# MATH 728D: Machine Learning Solutions to Homework \#1: 

Linear Algebra
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## 1 Householder Transformations

1. Show that $Q$ is symmetric;

$$
\begin{aligned}
Q & =I-\frac{2}{v^{\prime} v} v v^{\prime} \\
Q^{\prime} & =\left(I-\frac{2}{v^{\prime} v} v v^{\prime}\right)^{\prime} \\
& =I^{\prime}-\frac{2}{v^{\prime} v}\left(v v^{\prime}\right)^{\prime} \\
& =I-\frac{2}{v^{\prime} v} v v^{\prime} \\
& =Q ;
\end{aligned}
$$

2. Show that $Q$ is orthogonal;

$$
\begin{aligned}
Q * Q^{\prime} & =Q * Q \\
& =\left(I-\frac{2}{v^{\prime} v} v v^{\prime}\right) *\left(I-\frac{2}{v^{\prime} v} v v^{\prime}\right) \\
& =I-\frac{2}{v^{\prime} v} v v^{\prime}-\frac{2}{v^{\prime} v} v v^{\prime}+\frac{4}{\left(v v^{\prime}\right)^{2}} v v^{\prime} v v^{\prime} \\
& =I-\frac{4}{v^{\prime} v} v v^{\prime}+\frac{4}{\left(v^{\prime} v\right)^{2}} v\left(v^{\prime} v\right) v^{\prime} \\
& =I-\frac{4}{v^{\prime} v} v v^{\prime}+\frac{4}{v^{\prime} v} v v^{\prime} \\
& =I
\end{aligned}
$$

3. Show that $Q v=-v$;

$$
\begin{aligned}
Q * v & =\left(I-\frac{2}{v^{\prime} v} v v^{\prime}\right) * v \\
& =v-\frac{2}{v^{\prime} v} v v^{\prime} v \\
& =v-\frac{2}{v^{\prime} v} v\left(v^{\prime} v\right) \\
& =v-2 v \\
& =-v
\end{aligned}
$$

## 2 The QR Factorization

1. Based on this fact, what is the $Q$ factor for $A$ ?

$$
\begin{aligned}
Q_{1} * Q_{2} * \ldots * Q_{k} * A & =R \\
Q_{k}^{\prime} * \ldots * Q_{2}^{\prime} * Q_{1}^{\prime} * Q_{1} * Q_{2} * \ldots * Q_{k} * A & =Q_{k}^{\prime} * \ldots * Q_{2}^{\prime} * Q_{1}^{\prime} * R \\
A & =Q_{k}^{\prime} * \ldots * Q_{2}^{\prime} * Q_{1}^{\prime} * R \\
& =Q * R
\end{aligned}
$$

2. How do you know that $Q$ is an orthogonal matrix?

If $Q_{1}$ is orthogonal, then so is $Q_{1}^{\prime}$;
If $Q_{1}^{\prime}$ and $Q_{2}^{\prime}$ are orthogonal, then so is $Q_{2}^{\prime} * Q_{1}^{\prime}$;
Repeating this argument, $Q=Q_{k}^{\prime} * \ldots * Q_{2}^{\prime} * Q_{1}^{\prime}$ is orthogonal.
3. The value $k$ counts the number of Householder transformations we must apply. The $j$-th transformation reduces column $j$ to upper triangular form. What is the typical value of $k$ when $A$ is an $n \times n$ matrix? We have to "upper triangularize" $n-1$ columns of $A$, so $k=n-1$;
What happens if $A$ is an $m \times n$ matrix?
If $m<n, k=m-1$;
if $n<m, k=n$.

## 3 The LR Factorization

1. Describe how this factorization can be used to solve a linear system $A * x=b$;

$$
\begin{aligned}
A * x & =b \\
P^{\prime} * L * R * x & =b \\
L * R * x & =P * b \text { (easy to multiply by permutation) } \\
\text { Solve } L *(R * x) & =P * b \text { (easy to solve unit lower triangular system) } \\
\text { Solve } R * x & =L^{-1} * P * b \text { (easy to solve upper triangular system) } \\
x & =R^{-1} * L^{-1} * P * b
\end{aligned}
$$

2. The inverse of a triangular matrix is easy to compute. Assuming this is so, what is a formula for the inverse of a matrix $A$ for which we have computed the LR factorization?

$$
A^{-1}=R^{-1} * L^{-1} * P
$$

## 4 The SVD Factorization

1. Show that the columns of $U$ are eigenvectors of $A A^{\prime}$

$$
\begin{aligned}
A * A^{\prime} * U & =U * S * V^{\prime} *\left(V * S^{\prime} * U^{\prime}\right) * U \\
& =U * S *\left(V^{\prime} * V\right) * S^{\prime} *\left(U^{\prime} * U\right) \\
& =U * S^{2}
\end{aligned}
$$

Here $S^{2}$ is an $m \times m$ diagonal matrix.
2. Show that the values $\sigma_{i}^{2}$ are (some of the) eigenvalues of $A A^{\prime}$ and $A^{\prime} A$

A similar argument shows that $A^{\prime} * A * V=V * S^{2}$, where $S^{2}$ is an $n \times n$ diagonal matrix;
3. Suppose that $A$ is symmetric and positive definite, so that it has a full set of eigenvectors $X$ and nonnegative eigenvalues $\Lambda$. Write a formula for the singular value decomposition of $A$;

$$
\begin{aligned}
X^{\prime} * A * X & =\Lambda ; \\
A & =X * \Lambda * X^{\prime} \\
A & =U(=X) * S(=\Lambda) * V^{\prime}\left(=X^{\prime}\right)
\end{aligned}
$$

4. Suppose that $A$ is a square, invertible matrix. Write a formula for the inverse of $A$ in terms of the singular value decomposition;

$$
\begin{aligned}
A & =U * S * V^{\prime} \\
A^{-1} & =V * S^{-1} * U^{\prime} \text { (Assertion) } \\
A * A^{-1} & =U * S * V^{\prime} * V * S^{-1} * U^{\prime} \\
& =U * S * S^{-1} * U^{\prime} \\
& =U * U^{\prime} \\
& =I
\end{aligned}
$$

and similarly for $A^{-1} * A . S^{-1}$ is meaningful because $S$ is square, and because each $\sigma_{i}$ is nonzero.

