0$, $A \in \mathbb{R}^{m \times n}$ with $\text{rank}(A) = m$ and $b \in \mathbb{R}^m$. For

- any BFS x with basis K to the standard system defined by A and b
- any $k^* \in n$ and the unique $y^{k^*} \in \mathbb{R}^n$ such that

$$\sum_{k \in K} y_k^{k^*} A_{\cdot k} = A_{\cdot k^*} \quad \text{i.e. } y^{k^*}|_K = A|_{\cdot K}^{-1} A_{\cdot k^*} \quad (14)$$

$$\forall k \in n \setminus K: \quad y_k^{k^*} = 0 \quad (15)$$

- any $k^\dagger \in K_{k^*} := \{k \in K \mid y_k^{k^*} > 0\}$ and the unique $\lambda' \in \mathbb{R}_0^+$ such that

$$\min \left\{ \frac{x_k}{y_k^{k^*}} \mid k \in K_{k^*} \right\} = \frac{x_{k^\dagger}}{y_{k^\dagger}^{k^*}} = \lambda', \quad (16)$$

the $x' \in \mathbb{R}^n$ such that

$$x'_{k^*} := \lambda' \quad (17)$$

$$\forall k \in n \setminus \{k^*\}: \quad x'_k := x_k - \lambda' y_k^{k^*} \quad (18)$$

is called the result of **pivoting** x in K such that k^* **enters** and k^\dagger **leaves** the basis.

Theorem 2. Let

- $m, n \in \mathbb{N}_0$, $A \in \mathbb{R}^{m \times n}$ with $\text{rank}(A) = m$ and $b \in \mathbb{R}^m$
- x a BFS with basis K to the standard system defined by A and b
- x' be the result of pivoting x in K such that k^* enters and k^\dagger leaves the basis.

Then, x' is a BFS with basis $(K \setminus \{k^\dagger\}) \cup \{k^*\}$ to the standard system defined by A and b .

Remark 4. Consider Definition 4.

- a) If $K_{k^*} = \emptyset$ then, in (17)–(18), $x' \geq 0$ for all $\lambda' \in \mathbb{R}_0^+$. Thus, X_{Ab} is unbounded.
- b) If $\lambda' = 0$ then $x' = x$ (while k^* enters and k^\dagger leaves the basis).
- c) If $k^* \in K$ then

$$\forall k \in K: \quad y_k^{k^*} = \begin{cases} 1 & \text{if } k = k^* \\ 0 & \text{otherwise} \end{cases} . \quad (19)$$

Therefore, $K_{k^*} = \{k^*\}$. Thus, $k^\dagger = k^*$ and $\lambda' = x_{k^*}$. Hence, the basis does not change and $x' = x$.

Linear optimization for machine learning

Proof. Since x is a BFS with basis K :

$$\sum_{k \in K} x_k A_{.k} = b . \quad (20)$$

For any $\lambda \in \mathbb{R}$, (20)– λ (14) yields

$$\lambda A_{.k^*} + \sum_{k \in K} (x_k - \lambda y_k^{k^*}) A_{.k} = b . \quad (21)$$

For $\lambda = \lambda'$ specifically follows $A x' = b$.

From $x_{k^\dagger} \geq 0$ and $y_{k^\dagger}^{k^*} > 0$ follows $\lambda' \geq 0$. Thus $x'_{k^\dagger} \geq 0$. For any $k \in n \setminus \{k^\dagger\}$, distinguish two cases: If $y_k^{k^*} \leq 0$ then (18), $x_k \geq 0$ and $\lambda' \geq 0$ imply $x'_k \geq 0$. If $y_k^{k^*} > 0$ then

$$x'_k = x_k - \lambda' y_k^{k^*} = x_k - \frac{x_{k^\dagger}}{y_{k^\dagger}^{k^*}} y_k^{k^*} = \left(\frac{x_k}{y_k^{k^*}} - \frac{x_{k^\dagger}}{y_{k^\dagger}^{k^*}} \right) y_k^{k^*} \stackrel{(16)}{\geq} 0 . \quad (22)$$

Thus, $x' \geq 0$.

It remains to be shown that $(K \setminus \{k^\dagger\}) \cup \{k^*\}$ is a basis. ...

Linear optimization for machine learning

Proof (contd.). Let $c \in \mathbb{R}^n$ such that

$$0 = \sum_{k \in (K \setminus \{k^\dagger\}) \cup \{k^*\}} c_k A_{.k} . \quad (23)$$

Now,

$$0 = c_{k^*} A_{.k^*} + \sum_{k \in K \setminus \{k^\dagger\}} c_k A_{.k} \quad (24)$$

$$\stackrel{(14)}{=} c_{k^*} \sum_{k \in K} y_k^{k^*} A_{.k} + \sum_{k \in K \setminus \{k^\dagger\}} c_k A_{.k} \quad (25)$$

$$= c_{k^*} y_{k^\dagger}^{k^*} A_{.k^\dagger} + \sum_{k \in K \setminus \{k^\dagger\}} (c_{k^*} y_k^{k^*} + c_k) A_{.k} . \quad (26)$$

The rhs. is a l.c. of the columns of A indexed by the basis K . Thus,

$$c_{k^*} y_{k^\dagger}^{k^*} = 0 \quad (27)$$

$$\forall k \in K \setminus \{k^\dagger\}: c_{k^*} y_k^{k^*} + c_k = 0 . \quad (28)$$

From (27) and $y_{k^\dagger}^{k^*} > 0$ follows $c_{k^*} = 0$. Together with (28) follows $c = 0$. Thus, $(K \setminus \{k^\dagger\}) \cup \{k^*\}$ is a basis. \square

Definition 5. For any $m, n \in \mathbb{N}_0$, any $A \in \mathbb{R}^{m \times n}$, any $A' \in \mathbb{R}^{m' \times n}$, any $b \in \mathbb{R}^m$, any $b' \in \mathbb{R}^{m'}$ and any $J \subseteq n$, the **general system** defined by A, A', b, b' and J is

$$Ax = b \tag{29}$$

$$A'x \geq b' \tag{30}$$

$$\forall j \in J: \quad x_j \geq 0 . \tag{31}$$

Definition 6. For any $A \in \mathbb{R}^{m \times n}$ and any $b \in \mathbb{R}^m$, the **canonical system** defined by A and b is

$$Ax \geq b \tag{32}$$

$$x \geq 0 . \tag{33}$$

Lemma 2. Standard, general, and canonical systems are mutually equivalent, in the sense that each can be transformed into any of the others.

Linear optimization for machine learning

Proof. A canonical system is a special case of a general system.

To turn any general system into an equivalent canonical system, proceed as follows:

- For any $j \in n \setminus J$, replace the unconstrained variable x_j by $x'_j - x''_j$ such that

$$x'_j \geq 0 \tag{34}$$

$$x''_j \geq 0 . \tag{35}$$

- Replace any equality $A_j \cdot x = b_j$ by the inequalities

$$A_j \cdot x \geq b_j \tag{36}$$

$$-A_j \cdot x \geq -b_j . \tag{37}$$

A standard system is a special case of a general system.

To turn any general system into an equivalent standard system, proceed as follows:

- Replace all unconstrained variables as described above.
- Replace any inequality $A_j \cdot x \geq b_j$ by

$$A_j \cdot x - x'''_j = b_j \tag{38}$$

$$x'''_j \geq 0 . \tag{39}$$

□

Definition 7. For any $m, n \in \mathbb{N}_0$, any $A \in \mathbb{R}^{m \times n}$, any $b \in \mathbb{R}^m$ and any $c \in \mathbb{R}^n$, the **linear optimization problem** or **linear program (LP)** in **standard form** is

$$\min \{ \langle c, x \rangle \mid Ax = b \wedge x \geq 0 \wedge x \in \mathbb{R}^n \} , \quad (40)$$

and the linear optimization problem or linear program (LP) in **canonical form** is

$$\min \{ \langle c, x \rangle \mid Ax \geq b \wedge x \geq 0 \wedge x \in \mathbb{R}^n \} . \quad (41)$$

For any $m, n \in \mathbb{N}_0$, any $A \in \mathbb{R}^{m \times n}$, any $A' \in \mathbb{R}^{m' \times n}$, any $b \in \mathbb{R}^m$, any $b' \in \mathbb{R}^{m'}$ and any $J \subseteq n$, the linear optimization problem or linear program (LP) in **general form** is

$$\min \{ \langle c, x \rangle \mid Ax = b \wedge A'x \geq b' \wedge (\forall j \in J: x_j \geq 0) \wedge x \in \mathbb{R}^n \} . \quad (42)$$

Lemma 3. Consider

- any $m, n \in \mathbb{N}_0$, $b \in \mathbb{R}^m$, $c \in \mathbb{R}^n$ and $A \in \mathbb{R}^{m \times n}$ such that $\text{rank}(A) = m$
- any BFS x with basis K to the standard system defined by A and b
- any $k^* \in n$ and the $y^{k^*} \in \mathbb{R}^n$ with $y^{k^*}|_K = A|_{\cdot, K}^{-1} A_{\cdot, k^*}$ and $y^{k^*}|_{n \setminus K} = 0$
- x' the result of pivoting x in K such that k^* enters the basis.

Then:

$$\langle c, x' \rangle - \langle c, x \rangle = \left(c_{k^*} - \sum_{k \in K} c_k y_k^{k^*} \right) x'_{k^*} \quad (43)$$

Definition 8. Under the assumptions of Lemma 3, the **relative cost** of k^* in the basis K is the number

$$c_{k^*} - \sum_{k \in K} c_k y_k^{k^*} . \quad (44)$$

Proof. If $k^* \in K$, the statement follows from Remark 4c.

Otherwise, $x_{k^*} = 0$. Thus:

$$\langle c, x' \rangle - \langle c, x \rangle = \langle c, x' - x \rangle \tag{45}$$

$$= \sum_{k \in K \cup \{k^*\}} c_k (x'_k - x_k) \tag{46}$$

$$= c_{k^*} (x'_{k^*} - 0) + \sum_{k \in K} c_k (x'_k - x_k) \tag{47}$$

$$\stackrel{(18)}{=} c_{k^*} x'_{k^*} + \sum_{k \in K} c_k (-x'_{k^*} y_k^{k^*}) \tag{48}$$

$$= \left(c_{k^*} - \sum_{k \in K} c_k y_k^{k^*} \right) x'_{k^*} . \tag{49}$$

□

Theorem 3. Let

- $m, n \in \mathbb{N}_0$, $b \in \mathbb{R}^m$, $c \in \mathbb{R}^n$ and $A \in \mathbb{R}^{m \times n}$ such that $\text{rank}(A) = m$
- x a BFS with basis K to the standard system defined by A and b
- for any $k \in n$, c'_k the relative cost of k in the basis K , and $c'_k \geq 0$.

Then, x is a solution to the LP in standard form defined by A and b .

Linear optimization for machine learning

Proof. Let x' be any feasible solution to the standard system defined by A and b , not necessarily basic. Now:

$$\begin{aligned}\langle c, x' \rangle &= \sum_{k \in n} c_k x'_k \\ &\geq \sum_{k \in n} \left(\sum_{k' \in K} c_{k'} y_{k'}^k \right) x'_k \\ &= \sum_{k' \in K} c_{k'} \sum_{k \in n} y_{k'}^k x'_k = \sum_{k' \in K} c_{k'} \sum_{k \in n} (A|_{\cdot K}^{-1} A_{\cdot k})_{k'} x'_k \\ &= \sum_{k' \in K} c_{k'} \sum_{k \in n} \left(\sum_{j \in m} (A|_{\cdot K}^{-1})_{k' j} A_{jk} \right) x'_k \\ &= \sum_{k' \in K} c_{k'} \sum_{j \in m} (A|_{\cdot K}^{-1})_{k' j} \sum_{k \in n} A_{jk} x'_k = \sum_{k' \in K} c_{k'} \sum_{j \in m} (A|_{\cdot K}^{-1})_{k' j} (Ax')_j \\ &= \sum_{k' \in K} c_{k'} \sum_{j \in m} (A|_{\cdot K}^{-1})_{k' j} b_j = \sum_{k' \in K} c_{k'} x_{k'} \\ &= \langle c, x \rangle\end{aligned}$$

□

Input: a BFS x^0 with basis K

$t := 0$

while true

 for any $k \in n$, let c'_k the relative cost of k in the basis K

 if $c' \geq 0$

 return x^t (solution)

 else

 choose k^* such that $c'_{k^*} < 0$

 if $K_{k^*} = \emptyset$

 return unbounded

 else

 choose k^\dagger and define λ' according to (16)

 let x^{t+1} the pivoting of x^t s.t. k^* enters and k^\dagger leaves K

$t := t + 1$

Simplex Algorithm

Input: a BFS x^0 with basis K

$t := 0$

while true

 for any $k \in n$, let c'_k the relative cost of k in the basis K

 if $c' \geq 0$

 return x^t (solution)

 else

 choose k^* such that $c'_{k^*} < 0$

 if $K_{k^*} = \emptyset$

 return unbounded

 else

 choose k^\dagger and define λ' according to (16)

 let x^{t+1} the pivoting of x^t s.t. k^* enters and k^\dagger leaves K

$t := t + 1$

Simplex Algorithm

Example 1. Pivoting rules:

- Choose k^* so as to minimize the relative cost

$$c_{k^*} - \sum_{k \in K} c_k y_k^{k^*} . \tag{50}$$

Not guaranteeing locally optimal reduction in cost; not preventing cycling.

- Choose k^* so as to minimize

$$\left(c_{k^*} - \sum_{k \in K} c_k y_k^{k^*} \right) x'_{k^*} . \tag{51}$$

Guaranteeing locally optimal reduction in cost; not preventing cycling.

- Bland's Rule: Define a total order $<$ on K . Among those k^* with a negative reduced cost, choose the one that is smallest wrt. $<$. If there is a tie in (16), choose k^\dagger to be the smallest wrt. $<$.

Not guaranteeing locally optimal reduction in cost; preventing cycling.