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Q. _____

COL726 Assignment 1

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A. 1

a) \Rightarrow We know that by the supremum definition:

$$k_f(x) = \frac{\|x\|}{\|f(x)\|} \cdot \sup_{\delta_x} \frac{\|\delta f(x)\|}{\|\delta_x\|} \quad \leftarrow ①$$

$$k_g(y) = \frac{\|y\|}{\|g(y)\|} \sup_y \frac{\|\delta g(y)\|}{\|\delta_y\|} \quad \leftarrow ②$$

$$k_h(x) = \frac{\|x\|}{\|h(x)\|} \sup_x \frac{\|\delta h(x)\|}{\|\delta_x\|} \quad \leftarrow ③$$

\Rightarrow Now, using the fact that $h(x) = g(f(x))$, where $y = f(x)$; we can get:

$$k_h(x) = \frac{\|x\|}{\|g(y)\|} \sup_y \frac{\|\delta g(y)\|}{\|\delta_x\|} \quad \leftarrow ④$$

where $y = f(x)$



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\Rightarrow For Equation ④, we can have :

*

$$\frac{\|x\|}{\|g(y)\|} = \frac{\|x\|}{\|g(y)\|} \cdot \frac{\|y\|}{\|y\|} = \left(\frac{\|x\|}{\|f(x)\|} \cdot \frac{\|y\|}{\|g(y)\|} \right) \quad (y = f(x))$$

← ⑤

* Similarly, we can get :

$$\sup_{S_x} \left(\frac{\|\delta g(y)\|}{\|\delta x\|} \right) = \sup_{S_y} \left(\frac{\|\delta g(y)\|}{\|\delta y\|} \cdot \frac{\|\delta f(x)\|}{\|\delta x\|} \right) \quad \leftarrow ⑥$$

\Rightarrow Thus, using ⑤ & ⑥ in Eq ④ gives :

$$k_n(x) = \frac{\|x\|}{\|f(x)\|} \cdot \frac{\|y\|}{\|g(y)\|} \left(\sup_{S_y} \left(\frac{\|\delta g(y)\|}{\|\delta y\|} \cdot \frac{\|\delta f(x)\|}{\|\delta x\|} \right) \right)$$

$$\downarrow \quad \text{Using } \frac{\|\delta g(y)\|}{\|\delta y\|} \leq \sup_{S_y} \left(\frac{\|\delta g(y)\|}{\|\delta y\|} \right)$$

$$k_n(x) \leq \left(\frac{\|x\|}{\|f(x)\|} \cdot \frac{\|y\|}{\|g(y)\|} \right) \cdot \left(\sup_{S_y} \left(\frac{\|\delta f(x)\|}{\|\delta x\|} \right) \cdot \left(\sup_{S_y} \frac{\|\delta g(y)\|}{\|\delta y\|} \right) \right)$$

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\Rightarrow From ⑦, we can write :

$$k_n(x) \leq \left(\frac{\|x\|}{\|f(x)\|} \cdot \sup_{S_n} \frac{\|sf(x)\|}{\|s_n\|} \right) \cdot \left(\frac{\|y\|}{\|g(y)\|} \cdot \sup_{S_y} \frac{\|sg(y)\|}{\|s_y\|} \right)$$

$$\therefore \boxed{k_n(x) \leq k_f(x) \cdot k_g(y)}$$



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Ans 2 \Rightarrow we have : $\hat{f}(x) = \bar{x} \otimes (1 \oslash \bar{x})$



$$(f_l(x) = x(1+t_1) \quad \text{and } |t_1| \leq t_m)$$

$$\hat{f}(x) = f_l(x) \circledast (1 \oslash f_l(x))$$

\downarrow By floaty Post axioms

Thus Operator can also
be converted like we did
for \ominus vsy FP axioms

$$(1 - f_l(x)) (1 + t_2)$$

$$\text{where } |t_2| \leq t_m$$



$$\hat{f}(x) = (f_l(x) \times (1 - f_l(x))) \times (1 + t_2) \times (1 + t_3)$$

$$\text{with } |t_2|, |t_3| \leq t_m$$



$$\hat{f}(x) = (x(1+t_1)) \times (1 - x(1+t_1)) \times (1 + t_4)$$

$$\text{where: } |t_1| \leq t_m \quad \& \quad |t_4| \leq 2t_m + O(t_m^2)$$

\Rightarrow The above equation can be written as :

$$\hat{f}(x) = x(1+t_1)(1+t_4) - x^2(1+t_1)(1+t_4)$$

$$= \boxed{x(1+t_5) - x^2(1+t_6)}$$

$$\text{where: } |t_5| \leq 3t_m + O(t_m^2) + O(t_m^3) \quad \text{And} \quad |t_6| \leq 4t_m + O(t_m^2) + O(t_m^3) + O(t_m^4)$$

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\Rightarrow Thus, $f(x) - f(x) = (x(1+t_5) - x^2(1+t_6)) - (x - x^2)$

$\therefore \text{f.e.} = |x(t_5) - x^2(t_6)|$

$O(t_m x^2)$

$\Downarrow (\text{vsg f.e.} \leq |xt_5| + |x^2 t_6|)$

$O(\text{f.e.}) = O(3t_m x) + O(4t_m x^2)$

(would get to infinity for $x \rightarrow \infty$)

b) \Rightarrow we get $\text{r.f.e.} = \frac{(\text{f.e.})}{(f(x))} = \frac{|t_5 - xt_6|}{|1-x|}$

\Downarrow

Bound on r.f.e. = $\frac{|3t_m|}{|1-x|} + \frac{|4t_m x|}{|1-x|}$

\Rightarrow In the vicinity of $x=1$, r.f.e. becomes very high.
Thus, not accurate at $x=1$



$$\boxed{\quad} + \boxed{\quad} + \boxed{\quad} + \boxed{\quad} = \boxed{\quad}$$

Q. \Rightarrow For Backward stability, we need:

$$\Rightarrow \boxed{\tilde{f}(x) = f(\tilde{x})} \text{ for some } \tilde{x} \text{ s.t. } \frac{|\tilde{x} - x|}{|x|} = O(\epsilon_m)$$

$$\Rightarrow \text{This we have: } \boxed{x(1+t_5) - x^2(1+t_6) = \tilde{x} - \tilde{x}^2}$$

↓

$$\tilde{x} = \tilde{x}^2 + x + xt_5 - x^2(1+t_6)$$

$$\Rightarrow (\tilde{x} - x) - (\tilde{x}^2 - x^2) = xt_5 - x^2t_6$$

$$\Rightarrow (\tilde{x} - x)(1 - (\tilde{x} + x)) = x(t_5 - xt_6)$$

$$\Rightarrow \left| \frac{\tilde{x} - x}{x} \right| = \left| \frac{t_5 - xt_6}{1 + (\tilde{x} + x)} \right|$$

\rightarrow Should be $O(\epsilon_m)$

\Rightarrow This, how it can be seen that the above eqn fails the Backward Stability condition when $x + \tilde{x} = 1$

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But we also know that $f(x) = f(1-x)$.
 So if for some \tilde{x} not close to x ,
 we get $x + \tilde{x} = 1$ & $\tilde{f}(x) = f(\tilde{x})$. Then
 we can have $1 - \tilde{x}$ close to x & $\tilde{f}(x) = f(1 - \tilde{x})$
 So for $\tilde{x} \neq x$ (i.e. $x \neq 0.5$), the system is still
 Backward Stable.

⇒ And when we look for $x = 0.5$, then it can be
 seen that \tilde{x} is always in the vicinity of x
 & satisfies $\tilde{f}(x) = f(\tilde{x})$. And so far a
 difference between $|1 - \tilde{x} - x|$ as S when $x = 0.5$,
 we can see that the R.H.S. is bounded as $O(1/\delta)$
 (which, despite of being very large, is still finite).

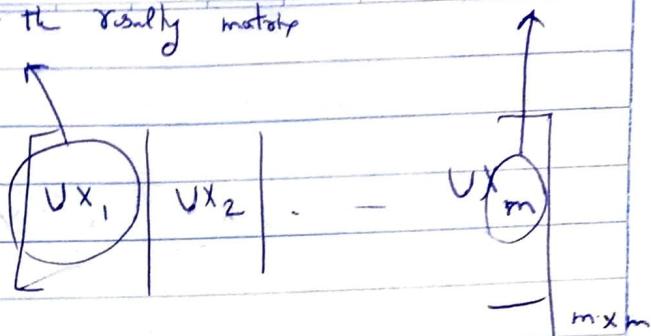
⇒ Thus the algorithm is backward stable at all values.

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Columns of the resulting matrix

A 3:

$$\Rightarrow \text{we can write } UX =$$



\Rightarrow Since X_L, Y can be broken down into columns to give us:

$$[(UX_1 + XL_1) \quad (UX_2 + XL_2) \quad \dots \quad UX_m + XL_m] = [y_1 \quad y_2 \quad \dots \quad y_m]$$

\Rightarrow If we start from the last column (i.e. m), we get:

$$UX_m + XL_m = y_m \rightarrow \text{Now as } L \text{ is a lower triangular matrix, we get: } XL_m = l_{mm} X_m$$

$$\Rightarrow \text{Thus, we get: } UX_m + l_{mm} X_m = y_m$$

Upper triangular matrix

$$((U + l_{mm} I) X_m = y_m)$$

Entry of m^{th} column
of m^{th} row

(Only non-zero entry
in the column L_m)

We solve this by Back Substitution in $O(m^2)$
we get the column X_m .

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\Rightarrow Then to find X_{m-1} , we look at the $(m-1)^{th}$ column:

$$U X_{m-1} + \circlearrowleft L_{m-1} = Y_{m-1}$$

$\downarrow L_{m-1}$ has only 2 non-zero elements (\because lower triangular)

$$(l_{(m-1), (m-1)} X_{m-1}) + (l_{m, m-1} X_m)$$

Upper

triangular

$$\xrightarrow{\text{Down}} ((U + l_{(m-1), (m-1)} I) X_{m-1}) = (Y_{m-1} - l_{m, m-1} X_m)$$

\hookrightarrow Given X_{m-1} by back substitution in $O(m^2)$.

\Rightarrow Similarly, we can find $X_{m-2}, X_{m-3}, \dots, X_1$. Thus we get X in $O(m^3)$ time.

\hookrightarrow To find

$$X_{m-j}$$

$$(U + l_{(m-j), (m-j)} I) X_{m-j}$$

$$= (Y_{m-j} - \sum_{i=0}^{j-1} l_{m-i, m-j} X_{m-i})$$

$$\boxed{\quad} + \boxed{\quad} + \boxed{\quad} + \boxed{\quad} = \boxed{\quad}$$

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Ans by:

$$\Rightarrow \text{Given } \|Ax\|_2 = \|x\|_2; \text{ we know that: } |(Ax)^*(Ax)| \\ = |x^*x|$$

say matrix B

$$\Rightarrow \text{So, } |x^* \underbrace{(A^* A)x}_B| = |x^*x|$$

\Rightarrow By many use of the expression for x^*Bx ,
we can see that: $B = I \Rightarrow A^*A = I$

\Rightarrow Thus, the matrix A is ~~Orthogonal~~ ^{Unitary} $\leftarrow ①$

\Rightarrow Now, if we try to break this into cases:

* If $m < n$: Using $\text{rank}(A^*A) = \text{rank}(A)$
 \downarrow Unitary \downarrow $\hookrightarrow m$ $\hookrightarrow \leq m$
 A is ~~Orthogonal~~ iff the columns are
~~Orthogonal~~ & so here $\text{rank}(A) = m$

* If $n < m$: Using $\text{rank}(A^*A) = \text{rank}(A) \rightarrow \leq n$

Now, we can see that the ranks of these
matrices can never be equal. And so, A ~~can't~~ can't be
a Unitary matrix here if $m > n$

⇒ So, the conditions that we obtain here are:

* Necessary: The matrix $A_{m \times n}$ is unitary

* Sufficient: $n > m$ & $\text{rank}(A) = m$

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A-5:

\Rightarrow Let us assume $M(\lambda)$ to be Singular. Thus implies that $\text{null}(M(\lambda)) \neq \{0\}$. It \Rightarrow take a Vector $x \in \text{null}(M(\lambda)) \ \& \ x \neq 0$.

$$\Rightarrow \text{So, } M(\lambda)x = 0 \Rightarrow (I + \lambda A)x = 0$$

$$\Rightarrow \lambda Ax = -x$$

$$\Rightarrow |\lambda| \|Ax\| = \|-x\| = \|x\|$$

$$\Rightarrow |\lambda| \|A\| \|x\| \leq \|x\|$$

$$(vz \quad \|AB\| \leq \|A\| \cdot \|B\|)$$

$$\Rightarrow \text{Thus, we get : } \boxed{|\lambda| > \frac{1}{\|A\|}} \quad (\text{Condns: q})$$

$(\because \|x\| \neq 0)$

\Rightarrow Thus by taking a counterexample of the above statement

$$\boxed{|\lambda| < \frac{1}{\|A\|}}$$

\rightarrow

$M(\lambda)$ is non-Singular

$$\text{Thus the Value of } S = \frac{1}{\|A\|}$$

Aus 6 : \Rightarrow From the graph, it can be seen that while the actual solution of the recurrence relation decreases with value of k , the computed solution first decreases slowly with the actual solution & then after a certain k , shows a dramatic increase in values.

\Rightarrow If we consider the difference $| \bar{x}(k) - x(k) |$ when $x(k)$ is the true soln & $\bar{x}(k)$ is the seq. computed soln at index k , it was observed that this difference monotonically increases with increasing values of k .

\Rightarrow The reason can be attributed to the fact that the floating point operations carried out while computing the different keep on accumulating errors.

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$$\Rightarrow \text{Thus : } \hat{x}_{k+1} = 2.25 \hat{x}_k - 0.5 \hat{x}_{k-1}$$

$$\Rightarrow \hat{x}_{k+1} = ((2.25 x_k (1+t_1)) - (0.5 x_{k-1} (1+t_2))) (1+t_3)$$

(where $|t_1|, |t_2|, |t_3| < t_m$)

$$\Rightarrow \hat{x}_{k+1} = (1+t_3) \left((1+t_1) (2.25) \left(\underbrace{2.25 \hat{x}_{k-1} (1+t_1)}_{x_{k-1}} - 0.5 \hat{x}_{k-2} (1+t_2) \right) (1+t_3) \right)$$

$$- (1+t_2) (0.5) \left((2.25 \hat{x}_{k-2} (1+t_1)) - 0.5 \hat{x}_{k-3} (1+t_2) \right) (1+t_3)$$

$$x_{k-1}$$

\Rightarrow Thus, we can see that these errors keep on getting accumulated for higher values of k .

\Rightarrow So initially $|\hat{x}(k) - x(k)|$ would be very small but with increasing k , the error would keep on increasing till it gets too high as compared to the actual value of $x(k)$.

(The absolute & relative errors start off from an order of 10^{-17} & exponentially rise to very high values)

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- ⇒ Another reason can also be attributed to the fact that the relative error is due to the fact that the values of relative & absolute errors, the computed sequence solution initially follows the same trend as the actual solution & then because of the exponential growth, the errors dominate the actual answer & so the sequence solution can be seen to be diverging linearly in the log scale plot.

Semi-log plot of difference equation values v/s Point indices K

