HW 7

2. Proofs:

a. Let A be an orthogonal matrix $(A^{-1}) = (A^T)$

$\det(A) = \det(A^T)$

$A(A^{-1}) = I$

$\det(I) = \det(AA^{-1}) = \det(A)\det(A^{-1}) = \cancel{\det(A^T)\det(A^{-1})}$

$\det(I) = \det(A^T)\det(A^{-1}) = \det(A^T)^2$

$\det(I) = 1$

$\det(I) = \det(A^T)^2 = 1$

$\det(A^T) = \boxed{\pm\sqrt{1} = \det(A)}$

QED.

b. Let A be an $n \times n$ square matrix. We will prove that $|\det(A)| = \prod_{i=1}^{n} \sigma_i$

$A = U\Sigma V^T$, U is $n\times r$, Σ is $r \times r$, V is $r \times n$

$\det(A) = \det(U\Sigma V^T) = \det(U)\det(\Sigma)\det(V^T)$

We proved in part a that the determinant of an orthogonal matrix equals ± 1

U and V are orthogonal matrices by the definition of SVD, hence:

$\det(A) = \pm 1 \cdot \det(\Sigma) \cdot \pm 1$

Given from 132 notes, ~~the~~ the determinant of ~~an orthogon~~ a diagonal matrix is the product of the diagonal values.

So, $\det(\Sigma) = \prod_{i=1}^{n} \Sigma_{i,i}$. Since Σ is the singular matrix, this equals $\prod_{i=1}^{n} \sigma_i$

Inserting this, we get:

$\det(A) = \pm 1 \cdot \prod_{i=1}^{n} \sigma_i \cdot \pm 1$,

So $|\det(A)| = |\pm 1 \prod_{i=1}^{n} \sigma_i \cdot \pm 1| = |\prod_{i=1}^{n} \sigma_i$

QED.

HW 8

3. SVD

$A = U\Sigma V^T$

a) ~~Show that $A^T u_j = \sigma_j v_j$, $\forall j\ 1 \le j \le \text{rank}(A)$~~

~~$V = v_1 \dots v_j$ (orthonormal basis for A, proved in 132, L25)~~

~~So for $(Av_i)^T(Av_j) = 0$ where $i \neq j$~~

~~$A = U\Sigma V^T$, $V^T = V^{-1}$~~

~~$AV = U\Sigma$ $A = n\times n$, $V = n\times r$, $U = r\times n$, $\Sigma = r\times r$,~~ where r is the matrix rank (of A)

~~So for all columns of A 1, r,~~

b.) Given $A = U\Sigma V^T$

U and V are orthogonal, so $U^{-1} = U^T$ and $V^{-1} = V^T$

$\Sigma^{-1} = \begin{bmatrix} 1/\sigma_1 & & 0 \\ & 1/\sigma_2 & \\ 0 & & \ddots \end{bmatrix}$

$A^{-1} = V\Sigma^{-1}U^T$

c)

1. Let $A^{n\times m}$ be a real matrix (given)
2. Let $P \in \mathbb{R}^{n\times n}$ be an orthogonal matrix (given)
3. $P^TP = I$ (definition of orthogonal matrix)
4. For $A = U\Sigma V^T$, $\Sigma^{r\times r}$ = eigenvalues of A down the diagonal
   U = eigenvectors of A, normalized
   V = eigenvectors of A
5. eig(A) = eigenvalue decomposition of A^TA

~~6. eig(AP) = eigenvalue decomposition of $(AP)^TAP$~~

~~7. $(AP)^TAP$~~

6. $(PA)^TPA = A^TP^TPA$ (def. transpose)
7. $A^TP^TPA = A^TIA = A^TA$ (product of P^TP when P is orthogonal)
8. eig(PA) = eig. decomposition of $(PA)^TPA$ = " , of A^TA
9. eig(A) = eig(PA), (7, 8)

HW 8

3. SVD

a. $A = U\Sigma V^T$

1. $A = U\Sigma V^T$ (given)
2. $AV = U\Sigma$ (multiply both sides by V, ($V^T = V^{-1}$ by orthogonal matrix definition))
3. $Av_i = U_i \sigma_i$ (decomposition of matrices into columns)
4. $u_j = Av_i / \|Av_i\| = \frac{1}{\sigma_i} Av_i$ (definition from 132 notes)
5. ~~$A^T = V\Sigma U^T$~~ $A^T = (U\Sigma V^T)^T$
6. $A^T = V\Sigma^T U^T$ (definition of transpose)
7. $A^T = V\Sigma U^{-1}$ (definition of orthogonal matrix)
8. $A^T U = V\Sigma$ (Multiply both sides by U)
9. $A^T u_j = V_j \sigma_j$ (decomposition of matrices into columns)
10. $A^T u_j$ is $m\times n$ times $n\times n$, $V_j \sigma_j$ is $n\times r \times r\times n$, so the range of j is r
11. $r = \text{rank}(A)$ (definition of singular value dimensions.
12. Thus for all j in range 0 through rank(A), $A^T u_j = V_j \sigma_j$

QED.

3c. (continued)

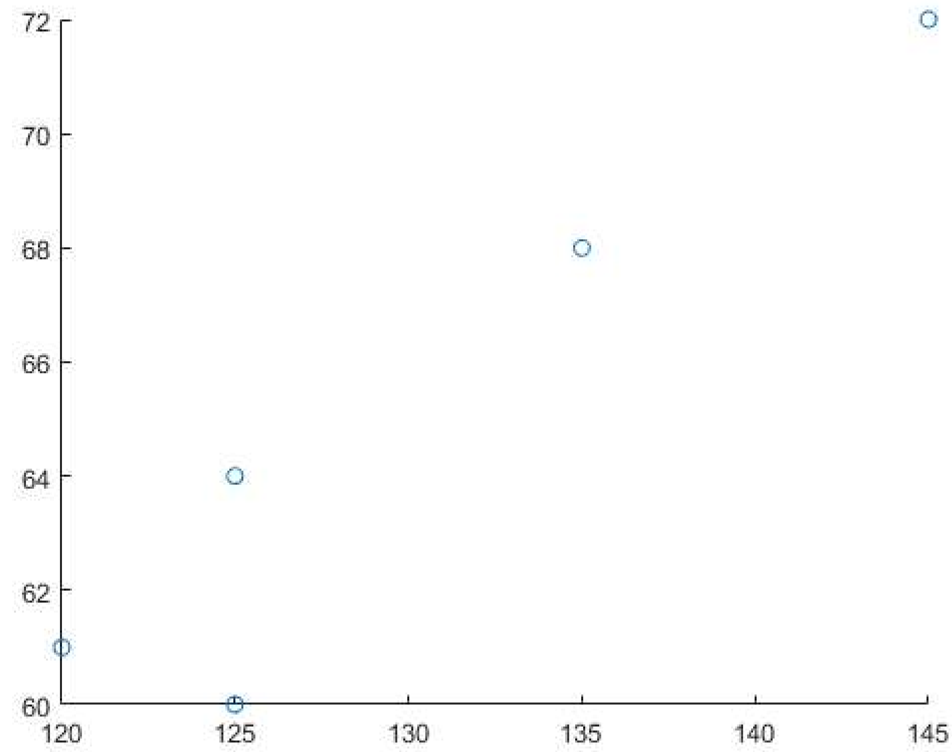
10. The singular values of a matrix are the square roots of the eigenvalues of that matrix

11. singular values for A = Singular values for PA because eig(A) = eig(PA), the values are the same so the square roots will be too.

```
data = [120 125 125 135 145 ; 61 60 64 68 72];

mean_vec = mean(data,2);
n = size(data,1)
B = data - mean_vec

S = (1/(n-1)) * B * transpose(B)

[U,L] = eig(S);

"Eigenvalues:"
l2 = L(1,1)
l1 = L(2,2)
"Eigenvectors:"
U

variance = l1/(l1+l2)

scatter(data(1,:),data(2,:))
```

```
n =

     2


B =

   -10    -5    -5     5    15
    -4    -5    -1     3     7


S =

   400   190
   190   100


ans =

    "Eigenvalues:"


l2 =

    7.9256


l1 =

  492.0744


ans =

    "Eigenvectors:"
```

```
U =

    0.4361   -0.8999
   -0.8999   -0.4361


variance =

    0.9841
```



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