

**Pr. 1.**

Show that for any **vector norm** on  $\mathbb{F}^N$ , the ball of radius  $r \geq 0$  with respect to that norm

$$\mathcal{B}_r \triangleq \{\mathbf{x} \in \mathbb{F}^N : \|\mathbf{x}\| \leq r\}$$

is a **convex set**.

**Pr. 2.**

A previous problem showed that if  $\mathbf{A}$  is an  $M \times N$  matrix, then  $\|\mathbf{A}\|_2 \leq \sqrt{N} \|\mathbf{A}\|_1$ .

- (a) Find a simple (but nonzero)  $1 \times 2$  or  $2 \times 1$  matrix where this inequality is equality. (When an inequality is achievable, we call it a **tight** bound.)
- (b) This bound is not tight for **normal** matrices. If  $\mathbf{A}$  is normal and  $N \times N$ , then  $\|\mathbf{A}\|_2 \leq c \|\mathbf{A}\|_1$  for a constant  $c$  that is much smaller than  $N$  in general. Determine (and prove) the best value for  $c$ .  
Hint. Think about **spectral radius**.
- (c) Give a nonzero  $2 \times 2$  matrix where the inequality in (b) is an equality, so it is also tight.

**Pr. 3.**

Enter the following Julia code that makes some **companion matrix** examples.

```
using LinearAlgebra: eigvals, I
n = rand(4:7)
a = randn(n+1) # random polynomial coefficients (a_0,a_1,...,a_n)
b = reverse(a) # reverse the coefficient order
# companion matrix maker:
compan = c -> [-transpose(reverse(c)); [I zeros(length(c)-1)]]
A = compan(a[1:end-1] / a[end])
B = compan(b[1:end-1] / b[end])
[eigvals(A) eigvals(B) 1 ./ eigvals(B)] # study array columns
```

What pattern do you see? Use `rand(ComplexF64, n)` to also try *complex* coefficients. Repeat multiple times to form a conjecture on how the **eigenvalues** of  $\mathbf{A}$  and  $\mathbf{B}$  are related. Prove your conjecture theoretically.

**Pr. 4.**

Let  $\mathbf{A}$  denote an  $N \times N$  **Vandermonde** matrix corresponding to the roots of the polynomial  $z^N - 1$ .

Let  $\mathbf{B}$  denote an  $N \times N$  **Vandermonde** matrix corresponding to  $\{e^{-i2\pi(n+1/2)/N} : n = 0, \dots, N-1\}$ .

Define the matrix  $\mathbf{X} \triangleq [\mathbf{aA} \quad \mathbf{bB}]$ , for  $a, b \in \mathbb{C}$ .

- (a) Determine the singular values of  $\mathbf{X}$ . Hint. Examine  $\mathbf{X}\mathbf{X}'$ .  
Optional:  
Determine whether the matrix  $\mathbf{X}$  is a **frame**, a **tight frame**, a **Parseval tight frame**, or none of the above.
- (b) Determine  $\mathbf{X}^+$ . (Simply as much as possible.) Hint. Think about the rank of  $\mathbf{X}$ .  
Optional:  
If  $\mathbf{X}$  is some type of frame, determine its **frame bound** (s).
- (c) Optional. Write a Julia function with inputs  $a, b$  and  $\mathbf{y} \in \mathbb{C}^N$  that computes efficiently the minimum-norm solution to the LS problem

$$\arg \min_{\mathbf{x} \in \mathbb{C}^{2N}} \|\mathbf{X}\mathbf{x} - \mathbf{y}\|_2.$$

Hint. For maximum efficiency, use a Vandermonde matrix form corresponding to the **DFT**. Aim for a solution with  $O(N \log_2 N)$  computation! The code `phase = cis.(pi / N * (0:N-1))` should be useful.

**Pr. 5.**

- (a) Show that all **circulant matrices** (of the same size) **commute**.
- (b) Show that all **circulant matrices** are **normal**.
- (c) Determine the eigenvalues of the following  $N \times N$  circulant matrix:

$$\mathbf{C} = \begin{bmatrix} -1 & 1 & 0 & \dots & 0 & 0 & 0 \\ 0 & -1 & 1 & 0 & \dots & 0 & 0 \\ \vdots & & \ddots & \ddots & & & \vdots \\ 0 & 0 & 0 & \dots & 0 & -1 & 1 \\ 1 & 0 & 0 & \dots & 0 & 0 & -1 \end{bmatrix}.$$

Give a simple expression that holds for any  $N \in \mathbb{N}$ . Multiplying this matrix by a vector performs **finite differences** of the vectors elements with **periodic end conditions**.

- (d) Check your expression for the previous part numerically for the case  $N = 4$ . Report the eigenvalues from your expression and from the `eigvals` command in **Julia**.
- (e) Write a very short **Julia** function that computes the **nuclear norm** of any **circulant matrix**  $\mathbf{C}$  *without* calling expensive functions like `eig` or `svd`. Suggestion: check your function using the previous part.
- (f) Optional. In image processing, matrices that are **block circulant with circulant blocks** (BCCB) are particularly important. Such matrices have the form  $\mathbf{B} = \mathbf{C}_2 \otimes \mathbf{C}_1$ , where  $\mathbf{C}_1$  and  $\mathbf{C}_2$  are both circulant matrices. Express the eigenvalues of  $\mathbf{B}$  in terms of the first columns of  $\mathbf{C}_1$  and  $\mathbf{C}_2$ .  
Challenge. Express the eigenvalues of  $\mathbf{B}$  in terms of the first column of  $\mathbf{B}$ .
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**Pr. 6.****Low-rank matrix denoising using non-convex Schatten  $p$ -“norm”**

The **Schatten  $p$ -norm**:  $\|\mathbf{A}\|_{S,p} = (\sum_{k=1}^r \sigma_k^p)^{1/p}$ , where  $\sigma_k$  denotes the singular values of  $\mathbf{A}$ , is a proper matrix norm for  $p \geq 1$ . Values of  $p \in (0, 1)$  are also useful as regularizers for **low-rank matrix denoising** problems even though it is not a proper norm for  $p < 1$ .

- (a) For  $\mathbf{Y} = \mathbf{X} + \varepsilon \in \mathbb{C}^{M \times N}$ , where we think  $\mathbf{X}$  is low rank, find an expression for the solution of the regularized low-rank matrix denoising method that uses the following **Schatten-norm regularizer** for  $p = 1/2$ :

$$\hat{\mathbf{X}} = \arg \min_{\mathbf{X} \in \mathbb{C}^{M \times N}} \frac{1}{2} \|\mathbf{Y} - \mathbf{X}\|_F^2 + \beta R(\mathbf{X}, 1/2), \quad R(\mathbf{X}, p) = \|\mathbf{X}\|_{S,p}^p = \sum_{k=1}^r \sigma_k^p(\mathbf{X}).$$

Hint: a previous problem will be helpful. Submit your written answer to this part to gradescope.

- (b) Write a Julia function that performs regularized low-rank matrix denoising using the above cost function.

In Julia, your file should be named `lr_schatten.jl` and should contain the following function:

```
"""
    lr_schatten(Y, reg::Real)

Compute the regularized low-rank matrix approximation as the minimizer over `X`
of `1/2 || Y - X ||_F^2 + reg R(X)`
where `R(X)` is the Schatten p-norm of `X` raised to the pth power, for `p=1/2`,
i.e., `R(X) = \sum_k (\sigma_k(X))^{1/2}`

# In:
- `Y` :      `M × N` matrix
- `reg`      regularization parameter

# Out:
- `Xh` :     `M × N` solution to above minimization problem
"""
function lr_schatten(Y, reg::Real)
```

Email your solution as an attachment to [eeecs551@autograder.eecs.umich.edu](mailto:eeecs551@autograder.eecs.umich.edu).

Think about your solution and consider whether it seems to be a good method for denoising.

- (c) Apply your denoising method to the noisy  $100 \times 30$  Block M image `Y` in the demo notebook `07_optshrink1.ipynb` at <http://web.eecs.umich.edu/~fessler/course/551/julia/demo> using  $\beta = 1000$ .

Report the NRMSE of your estimate  $\hat{\mathbf{X}}$  and submit to gradescope a picture of  $\hat{\mathbf{X}}$  and a scatter plot of the singular values of  $\hat{\mathbf{X}}$ ,  $\mathbf{X}$  and  $\mathbf{Y}$ . All of the plotting commands are in the notebook already; you simply need to `include` your `lr_schatten.jl` solution.

**Pr. 7.****Testing for common roots of polynomials**

- (a) Given two polynomials  $p(z) = \sum_{i=0}^m \alpha_i z^i$  and  $q(z) = \sum_{j=0}^n \beta_j z^j$ , for  $n \geq 0$  not necessarily equal to  $m \geq 0$ , where  $\alpha_m \neq 0$  and  $\beta_n \neq 0$ . How would you check whether  $p$  and  $q$  have a common (possibly complex) root?

You may use the determinant and/or the trace, but you may *not* explicitly compute the eigenvalues or eigenvectors of the respective companion matrices. Other matrix decompositions (QR, LU) are not allowed either.

Hint. Use the relationship between the eigenvalues of the **Kronecker sum** of matrices  $\mathbf{A}$  and  $\mathbf{B}$  with the eigenvalues of  $\mathbf{A}$  and  $\mathbf{B}$ .

- (b) Write a function called `common_root` that takes as input two vectors (not necessarily of equal dimension) whose elements represent the coefficients of the polynomials  $p(z)$  and  $q(z)$  and returns `true` if the two polynomials share a common root and `false` otherwise.

Caution: the leading coefficient is not necessary 1 here, but you can assume it is nonzero.

In Julia, your file should be named `common_root.jl` and should contain the following function:

```
"""
    haveCommonRoot = common_root(a, b ; atol)

Determine if the polynomials described by input coefficient vectors `a`
and `b` share a common root, to within an absolute tolerance parameter `atol`.
Assume leading coefficients `a[end]` and `b[end]` are nonzero.

# In:
- `a` : vector of length `m + 1` with `a[m+1] != 0` and `m ≥ 0`
  defining a degree `m` polynomial of the form:
  `p(z) = a[m+1] z^m + a[m] z^(m - 1) + ... + a[2] z + a[1]`

- `b` : vector of length `n + 1` with `b[n+1] != 0` and `n ≥ 0`
  defining a degree `n` polynomial of the form:
  `q(z) = b[n+1] z^n + b[n] z^(n - 1) + ... + b[1] z + b[1]`

# Option:
- `atol::Real` absolute tolerance for calling `isapprox`

# Out:
- `haveCommonRoot` = `true` when `p` and `q` share a common root, else `false`
"""
function common_root(a::AbstractVector, b::AbstractVector ; atol::Real=1e-6)
```

Email your solution as an attachment to [eeecs551@autograder.eecs.umich.edu](mailto:eeecs551@autograder.eecs.umich.edu).

Hint 1: Use the Julia function `kron`.

Hint 2: To consider finite numerical precision, use the `isapprox` function with the input absolute tolerance parameter `atol` to decide whether some value is “close enough” to zero. See the Julia manual for `isapprox` to see why `atol` is essential here.

Test your code with some polynomials of your own design before submitting to the autograder.

- Be sure to test some cases that have roots that are zero or complex.
- Be sure to handle cases where  $m = 0$  and/or  $n = 0$ .
- For randomly chosen Gaussian polynomial coefficients, there is an exceedingly small probability of having common roots, so check more cases than just random coefficients.

**Pr. 8.**

The following output is from chatGPT in Dec. 2022 when asked to write SVST code:



Write a singular value soft thresholding function in Julia

Here is a function that implements singular value soft thresholding in Julia:

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```
function svt(A::Array, lambda::Real)
    U, S, V = svd(A)

    for i in 1:length(S)
        if S[i] > lambda
            S[i] -= lambda
        elseif S[i] < -lambda
            S[i] += lambda
        else
            S[i] = 0
        end
    end

    return U * diagm(S) * V'
end
```



- (a) Does this code have the appropriate input type declarations? If not, describe how to improve.
- (b) Does this code work correctly? If not, describe how to fix any errors.
- (c) Is this code reasonably concise? If not, describe how to simplify.
- (d) Is this code efficient computationally? If not, describe how you would make it more efficient.  
Hint. Remember that Julia is a compiled language.
- (e) Do you think ChatGPT would work better with python? See this study.

**Non-graded problem(s) below**

(Solutions will be provided for self check; do not submit to gradescope.)

**Pr. 9.**

For  $1 \leq N \leq M$ , define the spectral-norm unit ball as

$$\mathcal{B} = \{\mathbf{A} \in \mathbb{F}^{M \times N} : \|\mathbf{A}\|_2 \leq 1\}.$$

Now define  $\mathcal{X}$  to be the subset of matrices in  $\mathcal{B}$  having maximal Frobenius norm:

$$\mathcal{X} = \{\mathbf{X} \in \mathcal{B} : \|\mathbf{X}\|_F \geq \|\mathbf{Y}\|_F, \forall \mathbf{Y} \in \mathcal{B}\}.$$

Show, or disprove with a counterexample, that  $\mathcal{X} = \mathcal{V}^{M \times N}$ , where  $\mathcal{V}^{M \times N}$  denotes the **Stiefel manifold** of  $M \times N$  matrices.

**Pr. 10.**

The set  $\{\mathbf{G}_N^0, \mathbf{G}_N^1, \dots, \mathbf{G}_N^{N-1}\}$  forms a **basis** for the subspace of  $N \times N$  circulant matrices in the vector space  $\mathbb{F}^{N \times N}$  of all  $N \times N$  matrices, where  $\mathbf{G}_N$  denotes the “generator” for circulant matrices.

- Is this set an **orthogonal basis** for that subspace? Explain.
- Is this set an **orthonormal basis** for that subspace? Explain.

**Pr. 11.**

Prove or disprove (by a counterexample) the following statement. If  $\mathbf{T}$  is any matrix for which  $\mathbf{T}^k = \mathbf{I}$  for some natural number  $k > 1$ , then  $\mathbf{T}$  is **normal**.

**Pr. 12.**

Let  $t_k = k\Delta$ , for some integer  $k$ , and  $\Delta \in \mathbb{R}$ . Consider the sum of sinusoids signal  $\mathbf{y}(t_k) = \sum_{i=1}^r \mathbf{b}_i e^{i w_i t_k}$ , where  $\mathbf{y}(t_k) \in \mathbb{C}^N$ ,  $\mathbf{b}_1, \dots, \mathbf{b}_r \in \mathbb{C}^N$  are linearly independent vectors, and  $w_i \in [0, 1]$  are distinct, and  $i = \sqrt{-1}$ . Express the recursion in the following simple matrix form:  $\mathbf{y}(t_{k+1}) = \mathbf{A} \mathbf{y}(t_k)$ .

- Determine the matrix  $\mathbf{A}$ .
- Determine the eigenvalues and eigenvectors of  $\mathbf{A}$ .

Hint. For a matrix  $\mathbf{B}$  of full column rank  $r$ , we have that  $\mathbf{B}^+ \mathbf{B} = \mathbf{I}_r$ , where  $\mathbf{I}_r$  is an  $r \times r$  identity matrix.

**Pr. 13.**

Define  $\mathbb{R}_+ \triangleq [0, \infty)$ . A **symmetric gauge** function  $\phi(\mathbf{x})$  is a mapping from  $\mathbb{R}^n$  into  $\mathbb{R}_+$  that satisfies the following four properties for all  $\mathbf{x}, \mathbf{y} \in \mathbb{R}^n$ .

- $\phi(\mathbf{x}) > 0$  if  $\mathbf{x} \neq \mathbf{0}$  (positivity)
- $\phi(\alpha \mathbf{x}) = |\alpha| \phi(\mathbf{x})$  for all  $\alpha \in \mathbb{R}$  (homogeneity)
- $\phi(\mathbf{x} + \mathbf{y}) \leq \phi(\mathbf{x}) + \phi(\mathbf{y})$  (triangle inequality)
- $\phi(s_1 x_{[1]}, \dots, s_n x_{[n]}) = \phi(\mathbf{x})$  for all  $s_k = \pm 1$  and for any permutation  $(x_{[1]}, \dots, x_{[n]})$  of the elements of  $\mathbf{x}$ . (symmetry)

Some examples are:

- $\phi(\mathbf{x}) = \|\mathbf{x}\|_1$
- $\phi(\mathbf{x}) = \max_i |x_i| = \|\mathbf{x}\|_\infty$
- $\phi(\mathbf{x}) = 7|x_{(1)}| + 5|x_{(2)}|$ , where  $x_{(1)}$  and  $x_{(2)}$  denote the first and second largest elements of  $\mathbf{x}$  in magnitude.

Such symmetric gauge functions are at the heart of many matrix norm properties.

Let  $\phi(\cdot)$  be any symmetric gauge function and define a matrix norm by

$$\|\mathbf{A}\|_\phi = \phi(\sigma_1, \dots, \sigma_{\min(M, N)}),$$

where  $\{\sigma_k\}$  denote the singular values of an  $M \times N$  matrix  $\mathbf{A}$ .

- Verify that this definition indeed defines a proper matrix norm.
- Prove or disprove (by counterexample) that any such matrix norm  $\|\mathbf{A}\|_\phi$  is **unitarily invariant**.