## Organisation: Lecs, Sems and Labs

MA2715_SB=Advanced Calculus and Numerical Methods

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Handouts: http://people.brunel.ac.uk/~icstmkw/ma2715/

Lectures times: Tue 15:00 and Thu 12:00.

The SEMs will be at Mon 11:00 and Tue 16:00 from week 18.

Matlab labs start this week and each person has one of the times Thu 10:00, 14:00 and 15:00. The labs are associated with 10 credit module MA2895_CB=Numerical Analysis Project.

## Organisation: The codes MA2715, MA2815, MA2895

Assessment:
MA2715 topics are part of the 20 credit 3-hour MA2815 exam.

MA2895 has a class test on Matlab in week 22 (30\%) and a Matlab assignment with a deadline in week 28 (70\%).

Labs in WLFB 106 breakdown:
M1: See your individual timetable.
M2: See your individual timetable.
F: FM degree+others, Thu 15:00.

## Overview of MA2715 Chapter 1 - revision, norms, ...

Vectors, matrices, norms of vectors and norms of matrices.
The notation for column vectors and matrices will be as follows.

$$
\underline{x}=\left(x_{i}\right)=\left(\begin{array}{c}
x_{1} \\
\vdots \\
x_{n}
\end{array}\right), \quad A=\left(a_{i j}\right)=\left(\begin{array}{ccc}
a_{11} & \cdots & a_{1 n} \\
\vdots & \cdots & \vdots \\
a_{n 1} & \cdots & a_{n n}
\end{array}\right) .
$$

Eigenvalues and eigenvectors are used in chapter 3 and also appear in some expressions and explanations in other parts of MA2715. Recall that $\underline{v} \neq \underline{0}$ is an eigenvector of $A$ if

$$
A \underline{v}=\lambda \underline{v}
$$

Norms: The notation will be $\|\underline{x}\|$ and $\|A\|$. Specific norms with be the 2-norm, $\infty$-norm and 1-norm.
Condition number: $\kappa(A)=\|A\|\left\|A^{-1}\right\| \geq 1$.
A large condition number means that $A$ is close to a singular matrix and it is difficult to accurately solve $A \underline{x}=\underline{b}$.

## Chapter 2 - solving $A \underline{x}=\underline{b}$

This will be about Gauss elimination methods to solve

$$
A \underline{x}=\underline{b}
$$

for a general system of $n$ equations in $n$ unknowns. Here $n$ may be large and thus everything is done on a computer.
Basic Gauss elimination is equivalent to a factorization

$$
A=L U
$$

where $L=$ unit lower triangular matrix and $U=$ upper triangular matrix. Gauss elimination with pivoting of some kind is equivalent to factorizations of the form

$$
P A=L U \quad \text { or } \quad P A Q=L U
$$

where $P$ and $Q$ are permutation matrices. Permutations matrices are obtained from the identity matrix $/$ by re-arranging the rows.

## The basic $L U$ factorization when $n=4$

Let $A$ be a non-singular matrix.

$$
\left(\begin{array}{llll}
a_{11} & a_{12} & a_{13} & a_{14} \\
a_{21} & a_{22} & a_{23} & a_{24} \\
a_{31} & a_{32} & a_{33} & a_{34} \\
a_{41} & a_{42} & a_{43} & a_{44}
\end{array}\right)=\left(\begin{array}{cccc}
1 & 0 & 0 & 0 \\
I_{21} & 1 & 0 & 0 \\
I_{31} & I_{32} & 1 & 0 \\
I_{41} & I_{42} & I_{43} & 1
\end{array}\right)\left(\begin{array}{cccc}
u_{11} & u_{12} & u_{13} & u_{14} \\
0 & u_{22} & u_{23} & u_{24} \\
0 & 0 & u_{33} & u_{34} \\
0 & 0 & 0 & u_{44}
\end{array}\right) .
$$

This works if and only if all principal sub-matrices are non-singular. In this case we also have

$$
\begin{aligned}
\left(\begin{array}{lll}
a_{11} & a_{12} & a_{13} \\
a_{21} & a_{22} & a_{23} \\
a_{31} & a_{32} & a_{33}
\end{array}\right) & =\left(\begin{array}{ccc}
1 & 0 & 0 \\
l_{21} & 1 & 0 \\
l_{31} & l_{32} & 1
\end{array}\right)\left(\begin{array}{ccc}
u_{11} & u_{12} & u_{13} \\
0 & u_{22} & u_{23} \\
0 & 0 & u_{33}
\end{array}\right), \\
\left(\begin{array}{ll}
a_{11} & a_{12} \\
a_{21} & a_{22}
\end{array}\right) & =\left(\begin{array}{cc}
1 & 0 \\
l_{21} & 1
\end{array}\right)\left(\begin{array}{cc}
u_{11} & u_{12} \\
0 & u_{22}
\end{array}\right), \\
a_{11} & =u_{11} .
\end{aligned}
$$

Also $\operatorname{det}(A)=\operatorname{det}(U)=u_{11} u_{22} u_{33} u_{44}$.

## Chapter $3-\underline{u}^{\prime}=A \underline{u}, \underline{u}(0)=\underline{u}_{0}$

This will be about solving the following problem.

$$
\underline{u}^{\prime}=A \underline{u}, \quad \underline{u}(0)=\underline{u}_{0},
$$

where $A$ is a constant matrix. This involves a linear system of differential equations. In full the differential equation part is

$$
\frac{\mathrm{d}}{\mathrm{~d} x}\left(\begin{array}{c}
u_{1}(x) \\
\vdots \\
u_{n}(x)
\end{array}\right)=\left(\begin{array}{ccc}
a_{11} & \cdots & a_{1 n} \\
\vdots & \cdots & \vdots \\
a_{n 1} & \cdots & a_{n n}
\end{array}\right)\left(\begin{array}{c}
u_{1}(x) \\
\vdots \\
u_{n}(x)
\end{array}\right)
$$

The solution can be given in terms of the eigenvalues and eigenvectors of the matrix $A$ when $A$ is diagonalisable.
In all cases, diagonalisable or not, the solution can be expressed as

$$
\underline{u}(x)=\exp (x A) \underline{u}(0)
$$

where here $\exp (x A)$ means the exponential matrix of $x A$.

## Chapter 4-2 point BVP

This will be about the two-point boundary value problem

$$
u^{\prime \prime}(x)=p(x) u^{\prime}(x)+q(x) u(x)+r(x), \quad a<x<b
$$

with

$$
u(a)=g_{1}, \quad u(b)=g_{2}
$$

Here $p, q$ and $r$ are suitable functions. Generally we cannot give a "simple closed form expression" for the solution. Instead we approximate the solution by using the finite difference method.

The relevant previous study for this is Taylor expansions which you have seen in MA2730.

## A Taylor expansion about every mesh point

The "continuous problem" involving $a \leq x \leq b$ is approximated by a "discrete problem" involving points $a=x_{0}<x_{1}<\cdots<x_{n}=b$. Equally spaced points corresponds to $n \geq 1, h=(b-a) / n$ and $x_{i}=a+i h, i=0,1, \ldots, n$.
The finite difference approximation is derived by considering Taylor expansions about every interior point $x_{i}$. With
$u_{i-1}=u\left(x_{i-1}\right)=u\left(x_{i}-h\right)$ and $u_{i+1}=u\left(x_{i}+h\right)=u\left(x_{i}+h\right)$ we have

$$
\begin{aligned}
& u_{i+1}=u_{i}+h u_{i}^{\prime}+\frac{h^{2}}{2} u_{i}^{\prime \prime}+\frac{h^{3}}{6} u_{i}^{\prime \prime \prime}+\frac{h^{4}}{24} u_{i}^{\prime \prime \prime \prime}+\cdots \\
& u_{i-1}=u_{i}-h u_{i}^{\prime}+\frac{h^{2}}{2} u_{i}^{\prime \prime}-\frac{h^{3}}{6} u_{i}^{\prime \prime \prime}+\frac{h^{4}}{24} u_{i}^{\prime \prime \prime \prime}+\cdots
\end{aligned}
$$

Using these we get finite difference approximations to the derivatives at all the points $x_{i}$.

## Chapter 5 - Fourier series

Let $f: \mathbb{R} \rightarrow \mathbb{R}$ denote a $2 \pi$-periodic function which is piecewise continuous. For "most" values of $x$ we can represent this in the form

$$
f(x)=\frac{a_{0}}{2}+\sum_{n=1}^{\infty}\left(a_{n} \cos (n x)+b_{n} \sin (n x)\right)
$$

where the Fourier coefficients $a_{n}$ and $b_{n}$ are

$$
a_{n}=\frac{1}{\pi} \int_{-\pi}^{\pi} f(x) \cos (n x) \mathrm{d} x, \quad b_{n}=\frac{1}{\pi} \int_{-\pi}^{\pi} f(x) \sin (n x) \mathrm{d} x .
$$

Among the things that is likely to be considered are the following.

- Determining the coefficients for several functions which will often need integration by parts.
- Stating conditions when the series converges to $f(x)$.
- When it is valid to integrate or differentiate the series to obtain another Fourier series.
- If time permits then some applications of Fourier series may be briefly mentioned.


## Key points in the week 17 lectures

Let $\underline{x}=\left(x_{i}\right)$ and $\underline{y}=\left(y_{i}\right)$ denote real column vectors of length $n$. Inner product of $\underline{x}$ and $\underline{y}$ :

$$
\underline{x}^{T} \underline{y}=x_{1} y_{1}+\cdots+x_{n} y_{n} .
$$

Outer product of $\underline{x}$ and $\underline{y}: \underline{x}_{\underline{y}}{ }^{T}$, an $n \times n$ matrix.
$\underline{v}_{1}, \ldots, \underline{v}_{n}$ are linearly dependent if $\exists \underline{\alpha}=\left(\alpha_{i}\right) \neq \underline{0}$ such that

$$
\alpha_{1} \underline{v}_{1}+\cdots+\alpha_{n} \underline{v}_{n}=\underline{0} .
$$

Represent a matrix $A$ in terms of its columns as

$$
A=\left(\underline{a}_{1}, \ldots, \underline{a}_{n}\right)
$$

Then

$$
A \underline{x}=x_{1} \underline{a}_{1}+\cdots+x_{n} \underline{a}_{n},
$$

a linear combination of the columns of $A$. For $A$ to be invertible (i.e. non-singular) we need the columns to be linearly independent. When $A$ is invertible the columns of $A^{T}$ are also linearly independent.

## Eigenvalues/Eigenvectors

$\underline{v} \neq \underline{0}$ is an eigenvector of $A$ with eigenvalue $\lambda$ if $A \underline{v}=\lambda \underline{v}$.
$A-\lambda I$ is a singular matrix when $\lambda$ is an eigenvalue and $\lambda$ satisfies the characteristic equation

$$
\operatorname{det}(A-\lambda I)=0
$$

$\operatorname{det}(t l-A)$ is called the characteristic polynomial.
Suppose $A \underline{v}_{i}=\lambda \underline{v}_{i}, \underline{v}_{i} \neq \underline{0}, i=1, \ldots, n$. The spectrum of $A$ is the set

$$
\left\{\lambda_{1}, \ldots, \lambda_{n}\right\} .
$$

The spectral radius of $A$ is

$$
\rho(A)=\max \left\{\left|\lambda_{1}\right|, \ldots,\left|\lambda_{n}\right|\right\} .
$$

## Some results about eigenvalues and eigenvectors

1. $A$ is non-singular if and only if $\lambda_{i} \neq 0$ for $i=1, \ldots, n$.
2. Let $\underline{v}_{1}, \ldots, \underline{v}_{n}$ be eigenvectors of $A$ with $A \underline{v}_{i}=\lambda_{i} \underline{v}_{i}$.

$$
A\left(\underline{v}_{1}, \ldots, \underline{v}_{n}\right)=\left(A \underline{v}_{1}, \ldots, A \underline{v}_{n}\right)=\left(\lambda_{1} \underline{v}_{1}, \ldots, \lambda_{n} \underline{v}_{n}\right) .
$$

The last right hand side expression can be written as $V D$, i.e.
$A V=V D, \quad$ with $V=\left(\underline{v}_{1}, \ldots, \underline{v}_{n}\right) \quad$ and $\quad D=\left(\begin{array}{lll}\lambda_{1} & & \\ & \ddots & \\ & & \lambda_{n}\end{array}\right)$.
When $\underline{v}_{1}, \ldots, \underline{v}_{n}$ are linearly independent $V$ is invertible and

$$
V^{-1} A V=D, \quad A=V D V^{-1}
$$

$A$ is diagonalisable when this is the case. Otherwise the matrix is deficient.

## Examples with $2 \times 2$ matrices

1. 

$$
\begin{aligned}
& A=I_{2}=\left(\begin{array}{ll}
1 & 0 \\
0 & 1
\end{array}\right) . \\
& \operatorname{det}\left(I_{2}-t I_{2}\right)=\left|\begin{array}{cc}
1-t & 0 \\
0 & 1-t
\end{array}\right|=(1-t)^{2} .
\end{aligned}
$$

We have repeated eigenvalues with $\lambda_{1}=\lambda_{2}=1$ and every non-zero vector in $\mathbb{R}^{2}$ is an eigenvector. $\rho(A)=1$.
2.

$$
A=\left(\begin{array}{ll}
2 & 1 \\
1 & 2
\end{array}\right), \quad\left|\begin{array}{cc}
2-t & 1 \\
1 & 2-t
\end{array}\right|=(2-t)^{2}-1=(1-t)(3-t) .
$$

Symmetric matrix, distinct eigenvalues $\lambda_{1}=1$ and $\lambda_{2}=3$. $\rho(A)=3$.

$$
\begin{gathered}
A-\lambda_{1} I=\left(\begin{array}{ll}
1 & 1 \\
1 & 1
\end{array}\right), \quad A-\lambda_{2} I=\left(\begin{array}{cc}
-1 & 1 \\
1 & -1
\end{array}\right) \\
\underline{v}_{1}=\binom{1}{-1}, \quad \underline{v}_{2}=\binom{1}{1} .
\end{gathered}
$$

## Examples with $2 \times 2$ matrices continued

3. 

$$
A=\left(\begin{array}{cc}
0 & -1 \\
1 & 0
\end{array}\right), \quad\left|\begin{array}{cc}
-t & -1 \\
1 & -t
\end{array}\right|=t^{2}+1=(i-t)(-i-t)
$$

A real matrix with complex eigenvalues $\lambda_{1}=i, \lambda_{2}=-i$. The eigenvectors are also complex. $\rho(A)=1$. 4.

$$
A=\left(\begin{array}{ll}
0 & 1 \\
0 & 0
\end{array}\right), \quad\left|\begin{array}{cc}
-t & 1 \\
0 & -t
\end{array}\right|=t^{2}
$$

Repeated eigenvalues with $\lambda_{1}=\lambda_{2}=0 . \rho(A)=0$.

$$
A=A-\lambda_{1} I=\left(\begin{array}{ll}
0 & 1 \\
0 & 0
\end{array}\right)
$$

The only direction which is an eigenvector is

$$
\underline{v}_{1}=\binom{1}{0}
$$

The matrix is deficient.

## Norms

We consider these for vectors and square matrices. The value of a norm is usually written using the $\|$.$\| notation rather than the$ function notation. To be called a norm the following properties must hold.

## Vector norm axioms

$$
\begin{aligned}
& \|\underline{x}\| \geq 0 \forall \underline{x} \in \mathbb{R}^{n} \text { with }\|\underline{x}\|=0 \text { if and only if } \underline{x}=\underline{0} . \\
& \|\alpha \underline{x}\|=|\alpha|\|\underline{x}\| \forall \alpha \in \mathbb{R} \text { and } \forall \underline{x} \in \mathbb{R}^{n} . \\
& \|\underline{x}+\underline{y}\| \leq\|\underline{x}\|+\|\underline{y}\| \forall \underline{x}, \underline{y} \in \mathbb{R}^{n} .
\end{aligned}
$$

## The common vector norms

$$
\begin{aligned}
\|\underline{x}\|_{2} & =\left(x_{1}^{2}+x_{2}^{2}+\cdots+x_{n}^{2}\right)^{1 / 2}=\left(\underline{x}^{\top} \underline{x}\right)^{1 / 2} \\
\|\underline{x}\|_{\infty} & =\max \left\{\left|x_{1}\right|, \ldots,\left|x_{n}\right|\right\} \\
\|\underline{x}\|_{1} & =\left|x_{1}\right|+\left|x_{2}\right|+\cdots+\left|x_{n}\right| .
\end{aligned}
$$

## Matrix norm

The matrix norm induced by a vector norm is

$$
\|A\|=\max \{\|A \underline{x}\|:\|\underline{x}\|=1\} .
$$

All of the following norm requirements are satisfied.
$\|A\| \geq 0 \forall A \in \mathbb{R}^{n, n}$ with $\|A\|=0$ if and only if $A=0$.
$\|\alpha A\|=|\alpha|\|A\| \forall \alpha \in \mathbb{R}$ and $\forall A \in \mathbb{R}^{n, n}$.
$\|A+B\| \leq\|A\|+\|B\| \forall A, B \in \mathbb{R}^{n, n}$.

We also have $\|A B\| \leq\|A\|\|B\|$.

For any norm of this type $\rho(A) \leq\|A\|$.

