These are brief notes for the lecture on Friday November 13, and Monday November 16, 2009: they are not complete, but they are a guide to what I want to say on those days. They are guaranteed to be incorrect.

### 6.1. Inner Product, Length and Orthogonality

It's very useful to be able to talk about geometric concepts such as the length of a vector, the angle between two vectors, and the projection of one vector onto another.

## The Inner Product:

The key tool will turn out to be the inner product of two vectors in $\mathbb{R}^{n}$. If we have two vectors $\underline{u}$ and $\underline{v}$ in $\mathbb{R}^{n}$, we can regard them as $n \times 1$ matrices. Then $\underline{u}^{T}$ is a $1 \times n$ matrix, and the matrix product $\underline{u}^{T} \underline{v}$ is a $1 \times 1$ matrix, which we can regard as a scalar.
We call $\underline{u}^{T} \underline{v}$ the inner product of $\underline{u}$ and $\underline{v}$, and we write it $\underline{u} \cdot \underline{v}$. If

$$
\underline{u}=\left(\begin{array}{c}
u_{1} \\
u_{2} \\
\cdots \\
u_{n}
\end{array}\right) \quad \text { and } \quad \underline{v}=\left(\begin{array}{c}
v_{1} \\
v_{2} \\
\ldots \\
v_{n}
\end{array}\right)
$$

then

$$
\underline{u} \cdot \underline{v}=\left[\begin{array}{llll}
u_{1} & u_{2} & \ldots & u_{n}
\end{array}\right]\left(\begin{array}{c}
v_{1} \\
v_{2} \\
\ldots \\
v_{n}
\end{array}\right)=u_{1} v_{1}+u_{2} v_{2}+\ldots u_{n} v_{n} .
$$

The reason that the inner product is useful is that it satisfies the following properties
Theorem 1. Let $\underline{u}, \underline{v}, \underline{w} \in \mathbb{R}^{n}$ and let $c$ be a scalar. Then
(1) $\underline{u} \cdot \underline{v}=\underline{v} \cdot \underline{u}$.
(2) $(\underline{u}+\underline{v}) \cdot \underline{w}=\underline{u} \cdot \underline{w}+\underline{v} \cdot \underline{w}$.
(3) $(c \underline{u}) \cdot \underline{v}=c(\underline{u} \cdot \underline{v})$.
(4) $\underline{u} \cdot \underline{u} \geq 0$ and $\underline{u} \cdot \underline{u}=0$ if and only if $\underline{u}=\underline{0}$.
(5) $\left(c_{1} \underline{u}_{1}+\cdots+c_{p} \underline{u}_{p}\right) \cdot \underline{w}=c_{1} \underline{u}_{1} \cdot \underline{w}+c_{p} \underline{u}_{p} \cdot \underline{w}$.

Example: Let

$$
\underline{u}=\left(\begin{array}{l}
1 \\
2 \\
3 \\
4
\end{array}\right) \quad \underline{v}=\left(\begin{array}{r}
1 \\
-2 \\
0 \\
-1
\end{array}\right)
$$

Compute $\underline{u} \cdot \underline{v}$

Definition (Length). The length (or norm) of $\underline{v}$ is the non-negative scalar $\|\underline{v}\|$ defined by

$$
\|\underline{v}\|=\sqrt{\underline{v} \cdot \underline{v}}=\sqrt{v_{1}^{2}+v_{2}^{2}+\cdots+v_{n}^{2}} \text { and }\|\underline{v}\|^{2}=\underline{v} \cdot \underline{v} .
$$

This definition is chosen so that the Pythagorean theorem holds (that is, in two dimensions the length $c$ of the vector which is the hypotenuse of a right triangle with horizontal length $a$ and vertical height $b$ satisfies $a^{2}+b^{2}=c^{2}$.
For any scalar $c,\|c \underline{v}\|=|c|\|\underline{v}\|$. A vector of length 1 is called a unit vector, and if $\underline{v} \neq \underline{0}$ then

$$
\frac{1}{\|v\|} \underline{v}
$$

is a unit vector (and is in the same direction as $\underline{v}$ ). This is called normalizing. We will often want to take a basis for a subspace and replace it with normalized vectors.
Example: Find a unit vector which is in the same direction as $\underline{v}=\left(\begin{array}{l}1 \\ 1 \\ 2\end{array}\right)$.

Regarding $\underline{u}$ and $\underline{v}$ as points in $\mathbb{R}^{n}$, we can compute the distance between $\underline{u}$ and $\underline{v}$.

Definition. For $\underline{u}$ and $\underline{v}$ in $\mathbb{R}^{n}$, the distance between $\underline{u}$ and $\underline{v}$, written as $\operatorname{dist}(\underline{u}, \underline{v})$ is the length of the vector $\underline{u}-\underline{v}$. That is,

$$
\operatorname{dist}(\underline{u}, \underline{v})=\|\underline{u}-\underline{v}\| .
$$

Example: Compute the distance $\operatorname{dist}\left(\binom{7}{2},\binom{4}{3}\right)$.

## Orthogonal Vectors

We now generalize the concept of perpendicularity: however, perpendicular is defined with respect to an underlying geometry, and often carries a sense of "vertical" in colloquial speech: since we wish to extend the idea to a much broader sense, we use the special word "orthogonal" instead. However, for our purposes, othogonal and perpendicular will mean the same thing.

Definition. Two vectors in $\mathbb{R}^{n}$ are orthogonal if and only if $\underline{u} \cdot \underline{v}=0$.

Why should this be a good definition? If $\underline{u}$ and $\underline{v}$ are perpendicular then the Pythagorean theorem says that

$$
\|\underline{u}\|^{2}+\|\underline{v}\|^{2}=\operatorname{dist}(\underline{u}-\underline{v})^{2}
$$

so that

$$
\begin{aligned}
\|\underline{u}\|^{2}+\|\underline{v}\|^{2} & =\|\underline{u}-\underline{v}\|^{2} \\
& =(\underline{u}-\underline{v}) \cdot(\underline{u}-\underline{v}) \\
& =\underline{u} \cdot \underline{u}-\underline{u} \cdot \underline{v}-\underline{v} \cdot \underline{u}+\underline{v v} \\
& =\|\underline{u}\|^{2}+\|\underline{v}\|^{2}-2 \underline{u} \cdot \underline{v}
\end{aligned}
$$

so that the Pythagorean theorem is satisfied if and only if $\underline{u}$ and $\underline{v}$ are orthogonal.
If we have two vectors $\underline{u}$ and $\underline{w}$, then we can express $\underline{w}$ as a multiple of $\underline{u}$ plus a vector orthogonal to $\underline{u}$. To do this, we wish to find $\underline{v} \in \mathbb{R}^{n}$ and $c \in \mathbb{R}$ so that

$$
\underline{w}=c \underline{u}+\underline{v} \quad \text { and } \quad \underline{u} \cdot \underline{v}=0
$$

So, eliminating $\underline{v}$ in these, we obtain

$$
\underline{u} \cdot(\underline{w}-c \underline{u})=0
$$

and this implies that

$$
c=\frac{\underline{w} \cdot \underline{u}}{\underline{u} \cdot \underline{u}}=\frac{\underline{w} \cdot \underline{u}}{\|\underline{u}\|^{2}} .
$$

Hence

$$
\underline{v}=\underline{w}-\frac{\underline{w} \cdot \underline{u}}{\|\underline{u}\|^{2}} \underline{u}
$$

We call $c \underline{u}$ the projection of $\underline{v}$ onto $\underline{u}$, and $\underline{v}$ the component of $\underline{v}$ orthogonal to $\underline{u}$.

In two or three dimensions, the projection of $\underline{v}$ onto $\underline{u}$ has length $\|\underline{v}\| \cos \theta$, where $\theta$ is the angle between the vectors. Hence

$$
\|\underline{v}\| \cos \theta=c\|\underline{u}\|
$$

so that

$$
\underline{u} \cdot \underline{v}=\|\underline{u}\|\|\underline{v}\| \cos \theta
$$

In higher dimensions than three we use this to define the angle between two vectors.

### 6.2. Orthogonal Sets

Definition. A set $\left\{\underline{u}_{1}, \underline{u}_{2}, \ldots, \underline{u}_{k}\right\}$ of non-zero vectors is said to be orthogonal if for every $i \neq j$,

$$
\underline{u}_{i} \cdot \underline{u}_{j}=0,
$$

that is, if every pair of vectors is orthogonal.
Example: Show that the following set of vectors is orthogonal:

$$
\left\{\left(\begin{array}{l}
3 \\
1 \\
1
\end{array}\right),\left(\begin{array}{r}
-1 \\
2 \\
1
\end{array}\right),\left(\begin{array}{r}
1 \\
4 \\
-7
\end{array}\right)\right\}
$$

Theorem 4. If $\left\{\underline{u}_{1}, \underline{u}_{2}, \ldots, \underline{u}_{k}\right\}$ is an orthogonal set of vectors, then it is linearly independent. Hence it is a basis for the space that it spans.

Proof: proof strategy: suppose that we have a non-trivial linear combination giving zero. By taking the inner product with $\underline{u}_{j}$, show that the coefficient of $\underline{u}_{j}$ must be zero. Hence the set is linearly independent.

Definition. An orthogonal basis for a subspace $W<\mathbb{R}^{n}$ is a basis for $W$ which is an orthogonal set.

Theorem 5. Let $W<\mathbb{R}^{n}$, and let $S=\left\{\underline{u}_{1}, \underline{u}_{2}, \ldots, \underline{u}_{k}\right\}$ be an orthogonal basis for $W$. Then if the vector $\underline{y}$ in $W$ is given in terms of the basis $S$ by

$$
\underline{y}=c_{1} \underline{u}_{1}+c_{2} \underline{u}_{2}+\cdots+c_{k} \underline{u}_{k}
$$

then

$$
c_{j}=\frac{\underline{y} \cdot \underline{u}_{j}}{\underline{u}_{j} \cdot \underline{u}_{j}}
$$

Proof: Proof strategy: we know that every vector in $W$ has a unique representation as a linear combination of vectors in $S$, since $S$ is a basis for $W$. If we take the inner product of $\underline{y}$ with $\underline{u}_{j}$, then since $W$ is orthogonal, all the inner products vanish except for the terms in the theorem.

Example: We saw above that

$$
S=\left\{\left(\begin{array}{l}
3 \\
1 \\
1
\end{array}\right),\left(\begin{array}{r}
-1 \\
2 \\
1
\end{array}\right),\left(\begin{array}{r}
1 \\
4 \\
-7
\end{array}\right)\right\}
$$

is an orthogonal set in $\mathbb{R}^{3}$. Since it is linearly independent and has three vectors in it, it must be a basis for $\mathbb{R}^{3}$. Express the vector

$$
\left(\begin{array}{l}
2 \\
4 \\
6
\end{array}\right)
$$

in terms of the vectors in $S$.

## Orthogonal Projections

Earlier we saw how to find the component of $\underline{v}$ in the direction of $\underline{u}$ and the component orthogonal to $\underline{u}$. We revisit this idea to introduce some notation, and to extend it to projecting onto a subspace.
Given $\underline{y} \in \mathbb{R}^{n}$ and $\underline{u} \in \mathbb{R}^{n}$, find $\underline{\hat{y}}, \underline{z} \in \mathbb{R}^{n}$ so that
(1) $\underline{y}=\underline{\hat{y}}+\underline{z}$.
(2) $\underline{\hat{y}}=\alpha \underline{u}(\alpha \in \mathbb{R})$.
(3) $\underline{u} \cdot \underline{z}=0$.

As before, we see that

$$
\underline{y} \cdot \underline{u}=\underline{\hat{y}} \cdot \underline{u}=\alpha\|\underline{u}\|^{2}
$$

so

$$
\alpha=\frac{\underline{y} \cdot \underline{u}}{\|\underline{u}\|^{2}}
$$

and

$$
\underline{z}=\underline{y}-\frac{\underline{y} \cdot \underline{u}}{\|\underline{u}\|^{2}} \underline{u}
$$

## Notation:

$$
\underline{\hat{y}}=\operatorname{Proj}_{L}(\underline{y})=\frac{\underline{y} \cdot \underline{u}}{\|\underline{u}\|^{2}} \underline{u}
$$

where $L=\operatorname{Span}(\underline{u})$.
Terminology: $\underline{y}=\underline{\hat{y}}+\underline{z}$ :
$\underline{\hat{y}}$ is the orthogonal projection of $\underline{y}$ onto $L$
$\underline{z}$ is the component of $\underline{y}$ orthogonal to $L$.
Example: Let $\underline{y}=\binom{7}{6}, \underline{u}=\binom{4}{2}$ and $L=\operatorname{Span}(\underline{u})$. Compute the orthogonal projection of $\underline{y}$ onto $L$ and the component of $\underline{y}$ orthogonal to $L$. Plot $\underline{y}, \underline{u}, \underline{\hat{y}}$ and $\underline{z}$. Compute the distance $\overline{\text { from }} \underline{y}$ to $L$. (Note: the subspace $L$ here is the line through $\underline{\underline{0}}$ and $\underline{u}$.)

Geometric Interpretation of Theorem 5: Let $\left\{\underline{u}_{1}, \underline{u}_{2}\right\}$ be an orthogonal basis for $\mathbb{R}^{2}$. Put

$$
\begin{aligned}
& \underline{\hat{y}}_{1}=\frac{\underline{y} \cdot \underline{u}_{1}}{\left\|\underline{u}_{1}\right\|^{2}} \underline{u}_{1}=\operatorname{Proj}_{\underline{u}_{1}}(\underline{y}) \\
& \underline{\hat{y}}_{2}=\frac{\underline{y} \cdot \underline{u}_{2}}{\left\|\underline{u}_{2}\right\|^{2}} \underline{u}_{2}=\operatorname{Proj}_{\underline{u}_{2}}(\underline{y})
\end{aligned}
$$

Then

$$
\underline{y}=\underline{\hat{y}}_{1}+\hat{\underline{y}}_{2} .
$$

## Orthonormal Sets

Definition. A set $\underline{u}_{1}, \underline{u}_{2}, \ldots, \underline{u}_{p}$ is called orthonormal if it is orthogonal and $\left\|\underline{u}_{i}\right\|=1$ for $1 \leq i \leq p$. In this case, if $W=\operatorname{Span}\left(\underline{u}_{1}, \ldots, \underline{u}_{p}\right)$, then the set is called an orthonormal basis for $W$.

Example: The set $\underline{e}_{1}, \underline{e}_{2}, \ldots, \underline{e}_{n}$ is an orthonormal basis for $\mathbb{R}^{n}$.
Example: Show that the set $\underline{v}_{1}, \underline{v}_{2}, \underline{v}_{3}$ is an orthornormal basis for $\mathbb{R}^{3}$, where

$$
\underline{v}_{1}=\left(\begin{array}{l}
3 / \sqrt{11} \\
1 / \sqrt{11} \\
1 / \sqrt{11}
\end{array}\right), \quad \underline{v}_{2}=\left(\begin{array}{c}
-1 / \sqrt{6} \\
2 / \sqrt{6} \\
1 / \sqrt{6}
\end{array}\right), \quad \underline{v}_{3}=\left(\begin{array}{c}
1 / \sqrt{66} \\
4 / \sqrt{66} \\
-7 / \sqrt{66}
\end{array}\right) .
$$

Theorem 6. An $m \times n$ matrix $U$ has orthonormal columns if and only if $U^{T} U=I$.
Proof: proof strategy: interpret the entries of $U^{T} U$ in terms of inner products of the columns of $U$.

THEOREM 7. Let $U$ be an $m \times n$ matrix with orthonormal columns, and $\underline{x}, \underline{y} \in \mathbb{R}^{n}$. Then
(1) $\|U \underline{x}\|=\|\underline{x}\|$.
(2) $(U \underline{x}) \cdot(U \underline{y})=\underline{x} \cdot \underline{y}$.
(3) $(U \underline{x}) \cdot(U \underline{y})=0$ if and only if $\underline{x} \cdot \underline{y}$.

Note: (a) $U$ preserves length
(b) $U$ preserves orthonormality.

Proof: proof strategy: write $(U \underline{x}) \cdot(U \underline{y})$ as

$$
(U \underline{x}) \cdot(U \underline{y})=(U \underline{x})^{T}(U \underline{y})=\left(\underline{x}^{T} U^{T}\right)(U \underline{y})=\underline{x}^{T}\left(U^{T} U\right) \underline{y} .
$$

Example: Let

$$
U=\left(\begin{array}{rr}
1 / \sqrt{2} & 2 / 3 \\
1 / \sqrt{2} & -2 / 3 \\
0 & 1 / 3
\end{array}\right) \quad \text { and } \quad \underline{x}=\binom{\sqrt{2}}{3}
$$

Note that $U$ has orthonormal columns and that $\|U \underline{x}\|=\|\underline{x}\|$.

In the case where $U$ is a an $n \times n$ matrix with orthonormal columns, we see that $U^{T} U=I$ so $U^{T}=U^{-1}$, so $U U^{T}=I$ as well: that is, $U$ has orthonormal rows too!

