

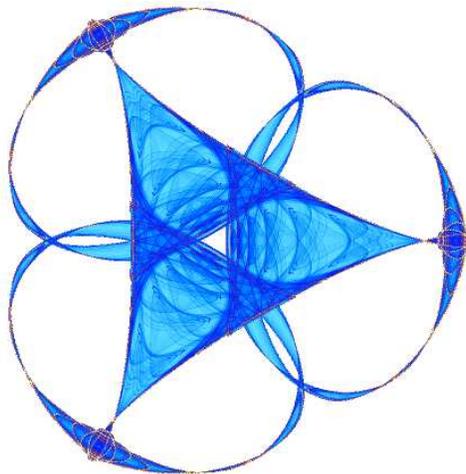
**A GLOBALLY CONVERGENT FLOW FOR
COMPUTING THE BEST LOW RANK APPROXIMATION
OF A MATRIX**

By

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ABSTRACT

We work in the space of m -by- n real matrices with the Frobenius inner product. Consider the following problem:

Problem. : Given an m -by- n real matrix A and a positive integer k , find the m -by- n matrix with rank k that is closest to A .

I discuss a rank-preserving differential equation (d.e.) which solves this problem. If $X(t)$ is a solution of this d.e., then the distance between $X(t)$ and A decreases as t increases; this distance function is a Lyapunov function for the d.e. If A has distinct positive singular values (which is a generic condition) then this d.e. has only one stable equilibrium point. The other equilibrium points are finite in number and unstable. In other words, the basin of attraction of the stable equilibrium point on the manifold of matrices with rank k consists of almost all matrices. This special equilibrium point is the solution of the given problem. Usually constrained optimization problems have many local minimums (most of which are undesirable). So the constrained optimization problem considered here is very special.

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1. INTRODUCTION

We work in the space $\mathbb{R}^{m \times n}$ of m by n real matrices with the “Frobenius” (or “euclidean”) inner product. (In an appendix we review the definition and elementary properties of this inner product.) We consider the following problem:

*Problem: **Low rank approximation.*** Given a matrix A in $\mathbb{R}^{m \times n}$ and a positive integer k , find the matrix with rank k which is closest to A .

This problem is closely connected with the singular value decomposition of matrices. If $A = UDV^T$ where U is an $m \times m$ orthogonal matrix, V is an $n \times n$ orthogonal matrix, and $D = \text{Diag}(\sigma_1 \geq \sigma_2 \geq \dots \geq \sigma_n)$ is a diagonal matrix, then the product UDV^T is called the **singular value decomposition of A** . The diagonal entries of D are the **singular values of A** . It is well-known that every matrix has a singular value decomposition. (See, for example, Horn and Johnson(1985) or Demmel(1997).)

The following result provides a solution of the low rank approximation problem:

Proposition 1. *Assume $m \geq n$ and that the rank of A is greater than the positive integer k . Let $A = UDV^T$ be the singular value decomposition of A . Let $D' := \text{Diag}(\sigma_1, \sigma_2, \dots, \sigma_k, 0, \dots, 0)$ and let $A' := UD'V^T$. Then A' is the matrix with rank k which most closely approximates A in the Frobenius norm.*

This result is often called the Eckart-Young theorem. The result appeared in Eckart-Young(1936). However, Stewart(1993) points out that it was known earlier.

For a textbook proof of this proposition, see, for example, Horn and Johnson(1985) Section 7.4 “Examples and applications of the singular value decomposition”. I present an alternative proof of this result in this paper. In particular, I discuss a quasi-gradient differential equation which computes the solution of the given problem. This proof provides more information than other proofs. In particular, it shows that (generically) A' is the unique local minimum for the low rank approximation problem. In other words, the basin of attraction of this matrix consists of almost all matrices on the surface of matrices with rank k .

The proposition suggests a way to compute the solution of the low rank approximation problem: Compute the singular value decomposition of A then compute the approximation A' . This procedure is obviously inefficient: Why compute all the singular values of A if we only need the largest ones for the solution? We shall see that the differential equation is more “economical” since its flow is on the manifold $\text{Rank}(k)$ of matrices with rank k . If k is small then this manifold has dimension much smaller than the dimension of $\mathbb{R}^{m \times n}$. I hope that this differential equation can be used to design an efficient algorithm for low rank approximation.

Since the 1980's there has been significant work with flows on manifolds of matrices. In particular, during the 1980's, there was considerable interest in continuous analogues of the QR algorithm for computing eigenvalues of matrices. The connection between the QR algorithm and the Toda flow was discovered by Symes about 1980. For more on this connection, see, for example, Symes(1980a,1980b,1982), Deift, Nanda and Tomei (1983), Nanda (1982,1985), Chu(1984), and Watkins (1984a,1984b). There are now also textbook descriptions of this connection: See, for example, Demmel (1997). For some other flows on matrices, see Chu(1986a,1986b), Chu and Driessel (1990), Helmke and Moore(1995), Driessel(2004), Driessel and Gerisch(2007) and the works cited in these references.

Flows on manifolds of matrices are interesting not just because of their connections with computation, but also for the insight they provide into the geometry of the manifolds of interest. This is the main idea in Morse theory. Let me say more about such geometric insights. Let W be a real vector space with an inner product $\langle \cdot, \cdot \rangle$. Let S be a subset of W and let $f : S \rightarrow \mathbb{R}$ be a real-valued function on S . Then $m \in S$ is a **local minimum** of f on S , if there is a neighborhood N of m such that $f(m)$ is a minimum of f on N . I say that $f : S \rightarrow \mathbb{R}$ has the **unique local minimum property** if f is bounded below and has a unique local minimum. In this case the local minimum is also the global minimum. Usually an optimization problem has numerous (mostly undesirable) local minimums. An optimization problem with the unique local minimum property is an especially nice optimization problem.

Here are a few examples. Let S be a convex set in \mathbb{R}^n with the euclidean inner product; let a be a point in \mathbb{R}^n ; let $f_a : S \rightarrow \mathbb{R}$ be defined by to be the square of the distance from $s \in S$ to a : $f_a(s) := \langle a - s, a - s \rangle$; this function has the unique local minimum property for all a . Let S be a circle in the euclidean plane \mathbb{R}^2 and, for a point a in \mathbb{R}^2 let $f_a : S \rightarrow \mathbb{R}$ be the square of the distance from s to a ; this function has the unique local minimum property unless a is the center of the circle.

Here is another example. Consider the following problem:

*Problem: **Approximation with spectral constraint.*** Given an $n \times n$ symmetric matrix and real eigenvalues $\lambda_1, \lambda_2, \dots, \lambda_n$, find the matrix with these eigenvalues that is closest (in the Frobenius norm) to A .

Chu and Driessel(1990) studied this problem. They showed (by means of a "gradient" flow) that it satisfies the unique local minimum property if the eigenvalues λ_i are distinct.

Let $\text{Rank}(k)$ denote the set of matrices in $\mathbb{R}^{m \times n}$ with rank k . Let A be a matrix in $\mathbb{R}^{m \times n}$. Define the function $f_A : \text{Rank}(k) \rightarrow \mathbb{R}$ by $f_A(X) := (1/2)\langle A - X, A - X \rangle$ where $\langle \cdot, \cdot \rangle$ is the Frobenius inner product. In this paper I show that if A has distinct positive singular values then the function f_A has a finite number of critical values only one of which is a local minimum and hence f_A has the unique local minimum property.

Remark: Helmke and Shayman(1985), in Theorem 4.2(ii), say that f_A has a finite number of critical points if and only if $m = n$ and A has m distinct nonzero singular values. The results that I present here show that the condition $m = n$ is not necessary.

Contents summary: In the section with the title “Setting up the differential equation”, I review the differential geometry associated with the rank approximation problem. (This material appears in Helmke and Moore(1995) and in Helmke and Shayman(1995). I include it to make this paper more self-contained.) I also describe the quasi-projection operator associated with this problem. (For more on such operators see Driessel(2004).) In the section with title “Properties of the differential equation”, I show that this differential equation has the convergence properties asserted above. (This differential equation appears in Helmke and Moore(1995) and Helmke and Shayman(1995) but they derive it in a more complicated way than I do. Their discussion of its equilibrium points is not very clear. They do not classify the equilibrium points. They do not discuss basins of attraction.)

The only prerequisites for understanding (almost all) of this paper are a basic knowledge of differential equations (see, for example, Hirsch and Smale(1974)) and basic differential geometry (see, for example, Thorpe(1979)).

2. SETTING UP THE DIFFERENTIAL EQUATION

In this section we view the sets $\text{Rank}(k)$ of matrices with fixed ranks k as parameterized surfaces in the space $\mathbb{R}^{m \times n}$. We compute the tangent spaces of these constant rank surfaces. Then we define a “quasi-projection” map which can be used to transform vector fields in $\mathbb{R}^{m \times n}$ into vector fields tangent to these surfaces. We also define an objective function associated with the constrained optimization problem of interest and we compute its gradient. Finally, we use the quasi-projection map to convert this gradient vector field into one which is tangent to the constant rank surfaces.

Let $Gl(m)$ denote the general linear group of m by m , invertible, real matrices. Recall (see, for example, Birkhoff and MacLane(1953)) that two matrices X and Y in $\mathbb{R}^{m \times n}$ are **equivalent** if there exist matrices $G \in Gl(m)$ and $H \in Gl(n)$ such that $Y = GXH^{-1}$. Also recall that every matrix M in $\mathbb{R}^{m \times n}$ is equivalent to a diagonal matrix D with ones and zeros on its main diagonal. The number of ones equals the rank of M .

We can use the groups $Gl(m)$ and $Gl(n)$ to “parameterize” the matrices with rank k as follows. We use the following group action:

$$Gl(m) \times Gl(n) \times \mathbb{R}^{m \times n} \rightarrow \mathbb{R}^{m \times n} : (G, H, X) \mapsto GXH^{-1}.$$

For $M \in \mathbb{R}^{m \times n}$, we use $\text{Orbit}(M)$ to denote the orbit of M under this group action; in symbols,

$$\text{Orbit}(M) := \{GMH^{-1} : G \in Gl(m), H \in Gl(n)\}.$$

Let

$$\text{Rank}(k) := \{X \in \mathbb{R}^{m \times n} : \text{Rank}(X) = k\}.$$

The following proposition summarizes the comments given above.

Proposition 2. *Let k be a positive integer and let K be any matrix with rank k . Then the set of matrices with rank k is the same as the orbit of K under the given group action; in symbols,*

$$\text{Rank}(k) = \text{Orbit}(K).$$

For $B \in \text{Orbit}(K)$, I use $\text{Tan.Orbit}(K).B$ to denote the space tangent to $\text{Orbit}(K)$ at B .

Proposition 3. *Let K and B be matrices in $\mathbb{R}^{m \times n}$ with B on the orbit of K . Then the space tangent to the orbit of K at B is given by*

$$\text{Tan.Orbit}(K).B = \{XB + BY : X \in \mathbb{R}^{m \times m}, Y \in \mathbb{R}^{n \times n}\}.$$

The dimension of this tangent space is $k^2 + k(m - k) + k(n - k)$ where $k := \text{Rank}(K)$.

Proof. We simply compute the derivative of the parameterizing map. We have (where D denotes the derivative operator)

$$\begin{aligned} D((G, H) \mapsto GBH^{-1}).(I, I).(X, Y) \\ &= (D(G \mapsto GB).I.X) \cdot (I^{-1}) + (IB) \cdot (D(H \mapsto H^{-1}).I.Y) \\ &= XB + BY \end{aligned}$$

since

$$D(H \mapsto H^{-1}).C.W = -C^{-1}WC^{-1}.$$

(I sometimes use dots for function evaluation in order to reduce the number of parentheses. I also use association to the left.)

Since the orbit is a homogeneous space, it looks the same at all its points. Consequently, we can compute the dimension of the tangent space at any convenient point. For example, we can do the computation at the diagonal matrix with exactly k ones on its diagonal and zeros elsewhere; in particular, we can take $B := \text{Diag}(1^{\times k}, 0^{\times(l-k)})$ where l is the minimum of m and n . \square

For B on the orbit of K , we consider the following linear map:

$$L_B := \mathbb{R}^{m \times m} \times \mathbb{R}^{n \times n} \rightarrow \mathbb{R}^{m \times n} : (X, Y) \mapsto XB + BY.$$

Note that the range of this map equals the space tangent to the orbit of K at B . We compute the adjoint L_B^* of this map.

Proposition 4. Adjoint of the tangent space map. *Let B be on the orbit of K . Then the adjoint L_B^* of the linear map L_B is the map*

$$\mathbb{R}^{m \times n} \rightarrow \mathbb{R}^{m \times m} \times \mathbb{R}^{n \times n} : Z \mapsto (ZB^T, B^T Z).$$

Proof. We have

$$\begin{aligned} \langle L_B(X, Y), Z \rangle &= \langle XB + BY, Z \rangle = \langle X, ZB^T \rangle + \langle Y, B^T Z \rangle \\ &= \langle (X, Y), (ZB^T, B^T Z) \rangle. \end{aligned}$$

Here we have used the “product” inner product on the space $\mathbb{R}^{m \times m} \times \mathbb{R}^{n \times n}$ which is defined in terms of the Frobenius inner product by:

$$\langle (X_1, Y_1), (X_2, Y_2) \rangle := \langle X_1, X_2 \rangle + \langle Y_1, Y_2 \rangle.$$

\square

I call the composition $L_B \circ L_B^*$ a “quasi-projection” map. We can use this operator to transform vector fields on $\mathbb{R}^{m \times n}$ into ones which are tangent to the orbits of interest. For more on the use of quasi-projections see Driessel(2004).

For A in $\mathbb{R}^{m \times n}$, we define the **objective function** $f := f_A$ **determined by** A as the following function:

$$\mathbb{R}^{m \times n} \rightarrow \mathbb{R} : X \mapsto (1/2)\langle X - A, X - A \rangle.$$

In other words, $f_A(X)$ is one half the square of the distance from X to A .

Proposition 5. Gradient of the objective function. *Let A and B be matrices in $\mathbb{R}^{m \times n}$. The gradient of the objective function f_A at B is $B - A$; in symbols,*

$$\nabla f_A(B) = B - A.$$

Proof. We simply compute the derivative of $f := f_A$: For X in $\mathbb{R}^{m \times n}$, we have

$$\begin{aligned} (1) \quad Df.B.X &= D(X \mapsto (1/2)\langle X - A, X - A \rangle).B.X \\ (2) \quad &= \langle B - A, D(X \mapsto X - A).B.X \rangle = \langle B - A, X \rangle. \end{aligned}$$

□

We have a gradient vector field on $\mathbb{R}^{m \times n}$ defined by $X \mapsto \nabla f_A(X) = X - A$. But this vector field is generally not tangent to the constant rank surfaces. In other words, the corresponding differential equation $X' = \nabla f_A(X)$ does not preserve rank. We want to adjust the gradient vector field so that the corresponding vector field does preserve rank. We can use the quasi-projection map to do so.

We now compute the quasi-projection of the negative gradient onto the tangent space. For B on the orbit of K , we have

$$\begin{aligned} (L_B \circ L_B^*)(-\nabla f_A(B)) &= L_B((A - B)B^T, B^T(A - B)) \\ &= (A - B)B^T B + BB^T(A - B). \end{aligned}$$

In the next section we shall use this formula to define a vector field on the space $\mathbb{R}^{m \times n}$. We shall then see that the corresponding differential equation provides a solution of the constrained optimization problem of interest.

3. PROPERTIES OF THE DIFFERENTIAL EQUATION

In the last section we saw how to adjust the gradient vector field determined by the objective function so that the resulting vector field is tangent to constant rank submanifolds. We now use that quasi-gradient vector field to define a differential equation.

Using the results of the last section we define the vector field F on $\mathbb{R}^{m \times n}$ as follows:

$$F(X) := (L_X \circ L_X^*)(A - X) = (A - X)X^T X + XX^T(A - X).$$

We consider the differential equation associated with this vector field:

$$(*) \quad X' = F(X).$$

We shall see later that the solutions of this differential equation are defined for all time. In particular we shall see that the solutions do not blow up. We shall also see that they converge.

Note that this differential equation is clearly rank preserving since the vector $F(X)$ is tangent to the space $\text{Rank}(X)$ at X . The following proposition provides a more concrete argument. (In the following analysis, we shall only use the fact that the differential equation preserves rank. We shall not use the other assertions of this result.)

Proposition 6. Rank preserving. *Let $X(t)$ be the solution of the initial value problem*

$$X' = F(X), \quad X(0) = K.$$

Let $G(t)$ and $H(t)$ be solutions of the following initial value problems:

$$\begin{aligned} G' &= (A - X)X^T G, & G(0) &= I \\ H' &= -X^T(A - X)H, & H(0) &= I. \end{aligned}$$

Then $X(t) = G(t)KH(t)^{-1}$ and the rank is invariant.

Remark: The differential equation for G is determined by a tangent vector field on $Gl(m)$ and the differential equation for H is determined by a tangent vector field on $Gl(n)$. Note that the expressions $(A - X)X^T$ and $X^T(A - X)$ appear in the expression defining the vector field $F(X)$.

Proof. Let $Z(t) := G(t)^{-1}X(t)H(t)$. Note $Z(0) = K$ and

$$\begin{aligned} Z' &= -G^{-1}G'G^{-1}XH + G^{-1}X'H + G^{-1}XH' \\ &= -G^{-1}(A - X)X^T GG^{-1}XH + G^{-1}((A - X)X^T X + XX^T(A - X))H \\ &\quad - G^{-1}XX^T(A - X)H \\ &= 0. \end{aligned}$$

Hence $Z(t) = K$ for all t . □

The following proposition says that for any solution $X(t)$ of the differential equation (*), the distance between $X(t)$ and A decreases.

Proposition 7. Lyapunov function. *The objective function f_A is a Lyapunov function for the differential equation (*).*

Proof. Let $X(t)$ be any solution of (*). To simplify the notation, let $f := f_A$ and $L := L_X$. We have

$$\begin{aligned} (d/dt)(f(X(t))) &= (1/2)(d/dt)\langle X - A, X - A \rangle \\ &= \langle X - A, X' \rangle \\ &= \langle X - A, -(L \circ L^*)(X - A) \rangle \\ &= -\langle L^*(X - A), L^*(X - A) \rangle \leq 0. \end{aligned}$$

□

Proposition 8. *The solutions of the differential equation (*) are defined for all positive times.*

Proof. Let $X(t)$ be a solution of the differential equation. By the last proposition the distance between A and $X(t)$ decreases as t increases. Hence the solution remains in the closed ball with radius $\|A - X(0)\|$ centered at A . Since this ball is compact the solution cannot blow up. □

Proposition 9. Equilibrium conditions. *Let E be an element of $\mathbb{R}^{m \times n}$. Then the following conditions are equivalent:*

- (i) E is an equilibrium point of the differential equation (*).
- (ii) E satisfies the equations

$$AE^T = EE^T, \quad E^T A = E^T E.$$

- (iii) $A - E$ is orthogonal to the space tangent the orbit of E at E .
- (iv) E is a critical point of the objective function f_A .

Proof. (i) implies (ii): Let E be an equilibrium point of (*). Then (by the proof of the Lyapunov proposition)

$$0 = L_E^*(A - E) = ((A - E)E^T, E^T(A - E)).$$

Hence $(A - E)E^T = 0$ and $E^T(A - E) = 0$.

(ii) implies (i): Assume the E satisfies the given equations. Then we have $L_E^*(A - E) = 0$ and hence $(L_E \circ L_E^*)(A - E) = 0$.

(ii) implies (iii): Assume that E satisfies the given equations. Then for any X in $\mathbb{R}^{m \times m}$ and Y in $\mathbb{R}^{n \times n}$, we have

$$\langle A - E, XE + EY \rangle = \langle (A - E)E^T, X \rangle + \langle E^T(A - E), Y \rangle = 0.$$

(iii) implies (ii): Assume that $A - E$ is orthogonal to the tangent space. Then, for all X in $\mathbb{R}^{m \times m}$ and Y in $\mathbb{R}^{n \times n}$, we have

$$0 = \langle A - E, XE + EY \rangle = \langle (A - E)E^T, X \rangle + \langle E^T(A - E), Y \rangle.$$

It follows that E satisfies the given equations.

(iii) is equivalent to (iv): This equivalence is obvious. □

Proposition 10. Quasi-commuting relations. *Let E be an equilibrium point of the differential equation (*). Then*

- *The matrix E satisfies the equations*

$$AE^T = EA^T, \quad A^T E = E^T A.$$

- *The matrix E satisfies the equations*

$$A^T A E = E^T A A^T, \quad A A^T E = E A^T A.$$

I call the two equations which appear in the first conclusion of this proposition, the “quasi-commuting” relations for E .

Proof. We have $AE^T = EE^T$ and $E^T A = E^T E$ from the proposition characterizing the equilibrium points. To get the quasi-commuting relations we simply use the symmetry of EE^T and $E^T E$.

To get the other relations we simply apply the quasi-commuting relations repeatedly. In particular, we have

- $A^T(AE^T) = A^T(EA^T) = (A^T E)A^T = (E^T A)A^T$ and
- $A(A^T E) = A(E^T A) = (AE^T)A = (EA^T)A$.

□

In the following proof and example, I use E^{pq} to denote the $m \times n$ matrix with a one in position pq and zeros elsewhere: $E_{ij}^{pq} := \delta(i, p)\delta(j, q)$. Note that these matrices form a basis of the vector space $\mathbb{R}^{m \times n}$.

Proposition 11. Stability of the equilibrium points. *If the matrix A has distinct positive singular values, then the differential equation (*) has isolated equilibrium points only one of which is stable. It follows that the solutions of the differential equation converge and that almost all of them converge to the stable equilibrium point.*

Remark: Note that the set of matrices with distinct positive singular values is a generic (that is, an open and dense) subset of $\mathbb{R}^{m \times n}$.

Proof. We do the case $m \geq n$. The proof in the case $m \leq n$ is essentially the same.

We have been working in a coordinate-free way until now. We now choose a convenient coordinate system in which to do calculations. In particular, we choose the basis so that A is a diagonal matrix of ordered singular values:

$$A = \text{Diag}(\sigma_1 > \sigma_2 > \cdots > \sigma_n).$$

Claim: If a matrix E is an equilibrium point of the differential equation then E is a diagonal matrix.

Recall that E must satisfy $AA^T E = EA^T A$. We simply calculate these matrix products and compare entries. We have $(AA^T E)_{ij} = \sigma_i^2 E_{ij}$ if $i \leq n$ and $(AA^T E)_{ij} = 0$ if $i > n$. We also have $(EA^T A)_{ij} = E_{ij} \sigma_j^2$. We conclude that if $i \leq n$ and $i \neq j$ then $\sigma_i^2 E_{ij} = E_{ij} \sigma_j^2$ and hence $E_{ij} = 0$ since $\sigma_i^2 \neq \sigma_j^2$.

If $i > n$ and $i \neq j$ then $0 = E_{ij}\sigma_j^2$ and hence $E_{ij} = 0$ since $\sigma_j^2 \neq 0$. Thus all the off-diagonal entries of E must be zero.

Claim: Let $E := \text{Diag}(e_1, \dots, e_n)$ be an equilibrium point of the differential equation. Then, for $i = 1, 2, \dots, n$, either $e_i = \sigma_i$ or $e_i = 0$.

Since the vector field vanishes at E , we have

$$0 = (\sigma_i - e_i)e_i^2 + e_i^2(\sigma_i - e_i) = 2(\sigma_i - e_i)e_i^2.$$

Claim: The solutions of the differential equation converge.

From the last claim we see that there are a finite number of equilibrium points. A gradient flow confined to a compact set with a finite number of equilibrium points must converge. See, for example, Palis and de Melo(1982).

We now turn to the classification of the equilibrium points. Let $E = \text{Diag}(e_1, \dots, e_n)$ be an equilibrium point. We compute the linearization of the differential equation at E : We get the linear differential equation

$$X' = D.F.E.X = (A - E)X^T E + EX^T(A - E) - XE^T E - EE^T X.$$

We regard $D.F.E$ as a linear map on the space tangent to the orbit of E at E . (By the way, it is easy to check that this map is self-adjoint.) The nature of the equilibrium is determined by this linear map. In particular, the equilibrium point E is stable if the eigenvalues of this map are all negative. If this map has a positive eigenvalue then the equilibrium point is unstable. We want to see that exactly one of the equilibrium points has all eigenvalues negative (a stable situation) and that all of the other equilibrium points have at least one positive eigenvalue (an unstable situation).

We have

$$(D.F.E.X)_{ii} = c_i x_{ii}.$$

where $c_i := 2e_i(\sigma_i - 2e_i)$. For $i \neq j$, we have

$$(D.F.E.X)_{ij} = b_{ij}x_{ji} - a_{ij}x_{ij}$$

where $a_{ij} := (e_i^2 + e_j^2)$ and $b_{ij} := (\sigma_i - e_i)e_j + e_i(\sigma_j - e_j)$.

Since the ij entry of $D.F.E.X$ involves only the ij and ji entry of X , we temporarily restrict our attention to 2 by 2 matrices.

We need to find the eigenvalues of the map:

$$\begin{pmatrix} x_{ij} \\ x_{ji} \end{pmatrix} \mapsto M \begin{pmatrix} x_{ij} \\ x_{ji} \end{pmatrix},$$

where

$$M := \begin{pmatrix} -a_{ij} & b_{ij} \\ b_{ij} & -a_{ij} \end{pmatrix}.$$

The matrix M has the following form:

$$\begin{pmatrix} -a & b \\ b & -a \end{pmatrix}.$$

This matrix has eigenvalues $-a \pm b$. In particular,

$$\begin{pmatrix} -a & b \\ b & -a \end{pmatrix} \begin{pmatrix} 1 \\ 1 \end{pmatrix} = (-a + b) \begin{pmatrix} 1 \\ 1 \end{pmatrix}$$

and

$$\begin{pmatrix} -a & b \\ b & -a \end{pmatrix} \begin{pmatrix} 1 \\ -1 \end{pmatrix} = -(a + b) \begin{pmatrix} 1 \\ -1 \end{pmatrix}.$$

Hence the eigenvalues of M are

$$\lambda_1 := -(e_i + e_j)^2 + \sigma_i e_j + e_i \sigma_j$$

and

$$\lambda_2 := -(e_i - e_j)^2 - \sigma_i e_j - e_i \sigma_j.$$

Note that $\lambda_2 \leq 0$ for all values of e_i, e_j, σ_i and σ_j since these values are always nonnegative.

Claim: The diagonal matrix $E^* := \text{Diag}(\sigma_1, \dots, \sigma_k, 0, \dots, 0)$, where k is the rank of the initial matrix K , is a stable equilibrium point.

We want to see that all the eigenvalues associated with this equilibrium point are negative. Note that the set $\{E^{pq} : 1 \leq p \leq k \text{ or } 1 \leq q \leq k\}$ is a basis of the space $\text{Tan.Orbit}(E^*).E$ tangent to the orbit of E^* at E^* .

If $1 \leq i \leq k$ and $1 \leq j \leq k$ and $i \neq j$ then $a_{ij} = -(\sigma_i^2 + \sigma_j^2)$; if $1 \leq j \leq k$ and $k < i \leq m$ then $a_{ij} = -\sigma_i^2$; if $k < i \leq m$ and $1 \leq j \leq n$ then $a_{ij} = -\sigma_j^2$. If $(1 \leq i \leq k \text{ or } 1 \leq j \leq k)$ and $i \neq j$ then $b_{ij} = 0$. For $i = 1, \dots, k$, $c_i = -\sigma_i^2$. The eigenvalue-vector pairs of $D.F.E^*$ are

- $(-(\sigma_i^2 + \sigma_j^2), E^{ij})$ for $1 \leq i \leq k, 1 \leq j \leq k, i \neq j$,
- $(-\sigma_i^2, E^{ij})$ for $1 \leq i \leq k$ and $k < j \leq n$,
- $(-\sigma_j^2, E^{ij})$ for $k < i \leq m$ and $1 \leq j \leq k$,
- $(-\sigma_k^2, E_{ii})$ for $1 \leq i \leq k$.

Note all these eigenvalues are negative.

Claim: If E is an equilibrium point is different than E^* then E is unstable.

In this case the set $\{E^{pq} : e_p \neq 0 \text{ or } e_q \neq 0\}$ is a basis for the tangent space.

We want to see that the linear map $D.F.E$ on the tangent space has at least one positive eigenvalue. Since E is different than E^* , there is an index p satisfying $1 \leq p \leq k$ and $e_p = 0$. Since E has rank k , there is an index q satisfying $p < q$ and $e_q \neq 0$. Then $e_q = \sigma_q$. Note that E^{pq} and E^{qp} are in the tangent space. We have

$$D.F.E.(E^{pq} + E^{qp}) = (b_{pq} + a_{pq})(E^{pq} + E^{qp}) = (\sigma_p - \sigma_q)\sigma_q(E^{pq} + E^{qp}).$$

□

Example: We do the case $m = 4, n = 3$ to illustrate the calculations which appear in the proof of the last proposition. We consider $A := \text{Diag}(\sigma_1, \sigma_2, \sigma_3)$

where $\sigma_1 > \sigma_2 > \sigma_3 > 0$. Let

$$E := \begin{pmatrix} e_{11} & e_{12} & e_{13} \\ e_{21} & e_{22} & e_{23} \\ e_{31} & e_{32} & e_{33} \\ e_{41} & e_{42} & e_{43} \end{pmatrix}$$

be an equilibrium point. We have that AA^T is the 4 by 4 diagonal matrix $\text{Diag}(\sigma_1^2, \sigma_2^2, \sigma_3^2, 0)$ and $A^T A$ is the 3 by 3 diagonal matrix $\text{Diag}(\sigma_1^2, \sigma_2^2, \sigma_3^2)$. Hence

$$AA^T E = \begin{pmatrix} \sigma_1^2 e_{11} & \sigma_1^2 e_{12} & \sigma_1^2 e_{13} \\ \sigma_2^2 e_{21} & \sigma_2^2 e_{22} & \sigma_2^2 e_{23} \\ \sigma_3^2 e_{31} & \sigma_3^2 e_{32} & \sigma_3^2 e_{33} \\ 0 & 0 & 0 \end{pmatrix}$$

and

$$EA^T A = \begin{pmatrix} \sigma_1^2 e_{11} & \sigma_2^2 e_{12} & \sigma_3^2 e_{13} \\ \sigma_1^2 e_{21} & \sigma_2^2 e_{22} & \sigma_3^2 e_{23} \\ \sigma_1^2 e_{31} & \sigma_2^2 e_{32} & \sigma_3^2 e_{33} \\ \sigma_1^2 e_{41} & \sigma_2^2 e_{42} & \sigma_3^2 e_{43} \end{pmatrix}.$$

Equating the entries of these two matrices, we see that that all the off-diagonal entries of E must be zero.

We now set $E := \text{Diag}(e_1, e_2, e_3)$. We consider the equilibrium equation $AE^T = EE^T$. We have $AE^T = \text{Diag}(\sigma_1 e_1, \sigma_2 e_2, \sigma_3 e_3, 0)$ and $EE^T = \text{Diag}(e_1^2, e_2^2, e_3^2, 0)$. Equating the entries of these two matrices we get, for $i=1,2,3$, $\sigma_i e_i = e_i^2$, and hence $e_i = \sigma_i$ or $e_i = 0$. The specified low rank k will determine the number of e_i which are zero.

We turn to the stability classification of the equilibrium points. We have

$$\begin{aligned} D.F.E.X &= (A - E)X^T E + EX^T(A - E) - XE^T E - EE^T X \\ &= \begin{pmatrix} (\sigma_1 - e_1)x_{11}e_1 & (\sigma_1 - e_1)x_{21}e_2 & (\sigma_1 - e_1)x_{31}e_3 \\ (\sigma_2 - e_2)x_{12}e_1 & (\sigma_2 - e_2)x_{22}e_2 & (\sigma_2 - e_2)x_{32}e_3 \\ (\sigma_3 - e_3)x_{13}e_1 & (\sigma_3 - e_3)x_{23}e_2 & (\sigma_3 - e_3)x_{33}e_3 \\ 0 & 0 & 0 \end{pmatrix} \\ &\quad + \begin{pmatrix} e_1 x_{11}(\sigma_1 - e_1) & e_1 x_{21}(\sigma_2 - e_2) & e_1 x_{31}(\sigma_3 - e_3) \\ e_2 x_{12}(\sigma_1 - e_1) & e_2 x_{22}(\sigma_2 - e_2) & e_2 x_{32}(\sigma_3 - e_3) \\ e_3 x_{13}(\sigma_1 - e_1) & e_3 x_{23}(\sigma_2 - e_2) & e_3 x_{33}(\sigma_3 - e_3) \\ 0 & 0 & 0 \end{pmatrix} \\ &\quad - \begin{pmatrix} x_{11}e_1^2 & x_{12}e_2^2 & x_{13}e_3^2 \\ x_{21}e_1^2 & x_{22}e_2^2 & x_{23}e_3^2 \\ x_{31}e_1^2 & x_{32}e_2^2 & x_{33}e_3^2 \\ x_{41}e_1^2 & x_{42}e_2^2 & x_{43}e_3^2 \end{pmatrix} - \begin{pmatrix} e_1^2 x_{11} & e_1^2 x_{21} & e_1^2 x_{31} \\ e_2^2 x_{12} & e_2^2 x_{22} & e_2^2 x_{32} \\ e_3^2 x_{13} & e_3^2 x_{23} & e_3^2 x_{33} \\ 0 & 0 & 0 \end{pmatrix} \\ &= \begin{pmatrix} 0 & b_{12}x_{21} & b_{13}x_{31} \\ b_{21}x_{12} & 0 & b_{23}x_{32} \\ b_{31}x_{13} & b_{32}x_{23} & 0 \\ 0 & 0 & 0 \end{pmatrix} + \begin{pmatrix} c_1 x_{11} & -a_{12}x_{12} & -a_{13}x_{13} \\ -a_{21}x_{21} & c_2 x_{22} & -a_{23}x_{23} \\ -a_{31}x_{31} & -a_{32}x_{32} & c_3 x_{33} \\ -e_1^2 x_{41} & -e_2^2 x_{42} & -e_3^2 x_{43} \end{pmatrix} \end{aligned}$$

where (using the same notation as that of the proof)

$$\begin{aligned} a_{ij} &:= e_i^2 + e_j^2, \\ b_{ij} &:= (\sigma_i - e_i)e_j + e_i(\sigma_j - e_j), \\ c_i &:= 2e_i(\sigma_i - 2e_i). \end{aligned}$$

We now consider the stability of the equilibrium points when $k := 2$ is the given rank. There are three cases.

Case: $E := E^* := \text{Diag}(\sigma_1, \sigma_2, 0)$

Note that the tangent space to $\text{Orbit}(E)$ at E consists of matrices $VE + EW$ where V is in $\mathbb{R}^{4 \times 4}$ and W is in $\mathbb{R}^{3 \times 3}$. It is easy to see that these matrices have the following form:

$$X := \begin{pmatrix} x_{11} & x_{12} & x_{13} \\ x_{21} & x_{22} & x_{23} \\ x_{31} & x_{32} & 0 \\ x_{41} & x_{42} & 0 \end{pmatrix}.$$

If X is such a matrix then

$$D.F.E^*.X = \begin{pmatrix} -2\sigma_1^2 x_{11} & -(\sigma_1^2 + \sigma_2^2)x_{12} & -\sigma_1^2 x_{13} \\ -(\sigma_1^2 + \sigma_2^2)x_{21} & -2\sigma_2^2 x_{22} & -\sigma_2^2 x_{23} \\ -\sigma_1^2 x_{31} & -\sigma_2^2 x_{32} & 0 \\ -\sigma_1^2 x_{41} & -\sigma_2^2 x_{42} & 0 \end{pmatrix}$$

since

$$\begin{aligned} a_{12} &= \sigma_1^2 + \sigma_2^2, a_{13} = \sigma_1^2, a_{23} = \sigma_2^2, \\ b_{12} &= b_{13} = b_{23} = 0, \\ c_1 &= -2\sigma_1^2, c_2 = -2\sigma_2^2, \text{ and } c_3 = 0. \end{aligned}$$

The eigenvalues of $D.F.E^*$ are all strictly negative. In particular, the eigenvalue-vector pairs are

$$\begin{aligned} &(-2\sigma_1^2, E^{11}), (-(\sigma_1^2 + \sigma_2^2), E^{12}), (-\sigma_1^2, E^{13}), \\ &(-(\sigma_1^2 + \sigma_2^2), E^{21}), (-2\sigma_2^2, E^{22}), (-\sigma_2^2, E^{23}), \\ &(-\sigma_1^2, E^{31}), (-\sigma_2^2, E^{32}), \\ &(-\sigma_1^2, E^{41}), (-\sigma_2^2, E^{42}). \end{aligned}$$

Case: $E := \text{Diag}(\sigma_1, 0, \sigma_3)$

Then the tangent space to $\text{Orbit}(E)$ at E consists of matrices having the following form:

$$X := \begin{pmatrix} x_{11} & x_{12} & x_{13} \\ x_{21} & 0 & x_{23} \\ x_{31} & x_{32} & x_{33} \\ x_{41} & 0 & x_{43} \end{pmatrix}.$$

If X is such a matrix then $D.F.E.X$ is the following matrix:

$$\begin{pmatrix} 0 & \sigma_1\sigma_2x_{21} & 0 \\ \sigma_1\sigma_2x_{12} & 0 & \sigma_2\sigma_3x_{32} \\ 0 & \sigma_2\sigma_3x_{23} & 0 \\ 0 & 0 & 0 \end{pmatrix} + \begin{pmatrix} -2\sigma_1^2x_{11} & -\sigma_1^2x_{12} & -(\sigma_1^2 + \sigma_3^2)x_{13} \\ -\sigma_1^2x_{21} & 0 & -\sigma_3^2x_{23} \\ -(\sigma_1^2 + \sigma_3^2)x_{31} & -\sigma_3^2x_{32} & -2\sigma_3^2x_{33} \\ -\sigma_1^2x_{41} & 0 & -\sigma_3^2x_{43} \end{pmatrix}$$

since

$$\begin{aligned} a_{12} &= \sigma_1^2, a_{13} = \sigma_1^2 + \sigma_3^2, a_{23} = \sigma_3^2, \\ b_{12} &= \sigma_1\sigma_2, b_{13} = 0, b_{23} = \sigma_2\sigma_3, \\ c_1 &= -2\sigma_1^2, c_2 = 0, \text{ and } c_3 = -2\sigma_3^2. \end{aligned}$$

There is a positive eigenvalue. In particular,

$$D.F.E.(E^{23} + E^{32}) = (\sigma_2 - \sigma_3)\sigma_3(E^{23} + E^{32}).$$

Case: $E := \text{Diag}(0, \sigma_2, \sigma_3)$

Then the tangent space to $\text{Orbit}(E)$ at E consists of matrices having the following form:

$$X := \begin{pmatrix} 0 & x_{12} & x_{13} \\ x_{21} & x_{22} & x_{23} \\ x_{31} & x_{32} & x_{33} \\ 0 & x_{42} & x_{43} \end{pmatrix}.$$

If X is such a matrix then $D.F.E.X$ is

$$\begin{pmatrix} 0 & \sigma_1\sigma_2x_{21} & \sigma_2\sigma_3x_{31} \\ \sigma_1\sigma_2x_{12} & 0 & 0 \\ \sigma_1\sigma_3x_{13} & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix} + \begin{pmatrix} 0 & -\sigma_2^2x_{12} & -\sigma_3^2x_{13} \\ -\sigma_2^2x_{21} & -2\sigma_2^2x_{22} & -(\sigma_2^2 + \sigma_3^2)x_{23} \\ -\sigma_3^2x_{31} & -(\sigma_2^2 + \sigma_3^2)x_{32} & -2\sigma_3^2x_{33} \\ 0 & -\sigma_2^2x_{42} & -\sigma_3^2x_{43} \end{pmatrix}$$

since

$$\begin{aligned} a_{12} &= \sigma_2^2, a_{13} = \sigma_3^2, a_{23} = \sigma_2^2 + \sigma_3^2, \\ b_{12} &= \sigma_1\sigma_2, b_{13} = \sigma_1\sigma_3, b_{23} = 0, \\ c_1 &= 0, c_2 = -2\sigma_2^2, \text{ and } c_3 = -2\sigma_3^2. \end{aligned}$$

There is a positive eigenvalue. In particular,

$$D.F.E.(E^{12} + E^{21}) = (\sigma_1 - \sigma_2)\sigma_2(E^{12} + E^{21}).$$

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5. APPENDIX: THE FROBENIUS INNER PRODUCT

We use the ‘‘Frobenius’’ (or ‘‘euclidean’’) inner product in the space $\mathbb{R}^{m \times n}$ of m by n real matrices. For X and Y in this space, the **Frobenius inner product** is defined by

$$\langle X, Y \rangle := \text{Trace}(XY^T).$$

In terms of coordinates, $\langle X, Y \rangle = \sum \{X_{ij}Y_{ij} : i = 1, \dots, m, j = 1, \dots, n\}$. Here we review a few of the properties of this inner product.

Proposition 12. Adjoints of multiplication maps. *Let B and Z be elements of $\mathbb{R}^{m \times n}$.*

- For $X \in \mathbb{R}^{m \times m}$, $\langle XB, Z \rangle = \langle X, ZB^T \rangle$.
- For $Y \in \mathbb{R}^{n \times n}$, $\langle BY, Z \rangle = \langle Y, B^T Z \rangle$.

Proof. We have

$$\text{Trace}(XBZ^T) = \text{Trace}(X(ZB^T)^T)$$

and

$$\text{Trace}(BYZ^T) = \text{Trace}(YZ^T B) = \text{Trace}(Y(B^T Z)^T).$$

□

Proposition 13. Orthogonal invariance. *Let U be an m by m real orthogonal matrix and let V be an n by n real orthogonal matrix. Then, for all X and Y in $\mathbb{R}^{m \times n}$,*

- $\langle UX, UY \rangle = \langle X, Y \rangle$ and
- $\langle XV, YV \rangle = \langle X, Y \rangle$.

Proof. By the result concerning the adjoints of multiplication maps, we have:

- $\langle UX, UY \rangle = \langle X, U^T UY \rangle = \langle X, Y \rangle$ and
- $\langle XV, YV \rangle = \langle X, YV V^T \rangle = \langle X, Y \rangle$

□

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