§4.5: Dimension

From last week:

- Given a vector space V, a basis for V is a linearly independent set that spans V.
- If $\mathcal{B} = \{\mathbf{b}_1, \ldots, \mathbf{b}_n\}$ is a basis for V, then the $\mathcal{B}$-coordinates of $\mathbf{x}$ are the weights c_i in the linear combination $\mathbf{x} = c_1\mathbf{b}_1 + \cdots + c_p\mathbf{b}_p$.
- Coordinate vectors allow us to test for spanning / linear independence, to solve linear systems, and to test for one-to-one / onto by working in $\mathbb{R}^n$.

Another example of this idea:

Theorem: Let $\mathcal{B} = \{\mathbf{b}_1, \ldots, \mathbf{b}_n\}$ be a basis for a vector space V.

i Any set in V containing more than n vectors must be linearly dependent (theorem 9 in textbook).

ii Any set in V containing fewer than n vectors cannot span V.

We prove this (next page) using coordinate vectors, and the fact that we already know it is true for $V = \mathbb{R}^n$.

Theorem: Let $\mathcal{B} = \{\mathbf{b}_1, \ldots, \mathbf{b}_n\}$ be a basis for a vector space V.

i Any set in V containing more than n vectors must be linearly dependent.

ii Any set in V containing fewer than n vectors cannot span V.

Proof: Let our set of vectors in V be $\{\mathbf{u}_1, \ldots, \mathbf{u}_p\}$, and consider the matrix

$$A = \begin{bmatrix} | & & | \\ [\mathbf{u}_1]_{\mathcal{B}} & \ldots & [\mathbf{u}_p]_{\mathcal{B}} \\ | & & | \end{bmatrix},$$

which has p columns and n rows.

i If $p > n$, then rref(A) cannot have a pivot in every column, so $\{[\mathbf{u}_1]_{\mathcal{B}}, \ldots, [\mathbf{u}_p]_{\mathcal{B}}\}$ is linearly dependent in $\mathbb{R}^n$, so $\{\mathbf{u}_1, \ldots, \mathbf{u}_p\}$ is linearly dependent in V.

ii If $p < n$, then rref(A) cannot have a pivot in every row, so the set of coordinate vectors $\{[\mathbf{u}_1]_{\mathcal{B}}, \ldots, [\mathbf{u}_p]_{\mathcal{B}}\}$ cannot span $\mathbb{R}^n$, so $\{\mathbf{u}_1, \ldots, \mathbf{u}_p\}$ cannot span V.

Theorem: Let $\mathcal{B} = \{\mathbf{b}_1, \ldots, \mathbf{b}_n\}$ be a basis for a vector space V.

i Any set in V containing more than n vectors must be linearly dependent.

ii Any set in V containing fewer than n vectors cannot span V.

As a consequence:

Theorem 10: Every basis has the same size: If a vector space V has a basis of n vectors, then every basis of V must consist of exactly n vectors.

So the following definition makes sense:

Definition: Let V be a vector space.

- If V is spanned by a finite set, then V is *finite-dimensional*.
  The *dimension* of V, written $\dim V$, is the number of vectors in a basis for V.
  (This number is finite because of the spanning set theorem.)
- If V is not spanned by a finite set, then V is *infinite-dimensional*.

Note that the definition does not involve "infinite sets".

Definition: (or convention) The dimension of the zero vector space $\{\mathbf{0}\}$ is 0.

Definition: The *dimension* of V is the number of vectors in a basis for V.

Examples:

- The standard basis for $\mathbb{R}^n$ is $\{\mathbf{e}_1, \ldots, \mathbf{e}_n\}$, so $\dim \mathbb{R}^n = n$.
- The standard basis for $\mathbb{P}_n$ is $\{1, t, \ldots, t^n\}$, so $\dim \mathbb{P}_n = n + 1$.
- Exercise: Show that $\dim M_{m \times n} = mn$.

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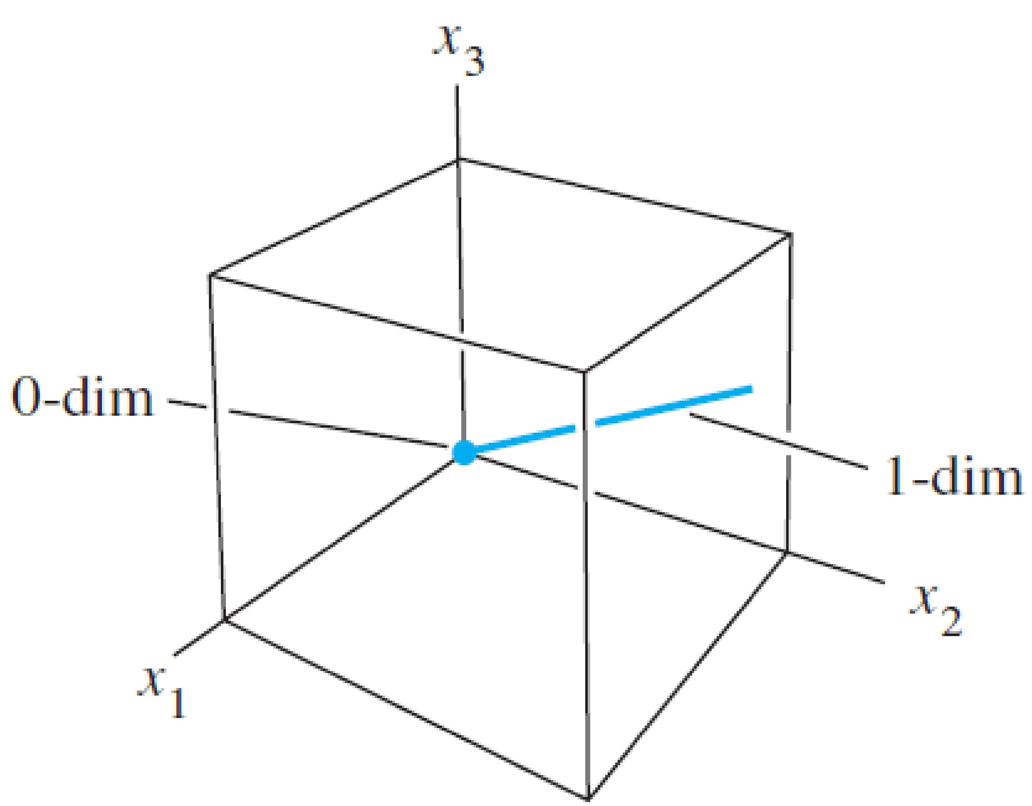
- Exercise: Show that $\dim M_{m\times n} = mn$.

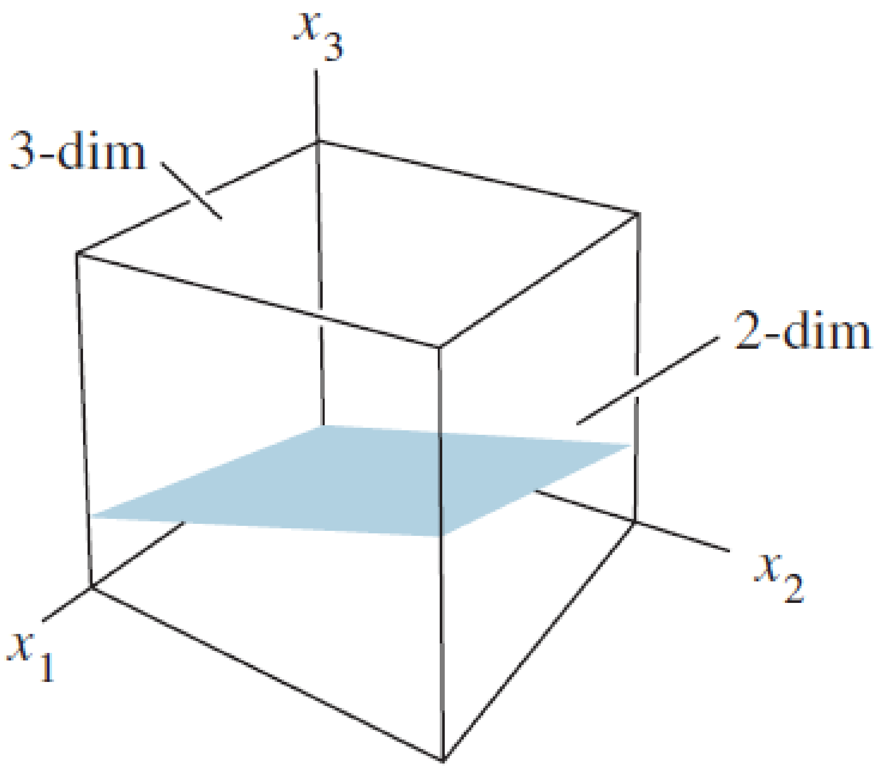
Example: Let $W = \left\{ \begin{bmatrix} a \\ 0 \\ b \end{bmatrix} \middle| a, b, \in \mathbb{R} \right\}$. We showed (week 8 p20) that a basis for W is $\left\{ \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \right\}$. So $\dim W$=2.

From the theorem on p2, we know that any set of 3 vectors in W must be linearly dependent, because $3 > \dim W$.

Example: We classify the subspaces of $\mathbb{R}^3$ by dimension:

- 0-dimensional: only the zero subspace $\{\mathbf{0}\}$.
- 1-dimensional, i.e. Span $\{\mathbf{v}\}$: lines through the origin.
- 2-dimensional, i.e. Span $\{\mathbf{u}, \mathbf{v}\}$ where $\{\mathbf{u}, \mathbf{v}\}$ is linearly independent: planes through the origin.
- 3-dimensional: by Invertible Matrix Theorem, 3 linearly independent vectors in $\mathbb{R}^3$ spans $\mathbb{R}^3$, so the only 3-dimensional subspace of $\mathbb{R}^3$ is $\mathbb{R}^3$ itself.





Here is a counterpart to the spanning set theorem (week 8 p10):

Theorem 11: Linearly Independent Set Theorem: Let W be a subspace of a finite-dimensional vector space V. If $\{\mathbf{v}_1, \dots, \mathbf{v}_p\}$ is a linearly independent set in W, we can find $\mathbf{v}_{p+1}, \dots, \mathbf{v}_n$ so that $\{\mathbf{v}_1, \dots, \mathbf{v}_n\}$ is a basis for W.

Proof:

- If Span $\{\mathbf{v}_1, \dots, \mathbf{v}_p\} = W$, then $\{\mathbf{v}_1, \dots, \mathbf{v}_p\}$ is a basis for W.
- Otherwise $\{\mathbf{v}_1, \dots, \mathbf{v}_p\}$ does not span W, so there is a vector $\mathbf{v}_{p+1}$ in W that is not in Span $\{\mathbf{v}_1, \dots, \mathbf{v}_p\}$. Adding $\mathbf{v}_{p+1}$ to the set still gives a linearly independent set. Continue adding vectors in this way until the set spans W. This process must stop after at most $\dim V - p$ additions, because a set of more than $\dim V$ elements must be linearly dependent.

The above logic proves something stronger:

Theorem 11 part 2: Subspaces of Finite-Dimensional Spaces: If W is a subspace of a finite-dimensional vector space V, then W is also finite-dimensional and $\dim W \leq \dim V$.

Because of the spanning set theorem and linearly independent set theorem:

Theorem 12: Basis Theorem: If V is a p-dimensional vector space, then

i Any linearly independent set of exactly p elements in V is a basis for V.

ii Any set of exactly p elements that span V is a basis for V.

In other words, to prove that $\mathcal{B}$ is a basis of a p-dimensional vector space V, we only need to show two of the following three things (the third will be automatic):

- $\mathcal{B}$ contains exactly p vectors;
- $\mathcal{B}$ is linearly independent;
- $\text{Span}\mathcal{B} = V$.

Because of the spanning set theorem and linearly independent set theorem:

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If V is a subspace of U, these two statements are usually easier to check because we can work in the big space U (see p9 and p14).

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- Span$\mathcal{B} = V$.

If V is a subspace of U, these two statements are usually easier to check because we can work in the big space U (see p9 and p14).

Proof:

i By the linearly independent set theorem, we can add elements to any linearly independent set to obtain a basis for V. But that larger set must contain exactly $\dim V = p$ elements. So our starting set must already be a basis.

ii By the spanning set theorem, we can remove elements from any set that spans V to obtain a basis for V. But that smaller set must contain exactly $\dim V = p$ elements. So our starting set must already be a basis.

Summary:

- If V is spanned by a finite set, then V is finite-dimensional and $\dim V$ is the number of vectors in any basis for V.
- If V is not spanned by a finite set, then V is infinite-dimensional.

- If $\{\mathbf{v}_1, \ldots, \mathbf{v}_n\}$ spans V, then some subset is a basis for V (week 8 p10).
- If $\{\mathbf{v}_1, \ldots, \mathbf{v}_n\}$ is linearly independent and V is finite-dimensional, then it can be expanded to a basis for V (p4).

If $\dim V = p$ (so V and $\mathbb{R}^p$ are isomorphic):

- Any set of more than p vectors in V is linearly dependent (p2).
- Any set of fewer than p vectors in V cannot span V (p2).
- Any linearly independent set of exactly p elements in V is a basis for V (p7).
- Any set of exactly p elements that span V is a basis for V (p7).

To prove that $\mathcal{B}$ is a basis of V, show two of the following three things:

- $\mathcal{B}$ contains exactly p vectors;
- $\mathcal{B}$ is linearly independent;
- Span$\mathcal{B} = V$.

The basis theorem is useful for finding bases of subspaces:

Example:

Let $W = \text{Span}\left\{ \begin{bmatrix}1\\0\\0\\0\end{bmatrix}, \begin{bmatrix}0\\0\\1\\0\end{bmatrix}, \begin{bmatrix}0\\0\\0\\1\end{bmatrix} \right\}$. Is $\mathcal{B} = \left\{ \begin{bmatrix}1\\0\\0\\3\end{bmatrix}, \begin{bmatrix}2\\0\\0\\5\end{bmatrix}, \begin{bmatrix}3\\0\\1\\2\end{bmatrix} \right\}$ a basis for W?

Answer: We are given that $W = \text{Span}\{\mathbf{e}_1, \mathbf{e}_3, \mathbf{e}_4\}$ and $\{\mathbf{e}_1, \mathbf{e}_3, \mathbf{e}_4\}$ is a linearly independent set, so $\{\mathbf{e}_1, \mathbf{e}_3, \mathbf{e}_4\}$ is a basis for W, and so $\dim W = 3$.
The vectors in $\mathcal{B}$ are all in W, and $\mathcal{B}$ consists of exactly 3 vectors, so it's enough to check whether $\mathcal{B}$ is linearly independent.

Row reduction: $\begin{bmatrix}1&2&3\\0&0&0\\0&0&1\\3&5&2\end{bmatrix} \xrightarrow[R_4-3R_1]{} \begin{bmatrix}1&2&3\\0&0&0\\0&0&1\\0&-1&-7\end{bmatrix} \xrightarrow[R_2]{R_4} \begin{bmatrix}1&2&3\\0&-1&-7\\0&0&1\\0&0&0\end{bmatrix}$ has a pivot in each column, so $\mathcal{B}$ is linearly independent, and is therefore a basis.
Note that we never had to work in W, only in $\mathbb{R}^4$.

§4.6: Rank

Next we look at how the idea of dimension can help us answer questions about existence and uniqueness of solutions to linear systems.

Definition: The *rank* of a matrix A is the dimension of its column space.
The *nullity* of a matrix A is the dimension of its null space.

Example: Let $A = \begin{bmatrix} 5 & -3 & 10 \\ 7 & 2 & 14 \end{bmatrix}$, $\text{rref}(A) = \begin{bmatrix} 1 & 0 & 1/2 \\ 0 & 1 & 0 \end{bmatrix}$.

A basis for Col$A$ is

A basis for Nul$A$ is

A basis for Row$A$ is
So rank$A =$ nullity$A =$

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A basis for Col$A$ is $\left\{ \begin{bmatrix} 5 \\ 7 \end{bmatrix}, \begin{bmatrix} -3 \\ 2 \end{bmatrix} \right\}$ $\longleftarrow$ one vector per pivot

A basis for Nul$A$ is $\left\{ \begin{bmatrix} -1/2 \\ 0 \\ 1 \end{bmatrix} \right\}$. $\longleftarrow$ one vector per free variable

A basis for Row$A$ is $\{(1, 0, 1/2), (0, 1, 0)\}$. $\longleftarrow$ one vector per pivot

So rank$A = 2$, nullity$A = 1$.

So rank$A$ + nullity$A$ =?

Theorem 14:

Rank Theorem: $\text{rank}A = \dim \text{Col}A = \dim \text{Row}A =$ number of pivots in $\text{rref}(A)$.

Rank-Nullity Theorem: For an $m \times n$ matrix A,

$$\text{rank}A + \text{nullity}A = n.$$

Proof: From our algorithms for bases of Col$A$ and Nul$A$ (see week 7 slides):
$\text{rank}A =$ number of pivots in $\text{rref}(A) =$ number of basic variables,
$\text{nullity}A =$ number of free variables.
Each variable is either basic or free, and the total number of variables is n, the number of columns.

Theorem 14:

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An application of the Rank-Nullity theorem:

Example: Suppose a homogeneous system of 10 equations in 12 variables has a solution set that is spanned by two linearly independent vectors (i.e. 2 free variables). Then the nullity of this system is 2, so the rank is $12 - 2 = 10$. So this system has 10 pivots. Since there are ten equations, there must be a pivot in every row, so any nonhomogeneous system with the same coefficients always has a solution.

Theorem 14:

Rank Theorem: rank$A = \dim$ Col$A = \dim$ Row$A =$ number of pivots in rref(A).

Rank-Nullity Theorem: For an $m \times n$ matrix A,

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Proof: From our algorithms for bases of Col$A$ and Nul$A$ (see week 7 slides):
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Using our new ideas of dimension, we can add more statements to the Existence theorem, the Uniqueness theorem, and the Invertible Matrix Theorem:

Theorem 8: Invertible Matrix Theorem (IMT): For a square $n \times n$ matrix A, the following are equivalent:

rref(A) has a pivot in every row.

$A\mathbf{x} = \mathbf{b}$ has at least one solution for each $\mathbf{b}$ in $\mathbb{R}^n$.

The columns of A span $\mathbb{R}^n$.

The linear transformation $\mathbf{x} \mapsto A\mathbf{x}$ is onto.

There is a matrix D such that $AD = I_n$.

Col$A = \mathbb{R}^n$.

rank$A = n$.

rref(A) has a pivot in every column.

$A\mathbf{x} = \mathbf{0}$ has only the trivial solution.

The columns of A are linearly independent.

The linear transformation $\mathbf{x} \mapsto A\mathbf{x}$ is one-to-one.

There is a matrix C such that $CA = I_n$.

Nul$A = \{\mathbf{0}\}$.

nullity$A = 0$.

$\det A \neq 0$.

rref$(A) = I_n$.

$A\mathbf{x} = \mathbf{b}$ has a unique solution for each $\mathbf{b}$ in $\mathbb{R}^n$.

The columns of A form a basis for $\mathbb{R}^n$.

The linear transformation $\mathbf{x} \mapsto A\mathbf{x}$ is an invertible function.

A is an invertible matrix.

Advanced application of the Rank-Nullity Theorem and the Basis Theorem:

Redo Example: (p10) Let $A = \begin{bmatrix} 5 & -3 & 10 \\ 7 & 2 & 14 \end{bmatrix}$. Find a basis for Nul$A$ and Col$A$.

Answer: (a clever trick without any row-reduction)

- Observe that $2 \begin{bmatrix} 5 \\ 7 \end{bmatrix} = \begin{bmatrix} 10 \\ 14 \end{bmatrix}$, so $\begin{bmatrix} 2 \\ 0 \\ -1 \end{bmatrix}$ is a solution to $A\mathbf{x} = \mathbf{0}$. So nullity$A \geq 1$.
- The first two columns of A are linearly independent (not multiples of each other), so $\left\{ \begin{bmatrix} 5 \\ 7 \end{bmatrix}, \begin{bmatrix} -3 \\ 2 \end{bmatrix} \right\}$ is a linearly independent set in Col$A$, so rank$A \geq 2$.

Advanced application of the Rank-Nullity Theorem and the Basis Theorem:

Redo Example: (p10) Let $A = \begin{bmatrix} 5 & -3 & 10 \\ 7 & 2 & 14 \end{bmatrix}$. Find a basis for Nul$A$ and Col$A$.

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- The first two columns of A are linearly independent (not multiples of each other), so $\left\{ \begin{bmatrix} 5 \\ 7 \end{bmatrix}, \begin{bmatrix} -3 \\ 2 \end{bmatrix} \right\}$ is a linearly independent set in Col$A$, so rank$A \geq 2$.
- But rank$A$ + nullity$A = 3$, so in fact rank$A = 2$ and nullity$A = 1$, and, by the Basis Theorem, the linearly independent sets we found above are bases: so $\left\{ \begin{bmatrix} 2 \\ 0 \\ -1 \end{bmatrix} \right\}$ is a basis for Nul$A$, $\left\{ \begin{bmatrix} 5 \\ 7 \end{bmatrix}, \begin{bmatrix} -3 \\ 2 \end{bmatrix} \right\}$ is a basis for Col$A$.

So for a general $m \times n$ matrix, it's enough to find k linearly independent vectors in Nul$A$ and $n - k$ linearly independent vectors in Col$A$.

The Rank-Nullity theorem also holds for linear transformations $T : V \to W$ whenever V is finite-dimensional (to prove it yourself, work through optional q7 of homework 5):

$$\dim \text{range of } T + \dim \text{kernel of } T = \dim V.$$

Advanced application:

Example: Find a basis for $K = \{\mathbf{p} \in \mathbb{P}_3 | \mathbf{p}(2) = 0\}$, i.e. polynomials $\mathbf{p}(t)$ of degree at most 3 with $\mathbf{p}(2) = 0$.

Answer: Remember (week 7 p46) that K is the kernel of the evaluation-at-2 function $E_2 : \mathbb{P}_3 \to \mathbb{R}$ given by $E_2(\mathbf{p}) = \mathbf{p}(2)$,

$$E_2(a_0 + a_1 t + a_2 t^2 + a_3 t^3) = a_0 + a_1 2 + a_2 2^2 + a_3 2^3.$$

E_2 is onto, so its range has dimension 1. So $\dim K = \dim \mathbb{P}_3 - 1 = 4 - 1 = 3$. Now $\mathcal{B} = \left\{(2-t), (2-t)^2, (2-t)^3\right\}$ is a subset of K, and is linearly independent (check with coordinate vectors relative to the standard basis of $\mathbb{P}_3$, or because these three polynomials have different degrees - see week 8 p14-15). Since $\mathcal{B}$ contains exactly 3 vectors, it is a basis for K.

Important special cases of the Rank-Nullity Theorem:

Theorem: Let $T : V \to W$ be a linear transformation.

i If T is one-to-one, then $\dim V \leq \dim W$.

ii If T is onto, then $\dim V \geq \dim W$.

if $V = \mathbb{R}^n$, $W = \mathbb{R}^m$

(matrix cannot be fat)

(matrix cannot be tall)

Proof: with RNT:

i
$$\begin{aligned} \dim V &= \dim\ker T + \dim \text{range}T \\ &= \quad 0 \quad + \dim \text{range}T \\ &\leq \qquad\qquad \dim W. \end{aligned}$$

T is one-to-one, so $\ker T = \{\mathbf{0}\}$, i.e. $\dim\ker T = 0$

because range$T$ is a subspace of W.

ii
$$\begin{aligned} \dim V &= \dim\ker T + \dim \text{range}T \\ &= \dim\ker T + \dim W \\ &\geq \qquad\qquad \dim W. \end{aligned}$$

T is onto, so range$T = W$

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Theorem: Let $T: V \to W$ be a linear transformation. if $V = \mathbb{R}^n$, $W = \mathbb{R}^m$

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ii If T is onto, then $\dim V \geq \dim W$. (matrix cannot be tall)

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T is onto, so range$T = W$

Proof: without RNT (outline): let $\{\mathbf{v}_1, \ldots, \mathbf{v}_n\}$ be a basis of V (so $\dim V = n$).

i As T is one-to-one, and $\{\mathbf{v}_1, \ldots, \mathbf{v}_n\}$ is linearly independent, so $\{T(\mathbf{v}_1), \ldots, T(\mathbf{v}_n)\}$ is linearly independent in W (see Homework 3 Q9v), so $\dim W \geq n$.

ii As $\{\mathbf{v}_1, \ldots, \mathbf{v}_n\}$ spans V, so $\{T(\mathbf{v}_1), \ldots, T(\mathbf{v}_n)\}$ spans range$T$. And, if T is onto, then range$T = W$. So $\{T(\mathbf{v}_1), \ldots, T(\mathbf{v}_n)\}$ spans W, so $\dim V \leq W$.