# Approximation by orthogonal transform

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#### Abstract

We work through the derivation of the standard solution to the orthogonal Procrustes problem.

### 1 Introduction

The orthogonal Procrustes problem is: given two matrices A, and B then find an orthogonal matrix W such that  $||AW - B||_F^2$  is minimized. We will limit or work to the case where A, B are real n by n matrices.

The current family of solutions goes back to Peter Schonemann's 1964 thesis[Wikipedia, 2014, Schonemann, 1966] and we adapt the proof from [Bindel, 2012] for this note.

## 2 Some Linear Algebra

To work the problem we will need some background definitions and facts from linear algebra, which we will state without proof.

**Definition 1.** For a m row by n column matrix A the transpose of A written tr(A) is a n row by m column matrix such that  $tr(A)_{j,i} = A_{i,j}$  for  $i = 1 \cdots m$ ,  $j = 1 \cdots n$ .

**Definition 2.** An orthogonal matrix W is a real matrix with n rows and n columns such that  $WW^{\top} = W^{\top}W = I$ . Note that in addition to having orthogonal rows and columns an orthogonal matrix is also full rank and has all rows and columns unit length.

**Definition 3.** The squared Frobenius norm of a n by n matrix X is written as  $||X||_F^2$  and is equal to  $\sum_{i=1}^n \sum_{j=1}^n |X_{i,j}|^2$ .

**Definition 4.** The trace of a n by n matrix X is written as tr(X) and is defined as  $\sum_{i=1}^{n} X_{i,i}$ .

**Lemma 1.** For real n by n matrices  $||X||_F^2 = ||X^\top||_F^2$ .

**Lemma 2.** For real n by n matrices  $||X||_F^2 = tr(XX^\top) = tr(X^\top X)$ .

**Lemma 3.** For real n by n matrices  $A_1, \dots A_k$   $tr(A_1 \dots A_k) = tr(A_k A_1 \dots A_{k-1})$ . That is: trace is invariant under cyclic re-ordering of a product (though not under arbitrary permutations in general).

**Lemma 4.**  $||AW||_F^2 = ||A||_F^2$  if W is orthogonal.

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Proof.

$$||AW||_F^2 = \operatorname{tr}(AWW^\top A^\top)$$
$$= \operatorname{tr}(AA^\top)$$
$$= ||A||_F^2$$

**Lemma 5.** If A is an m row by n column real matrix then there exists matrices U, D, V such that  $A = UDV^{\top}$  and:

- U is a m by m orthogonal matrix
- D is a m by n diagonal matrix
- $D_{i,i}$  are non-negative and decreasing in i
- $\bullet$  V is a n by n orthogonal matrix.

This factorization is called the singular value decomposition, and is available in most linear algebra libraries.

## 3 The solution

The problem is to find an orthogonal matrix W minimizing  $||AW - B||_F^2$  where A, B are n by n real matrices.

**Theorem 1.** Let  $UDV^{\top}$  be the singular value decomposition of  $A^{\top}B$  where A, B are real n by n matrices. Then  $W = UV^{\top}$  is an orthogonal matrix minimizing  $||AW - B||_F^2$ .

*Proof.* To derived the method we first expand  $||AW - B||_F^2$ .

$$||AW - B||_F^2 = \sum_{i,j} (AW - B)_{i,j}^2$$

$$= \sum_{i,j} (AW)_{i,j}^2 + (B)_{i,j}^2 - 2(AW)_{i,j}(B)_{i,j}$$

$$= ||AW||_F^2 + ||B||_F^2 - 2\operatorname{tr}(W^\top A^\top B)$$

$$= ||A||_F^2 + ||B||_F^2 - 2\operatorname{tr}(W^\top A^\top B)$$

So picking W to maximize  $\operatorname{tr}(W^{\top}A^{\top}B)$  will minimize  $||AW - B||_F^2$ . Let  $UDV^{\top}$  be the singular value decomposition of  $A^{\top}B$ .

$$\operatorname{tr}(W^{\top}A^{\top}B) = \operatorname{tr}(W^{\top}UDV^{\top})$$
$$= \operatorname{tr}(V^{\top}W^{\top}UD)$$

Write  $Z = V^{\top}W^{\top}U$ , notice Z is orthogonal (being the product of orthogonal matrices). The goal is re-stated: maximize  $\operatorname{tr}(ZD)$  through our choice of W. Because D is diagonal we have  $\operatorname{tr}(ZD) = \sum_{i=1}^{n} Z_{i,i}D_{i,i}$ . The  $D_{i,i}$  are non-negative and Z is orthogonal for any choice of W. The maximum is achieved by choosing W such that all of  $Z_{i,i} = 1$  which implies Z = I. So an optimal W is  $UV^{\top}$ .  $\square$ 

# 4 Application

An application of the orthogonal Procrustes solution to machine learning is given in a iPython notebook [Mount, 2014] (and soon to be followed up by a blog post on http://www.win-vector.com/blog).

### References

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