## CS205 Review Session #7 Notes

## **Useful Decompositions**

Consider an  $n \times n$  matrix **A** that is symmetric positive semi-definite and has a nullspace of dimension p < n. We wish to factor **A** into **MÃM** where the columns of the  $n \times (p - n)$  matrix **M** form an orthonormal basis for  $col(\mathbf{A}) = row(\mathbf{A})$ . It may help to first consider a concrete example:

$$\mathbf{A} = \begin{bmatrix} 2 & -1 & 0 \\ -1 & 2 & 0 \\ 0 & 0 & 0 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} 2 & -1 \\ -1 & 2 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} = \mathbf{M}\tilde{\mathbf{A}}\mathbf{M}^{T}$$

This particular choice for  $\tilde{\mathbf{A}}$  and  $\mathbf{M}$  is not necessarily unique. We can also write:

$$\mathbf{A} = \begin{bmatrix} 2 & -1 & 0\\ -1 & 2 & 0\\ 0 & 0 & 0 \end{bmatrix} = \begin{bmatrix} \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}}\\ \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}}\\ 0 & 0 \end{bmatrix} \begin{bmatrix} 1 & 0\\ 0 & 3 \end{bmatrix} \begin{bmatrix} \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} & 0\\ -\frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} & 0 \end{bmatrix}$$

One way to construct this factorization in general is to compute the spectral decomposition  $\mathbf{A} = \mathbf{Q} \mathbf{\Lambda} \mathbf{Q}^T$  of  $\mathbf{A}$  and trim of some of the unnecessary columns of  $\mathbf{Q}$ .

We can show, however, that no matter what method we use to determine  $\mathbf{A} = \mathbf{M}\tilde{\mathbf{A}}\mathbf{M}^{T}$ , if the columns of  $\mathbf{M}$  form an orthonormal basis for the column space of  $\mathbf{A}$ ,  $\tilde{\mathbf{A}}$  must have several desirable properties. In particular:

1.  $\tilde{\mathbf{A}}$  has full rank. To see why this is so, let  $\tilde{\mathbf{x}} \in \mathbb{R}^{n-p}$  be an arbitrary vector. Then  $\mathbf{M}\tilde{\mathbf{x}} \in \operatorname{col}(\mathbf{A}) = \operatorname{row}(\mathbf{A})$ . This means that  $\mathbf{A}(\mathbf{M}\tilde{\mathbf{x}}) = \mathbf{0} \iff \tilde{\mathbf{x}} = \mathbf{0}$  since the nullspace of a matrix is the orthogonal complement of its row space. This implies that, for general  $\tilde{\mathbf{x}}$ :

$$\mathbf{A}\mathbf{M}\mathbf{ ilde{\mathbf{x}}}
eq \mathbf{0} \Rightarrow \mathbf{M}\mathbf{ ilde{\mathbf{A}}}\mathbf{M}^{^{T}}\mathbf{M}\mathbf{ ilde{\mathbf{x}}}
eq \mathbf{0} \Rightarrow \mathbf{M}\mathbf{ ilde{\mathbf{A}}}\mathbf{ ilde{\mathbf{x}}}
eq \mathbf{0} \Rightarrow \mathbf{ ilde{\mathbf{A}}}\mathbf{ ilde{\mathbf{x}}}
eq \mathbf{0}$$

Therefore  $\tilde{\mathbf{A}}$  has only the trivial nullspace, and thus has full rank.

- 2.  $\tilde{\mathbf{A}}$  is symmetric.  $\mathbf{A} = \mathbf{M} \tilde{\mathbf{A}} \mathbf{M}^T \Rightarrow \tilde{\mathbf{A}} = \mathbf{M}^T \mathbf{A} \mathbf{M}$ , which is symmetric since  $\mathbf{A}$  is.
- 3.  $\tilde{\mathbf{A}}$  is positive definite.  $\tilde{\mathbf{A}}$  must be positive semi-definite since  $\tilde{\mathbf{x}}^T \tilde{\mathbf{A}} \tilde{\mathbf{x}} = (\mathbf{M} \tilde{\mathbf{x}})^T \mathbf{A} (\mathbf{M} \tilde{\mathbf{x}}) \geq$ 0. However,  $\mathbf{x}^T \mathbf{A} \mathbf{x} = 0$  in general if and only if  $\mathbf{x} \in \mathrm{NS}(\mathbf{A})$ . Since we chose  $\mathbf{M}$  to have columns that form an orthonormal basis for  $\mathrm{col}(\mathbf{A})$ ,  $\mathbf{M} \tilde{\mathbf{x}} \in \mathrm{col}(\mathbf{A}) = \mathrm{NS}(\mathbf{A})^{\perp}$  and so  $\tilde{\mathbf{x}}^T \tilde{\mathbf{A}} \tilde{\mathbf{x}} > 0$ .
- 4. The eigenvalues of  $\tilde{\mathbf{A}}$  are exactly the non-zero eigenvalues of  $\mathbf{A}$ . To see that this is the case, consider an eigenvector  $\tilde{\mathbf{x}}$  of  $\tilde{\mathbf{A}}$  and its associated eigenvalue  $\tilde{\lambda}$ :

$$\tilde{\mathbf{A}}\tilde{\mathbf{x}} = \lambda \tilde{\mathbf{x}} \Rightarrow \tilde{\mathbf{A}}\mathbf{M}^T \mathbf{M}\tilde{\mathbf{x}} = \lambda \tilde{\mathbf{x}} \Rightarrow \mathbf{M}\tilde{\mathbf{A}}\mathbf{M}^T \mathbf{M}\tilde{\mathbf{x}} = \lambda \mathbf{M}\tilde{\mathbf{x}} \Rightarrow \mathbf{A}(\mathbf{M}\tilde{\mathbf{x}}) = \lambda(\mathbf{M}\tilde{\mathbf{x}})$$

## More Subspace Decompositions

Consider any of the (possibly infinite) solutions to the matrix equation  $\mathbf{A}\mathbf{x} = \mathbf{b}$  where  $\mathbf{A}$  is symmetric. We recall that we can express each such solution as a sum  $\mathbf{x} = \mathbf{x}_c + \mathbf{x}_n$  where  $\mathbf{x}_c \in \operatorname{col}(\mathbf{A}) = \operatorname{row}(\mathbf{A})$  and  $\mathbf{x}_n \in \operatorname{NS}(\mathbf{A})$ .

Now, consider a solution that lies entirely within the column space of  $\mathbf{A}$ , that is, a solution of the form  $\mathbf{x}_c$  where  $\mathbf{A}\mathbf{x}_c = \mathbf{b}$ .

- (a)  $\mathbf{x}_r$  is unique. To see that this is the case, assume that  $\mathbf{A}\mathbf{x}_{r1} = \mathbf{b}$  and  $\mathbf{A}\mathbf{x}_{r2} = \mathbf{b}$ where  $\mathbf{x}_{r1}, \mathbf{x}_{r2} \in \operatorname{col}(\mathbf{A})$ . Clearly  $(\mathbf{x}_{r1} - \mathbf{x}_{r2}) \in \operatorname{col}(\mathbf{A})$ , but we also have that  $\mathbf{A}(\mathbf{x}_{r1} - \mathbf{x}_{r2}) = \mathbf{A}\mathbf{x}_{r1} - \mathbf{A}\mathbf{x}_{r2} = \mathbf{b} - \mathbf{b} = \mathbf{0}$ , which implies that  $(\mathbf{x}_{r1} - \mathbf{x}_{r2}) \in \operatorname{NS}(\mathbf{A})$ , yielding a contradiction.
- (b)  $\mathbf{x} = \mathbf{x}_r + \mathbf{x}_n$  is also a solution to  $\mathbf{A}\mathbf{x} = \mathbf{b}$  for any  $\mathbf{x}_n \in NS(\mathbf{A})$ . To see that this is true, consider  $\mathbf{A}(\mathbf{x}_r + \mathbf{x}_n) = \mathbf{A}\mathbf{x}_r + \mathbf{A}\mathbf{x}_n = \mathbf{b} + \mathbf{0} = \mathbf{b}$ .

## Particular Polynomials

The generic form of a quadratic polynomial is:

$$p(x) = c_2 x^2 + c_1 x + c_0$$

However, deriving a system of equations for the constraints  $p'(a) = f'(a), p'(b) = f'(b), p(\frac{a+b}{2}) = f(\frac{a+b}{2})$  for some generic f(x) is quite cumbersome if we express p(x) in this manner.

Instead, we may substitute a different quadratic polynomial g(x) that benefits from the symmetry of the given constraints:

$$g(x) = c_2 \left(x - \frac{a+b}{2}\right)^2 + c_1 \left(x - \frac{a+b}{2}\right) + c_0$$

Remember also that for a non-composite rule, the degree is given as the *maximum* degree of a polynomial that is exactly integrable using the particular rule. Note that it is enough to test exact integrability of the simple monomials  $(1, x, x^2, x^3, ...)$  since, by linearity, any linear combination of exactly integrable functions will be exactly integrable as well.