## CS/ENGRI 172, Fall 2003: Computation, Information, and Intelligence 9/26/03: Proof of PLA Convergence

## More Useful Properties of the Inner Product

It should be fairly easy to convince yourself that for vectors $\vec{v}, \vec{w}, \vec{y}$, and $\vec{z}$ of the same dimensionality,

$$
(\vec{v}+\vec{w}) \cdot(\vec{y}+\vec{z})=\vec{v} \cdot \vec{y}+\vec{w} \cdot \vec{y}+\vec{v} \cdot \vec{z}+\vec{w} \cdot \vec{z}
$$

For example, in the two-dimensional case,

$$
\begin{aligned}
(\vec{v}+\vec{w}) \cdot(\vec{y}+\vec{z}) & =\left(v_{1}+w_{1}, v_{2}+w_{2}\right) \cdot\left(y_{1}+z_{1}, y_{2}+z_{2}\right) \\
& =\left(v_{1}+w_{1}\right)\left(y_{1}+z_{1}\right)+\left(v_{2}+w_{2}\right)\left(y_{2}+z_{2}\right) \\
& =\left(v_{1} y_{1}+w_{1} y_{1}+v_{1} z_{1}+w_{1} z_{1}\right)+\left(v_{2} y_{2}+w_{2} y_{2}+v_{2} z_{2}+w_{2} z_{2}\right) \\
& =\left(v_{1} y_{1}+v_{2} y_{1}\right)+\left(w_{1} y_{1}+w_{2} y_{2}\right)+\left(v_{1} z_{1}+v_{2} z_{2}\right)+\left(w_{1} z_{1}+w_{2} z_{2}\right) \\
& =\vec{v} \cdot \vec{y}+\vec{w} \cdot \vec{y}+\vec{v} \cdot \vec{z}+\vec{w} \cdot \vec{z}
\end{aligned}
$$

This fact also implies, as a simpler case, that for any vectors $\vec{v}, \vec{y}$, and $\vec{z}$ of the same dimensionality,

$$
\vec{v} \cdot(\vec{y}+\vec{z})=\vec{v} \cdot \vec{y}+\vec{v} \cdot \vec{z}
$$

## Outline of our PLA Convergence Theorem Proof

We present a somewhat oblique, but therefore interesting, proof that the PLA converges. This is a general outline of the argument:

Given all of the constraints we have set for the oracle and the learner,

- First, define a score function which indicates how close the learner's weight vector $\vec{w}$ is to a "target" ${ }^{1}$ vector $\vec{w}^{*}$. Our score measure will start at 0 and have a fractional form with a numerator and a denominator.
- Now show that every time the perceptron learning algorithm updates, so that its weight vector $\vec{w}_{\text {old }}$ is changed to $\vec{w}_{\text {new }}$, the score measure must increase by a non-negligible amount:
- The score numerator must increase by at least $g$, the gap quantity.
- The square of the score denominator must increase by at most 1 .
- Therefore, after $t$ updates, the score must have increased by at least $\sqrt{t} g$ from the initial score of 0 .
- But, since our particular score measure has an upper-bound of $1, t$ can be at most $\frac{1}{g^{2}}$, which, since $g>0$, shows that only a finite number of updates get made.

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[^0]:    ${ }^{1}$ Note the quotation marks! We are performing this proof from a vantage point outside of the oracle-learner system.

