Scientific Computing, Courant Institute, Fall 2018
http://www.math.nyu.edu/faculty/goodman/teaching/ScientificComputing2018/ScientificComputing.html
Always check the classes message board before doing any work on the assignment.

## Assignment 3

Corrections: [none yet]

1. Suppose $A(s)$ is a differentiable family of positive definite symmetric matrices. Suppose that $A$ has a Cholesky factorization $A(s)=L(s) L^{t}(s)$. Here, $L$ is lower triangular. Find a formula for

$$
\dot{L}=\frac{d}{d s} L(s)
$$

as a function of $L, L^{-1}$ and $\dot{A}$. It is a useful fact that the inverse of a lower triangular matrix is lower triangular.
2. Suppose $A$ is an $n \times n$ matrix. Show that the power series

$$
e^{t A}=\sum_{0}^{\infty} \frac{1}{n!} t^{n} A^{n}
$$

converges in any matrix norm. Hint: Never mind the first $N$ terms. What matters is the "tails", the terms $M_{n}=\frac{1}{n!} t^{n} A^{n}$ for $n \geq N$. Choose $N$ so that $N \geq 2|t|\|A\|$. Then

$$
M_{n}=\frac{1}{n} t A M_{n-1}
$$

Therefore, if $n \geq N$,

$$
\left\|M_{n}\right\| \leq \frac{1}{N}|t|\|A\|\left\|M_{n-1}\right\| \leq \frac{1}{2}\left\|M_{n-1}\right\|
$$

Therefore, if $n>N$, we have $\left\|M_{n}\right\| \leq \frac{1}{2^{n-N}}\left\|M_{N}\right\|$. The tail sum satisfies

$$
\left\|\sum_{n=N}^{\infty} M_{n}\right\| \leq\left(\sum_{n \geq N} \frac{1}{2^{n-N}}\right)\left\|M_{N}\right\| \leq 2\left\|M_{N}\right\|<\infty
$$

The tail converges absolutely so the whole sum does too.
3. (Properties of the matrix exponential)
(a) Show that the matrix $S(t)=e^{t A}$ satisfies a matrix differential equation and commutes with $A$ :

$$
\frac{d}{d t} S(t)=A S(t)=S(t) A
$$

(b) Show that $S(t) \rightarrow I$ as $t \rightarrow 0$.
(c) Show that $S\left(t_{1}\right) S\left(t_{2}\right)=S\left(t_{1}+t_{2}\right)$. Hint: You can do this using part (d) below, or you can do it directly. For the direct argument, define $p=\frac{t_{1}}{t_{1}+t_{2}}$ and $q=\frac{t_{2}}{t_{1}+t_{2}}$ and write the formula $(p+q)^{n}=1$ as

$$
\sum_{j+k=n}\binom{n}{k} p^{j} q^{k}=\sum_{j+k=n} \frac{n!}{j!k!} p^{j} q^{k}=1 .
$$

Then write

$$
S\left(t_{1}\right) S\left(t_{2}\right)=\sum_{j} \sum_{k} \frac{1}{j!} \frac{1}{k!} t_{1}^{j} t_{2}^{k} A^{j+k}=\sum_{n}\left(\sum_{j+k=n} \frac{n!}{j!k!} p^{j} q^{k}\right) t^{n} A^{n} .
$$

(d) Suppose that $A=R \Lambda L$, where $R L=I$ and $\Lambda$ is the diagonal matrix of eigenvalues. Allow the possibility that $R, L$, and $\Lambda$ are complex. Show that $S(t)=R e^{t \Lambda} L$. Show that $e^{t \Lambda}$ is diagonal and find formulas for the numbers on the diagonal.
(e) The Python package linalg has routines for computing the eigenvalues and eigenvectors of a non-symmetric matrix. Use this to write a Python module that evaluates $S(t)$ given $A$ and $t$. Test your module by calling it for the case $A=\left(\begin{array}{cc}0 & 1 \\ -1 & 0\end{array}\right)$. In this case $S(t)=\left(\begin{array}{cc}\cos (t) & \sin (t) \\ -\sin (t) & \cos (t)\end{array}\right)$. Warning: because of roundoff in complex arithmetic, the computed result might not be real. The imaginary part of the computed $S(t)$ is all error.
4. Another way to compute the matrix exponential is to compute $S(\Delta t)$ using a few terms of the Taylor series, then take powers to apply the formula $S(n \Delta t)=S(\Delta t)^{n}$. Experiment with $k$ terms of the Taylor series. Then choose $n$ depending on $t$, and then $\Delta t=t / n$ so that $k$ terms are enough to get $S(\Delta t)$ ten significant digits.
(a) Compute the Taylor series numerically using Horner's rule which is

$$
\begin{aligned}
& x_{0} I+x_{1} A+\cdots+x_{k-1} A^{k-1}+x_{k} A^{k} \\
= & x_{0} I+x_{1} A+\cdots+x_{k-1} A^{k-1}\left(I+\frac{x_{k}}{x_{k-1}} A\right) \\
= & x_{0} I+x_{1} A+\cdots+x_{k-2} A^{k-2}\left(I+\frac{x_{k-1}}{x_{k-2}} A\left(I+\frac{x_{k}}{x_{k-1}} A\right)\right) \\
= & \cdots \\
= & x_{0}\left(I+\frac{x_{1}}{x_{0}} A\left(I+\frac{x_{2}}{x_{1}} A(\cdots)\right)\right)
\end{aligned}
$$

This gives a way to calculate the $k$ term sum using $k$ matrix multiplications. Doing it directly takes $O\left(k^{2}\right)$ multiplications.
(b) Compute a power $B^{n}$ in the following way. First compute $B_{1}=B^{2}$, then $B_{2}=B_{1}^{2}=B^{4}$, then $B_{3}=B_{2}^{2}=B^{2^{3}}$, etc. Then write $n=$ $n_{0}+2 n_{1}+4 n_{2}+\cdots$, where $n_{j}=0$ of $n_{j}=1$ (expand $n$ base 2 ) and compute

$$
B^{n}=\prod_{n_{j}=1} B_{j} .
$$

Show that this computes $B^{n}$ in $O(\log (n))$ matrix multiplications.
(c) Test your program on the $A$ from problem 3.
5. Consider the differential equation system

$$
\begin{aligned}
\frac{d x_{k}}{d t} & =p\left(x_{k+1}-x_{k}\right)+q\left(x_{k-1}-x_{k}\right) \text { if } 1<k<n \\
\frac{d x_{1}}{d t} & =p\left(x_{2}-x_{1}\right) \\
\frac{d x_{n}}{d t} & =q\left(x_{n-1}-x_{n}\right) .
\end{aligned}
$$

Here, $x_{k}$ could represent the number of particles at spot $k$, and $p$ represents the rate at which particles move to the left (from $k+1$ to $k$ or from $k$ to $k-1$ ) and $q$ represents the rate at which they move to the right. Particles cannot go from $k=1$ to $k=0$ or from $k=n$ to $k=n+1$. Try your codes from Problem 4 and Problem 5 on this system. If you explore $p>q$ and $n$ relatively large, you should find that the eigenvalue method breaks down because the eigenvalue/eigenvector calculation is too ill conditioned. You will need code to create the matrix $A$. Note (check) that $M=\sum_{k} x_{k}(t)$ is a constant. Start with $x_{1}(n)=1$, and $x_{k}(0)=0$ for $k<n$. The solution has $x(t) \rightarrow x_{*}$ as $t \rightarrow \infty$. You can find $x_{*}$ by setting $A x_{*}=0$ and $\sum_{k} x_{k}=1$. Here are some things to explore as time and interest permits

- Find values of $n, p>0, q>0$, and $t$ so that the eigenvalue method breaks down.
- The eigenvalues of $A$ are all real. Monitor the imaginary parts of the computed eigenvalues.
- The problem of finding $e^{t A}$ for this problem is well conditioned. The eigenvalue method is an unstable algorithm.

6. Write Python code to compute the matrix product $A B$ when $A$ and $B$ are $n \times n$ matrices. You can initialize the matrices how you want because the values are unimportant. Do it in three ways:

- Scalar loop, as

```
for i in range(n):
    for j in range(n):
        c[i,j] = 0.
        for k in range(n):
            c[i,j] += a[i,k]*b[k,j]
```

- Hand coded vector loops, as (names and syntax wrong, please fix)

$$
c[i, j]=\operatorname{np} \cdot \operatorname{sum}(a[i,:] * b[:, j])
$$

- The numpy matrix multiply routine, as
$c=n p . l i n a l g \cdot m a t r i x M u l t i p l y(a, ~ b) ~$
Learn how to time sections of Python code. Print the times for the three methods as a function of $n$ for an interesting range of $n$. Comment on the differences.

