

Computer Vision (600.461/600.661)

Homework 1: Mathematical Background

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Due 09/11/2014, 11.59PM Eastern

1. **Properties of Symmetric Matrices.** Let $S \in \mathbb{R}^{n \times n}$ be a real symmetric matrix. Show that:

- (a) All the eigenvalues of S are real, i.e., $\sigma(S) \subset \mathbb{R}$.

Assume $\lambda \in \Im S \tilde{v} = \tilde{\lambda} \tilde{v}$

- (b) Let (λ, v) be an eigenvalue-eigenvector pair. If $\lambda_i \neq \lambda_j$, then $v_i \perp v_j$; i.e., eigenvectors corresponding to distinct eigenvalues are orthogonal.
- (c) There always exist n orthonormal eigenvectors of S , which form a basis of \mathbb{R}^n .
- (d) S is positive definite (positive semidefinite) if and only if all of its eigenvalues are positive (non-negative), i.e., $S \succ 0$ ($S \succeq 0$), iff $\forall i = 1, 2, \dots, n, \lambda_i > 0$ ($\lambda_i \geq 0$).
- (e) If $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_n$ are the sorted eigenvalues of S , then $\max_{\|x\|_2=1} x^\top S x = \lambda_1$ and $\min_{\|x\|_2=1} x^\top S x = \lambda_n$.

2. **Properties of the SVD.** Let $A = U\Sigma V^\top$ be the SVD of a matrix $A \in \mathbb{R}^{m \times n}$ of rank r . Show that:

- (a) $Av_j = \sigma_j u_j$ for $j = 1, \dots, r$ and $A^\top u_j = \sigma_j v_j$ for $j = 1, \dots, r$.
- (b) The range or image of A is spanned by the left singular vectors of A associated with its nonzero singular values, i.e., $\text{range}(A) = \text{span}\{u_i\}_{i=1}^r$.
- (c) The kernel or null space of A is spanned by the right singular vectors of A associated with its zero singular values, i.e., $\ker(A) = \text{span}\{v_i\}_{i=r+1}^m$.
- (d) The squared Frobenius norm of A is equal to the sum of the squared singular values of A , i.e., $\|A\|_F^2 = \sum_{i,j} a_{ij}^2 = \sum_{k=1}^r \sigma_k^2$.
- (e) The right singular vector of A associated to its smallest singular value, v_m , is a solution to the optimization problem $\min_x \|Ax\|_2^2$ such that $\|x\|_2 = 1$.

3. **Least Squares.** Recall that the pseudo inverse of a matrix $A \in \mathbb{R}^{m \times n}$ is the unique matrix $A^\dagger \in \mathbb{R}^{n \times m}$ such that: (i) $AA^\dagger A = A$, (ii) $A^\dagger AA^\dagger = A^\dagger$, (iii) $(AA^\dagger)^\top = AA^\dagger$, and (iv) $(A^\dagger A)^\top = A^\dagger A$. Let $A = U\Sigma V^\top$ be the SVD of A , let $r = \text{rank}(A)$ and let $b \in \mathbb{R}^m$. Show that:

- (a) The pseudo-inverse of A is given by $A^\dagger = V_r \Sigma_r^{-1} U_r^\top$, where $A = U_r \Sigma_r V_r^\top$ is the compact SVD of A .
- (b) $x^* = A^\dagger b$ is a solution to the optimization problem $\min_x \|Ax - b\|_2^2$. When is x^* the unique solution?
- (c) If $b \in \text{range}(A)$, $x^* = A^\dagger b$ is the solution to the optimization problem $\min_x \|x\|_2^2$ such that $Ax = b$.

Submission instructions. Send email to vision14jhu@gmail.com with subject **600.461/600.661:HW1** and attachment `firstname-lastname-hw1-vision14.zip` or `firstname-lastname-hw1-vision14.tar.gz`. The attachment should have the following content:

1. A file called `hw1.pdf` containing your answers to each one of the analytical questions. If at all possible, you should generate this file using the latex template [hw1-vision14.tex](#). If not possible, you may use another editor, or scan your handwritten solutions. But note that you must submit a single PDF file with all your answers.