## The Gram-Schmidt process

Suppose that $\left\{u_{1}, u_{2}, \ldots, u_{n}\right\}$ is a basis for an inner product space $V$.
(1) Start with $u_{1}$ and "normalize" it (divide by its length so the result is of length 1 ); call this $v_{1}$.
(2) Consider $u_{2}$ and form $u_{2}^{\prime}=u_{2}-\operatorname{proj}_{W_{1}} u_{2}$ where $W_{1}$ is the span of $v_{1}$.
(3) Now normalize $u_{2}^{\prime}$ and call this $v_{2}$. Let $W_{2}$ be the span of $v_{1}, v_{2}$.
(4) Consider $u_{3}$ and form $u_{3}^{\prime}=u_{3}-\operatorname{proj}_{w_{2}} u_{3}$.
(5) Normalize $u_{3}^{\prime}$ and call it $v_{3}$. Let $W_{3}$ be the space spanned by $v_{1}, v_{2}, v_{3}$.
(6) Repeat this process by iteratively forming $v_{i}$ and $W_{i}$ until $i=n$.
(7) $\left\{v_{1}, v_{2}, \ldots, v_{n}\right\}$ forms an orthonormal basis for $V$.

## QR-decomposition

As a consequence of the Gram-Schmidt process, one can prove:

## Theorem

If $A$ is an $m \times n$ matrix with linearly independent column vectors then one can find $Q$, an $m \times n$ matrix with orthonormal column vectors and $R$, an $n \times n$ invertible upper triangular matrix such that

$$
A=Q R
$$

## Orthogonality and complex inner product spaces

Orthogonality in complex inner product spaces is nearly identical to the real case. In particular,

- the definitions of orthogonal vectors, orthogonal sets, orthonormal sets and orthonormal bases are the same.
- the Pythagorean Theorem holds as do all the main theorems from section 6.3.
- the Gram-Schmidt process is still valid.


## Projection as best approximation

## Theorem

Suppose that $W$ is a finite-dimensional subspace of an inner product space $V$. Then for any $u \in V$, projwu is the closest vector in $W$ to $u$; that is, if $w \in W$ is any vector other than projwu then

$$
\|u-w\|>\left\|u-\operatorname{proj}_{w} u\right\|
$$

## Least squares problem

- Suppose that $A$ is an $m \times n$ matrix and $b$ is in $R^{n}$. The linear equations $A x=b$ may or may not have a solution.
- The question is: find $x$ so that $A x$ is closest to $b$.
- As $x$ varies over all of $R^{n}, A x$ varies over the columnspace of $A$ so we are really asking for $x$ such that $A x$ equals the projection of $b$ on the columnspace.
- In fact, we can find the necessary $x$ by solving $A^{T} A x=A^{T} b$. These are called the normal equations.

