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PROBLEM-SET 5

- 1) Let $A \in \mathbb{R}^{n \times n}$ and $B \in \mathbb{R}^{m \times m}$. Show that $x(t) = e^{At} x(0) e^{Bt}$ is the solution to the following eqn

$$\dot{x}(t) = Ax(t) + x(t)B$$

- 1) We know that if $x(t) = e^{At} x(0) e^{Bt}$ is a solution of $\dot{x}(t) = Ax(t) + x(t)B$, then it should satisfy the equation.

Differentiating $x(t) = e^{At} x(0) e^{Bt}$

$$\dot{x}(t) = \frac{d}{dt} [e^{At} x(0) e^{Bt}] = Ae^{At} x(0) e^{Bt} + e^{At} x(0) Be^{Bt} - \textcircled{1}$$

w.k.t $\frac{d}{dt} e^{Bt} = Be^{Bt} = e^{Bt} B$, we can write above

$$\text{equation as } \dot{x}(t) = Ae^{At} x(0) e^{Bt} + e^{At} x(0) e^{Bt} B - \textcircled{2}$$

Now $x(t) = e^{At} x(0) e^{Bt}$

when $t=0$

$$x(0) = e^0 x(0) e^0 = x(0)$$

$$\therefore x(t) = x(t) \rightarrow \text{substitute in } \textcircled{2}$$

$$\textcircled{2} \rightarrow \dot{x}(t) = Ax(t) + x(t)B$$

↓

hence proved that $x(t) = e^{At} x(0) e^{Bt}$
is a solution of

Q) A Euclidean Ball, $B(x_c, r)$, in \mathbb{R}^n is given by $B(x_c, r) = \{\mathbf{x} \in \mathbb{R}^n / \|\mathbf{x} - \mathbf{x}_c\| \leq r\}$ where $r > 0$ and $\|\cdot\|$ is the Euclidean norm, $\|\mathbf{x}\| = \sqrt{\mathbf{x}^T \mathbf{x}}$. The vector \mathbf{x}_c is the center of the ball and r is the radius. Prove that $B(x_c, r)$ is a convex set.

A)



$$\|\mathbf{x}_1 - \mathbf{x}_c\| + \|\mathbf{x}_2 - \mathbf{x}_c\| \geq \|\mathbf{x}_1 - \mathbf{x}_2\|$$

Euclidean Ball - In Euclidean 3D space, a ball is taken to be the volume bounded by a 2D sphere. (In 2D space, a ball is a line segment.)

for a sphere (ball) with center \bar{x}_c and radius r . when we take an n-dimensional vector \bar{x} , which is an arbitrary point inside the sphere.

$$\|\bar{x} - \bar{x}_c\| \leq r$$

If the ball with center $\|\bar{x}_c\|$ is convex, then the shift will also be convex. (as shifting doesn't effect the convexity.)



convex,

Proof:- Consider 2 pts $\|\bar{x}_1 + \bar{x}_2\|$, Now we prove that the convex combination lies in the same ball.

By the definition of norm, the interior of the ball is given by $\|\mathbf{x}\| \leq r$ and $\|\mathbf{x}_1\| \leq r$

Considering the convex combination

$$\theta \bar{x}_1 + (1-\theta) \bar{x}_2 \in B(x_1, r)$$

$$\|\theta \bar{x}_1 + (1-\theta) \bar{x}_2\| \leq \|\theta \bar{x}_1\| + \|(1-\theta) \bar{x}_2\|$$

Now using the triangular inequality

$$\|\bar{a}\| + \|\bar{b}\| \geq \|\bar{a} + \bar{b}\|$$

we get that

$$\|\theta \bar{x}_1 + (1-\theta) \bar{x}_2\| \leq \|\theta \bar{x}_1\| + \|\bar{x}_2\|$$

which is true where $\theta \in [0, 1]$ and $\theta, (1-\theta) \geq 0$.

Thus, we have proved that $B(x_1, r)$ is convex.

$$\Rightarrow \theta_1 \|\bar{x}_1\| + (1-\theta_1) \|\bar{x}_2\|$$

Since θ_1 is also convex, we know that

$$\|\bar{x}_1\| \leq r_1 \text{ and } \|\bar{x}_2\| \leq r_2.$$

$$r \leq \|\bar{x}_1 - \bar{x}_2\|$$

$$\Rightarrow \theta_1 \|\bar{x}_1\| + (1-\theta_1) \|\bar{x}_2\| \leq \theta_1 r_1 + (1-\theta_1) r_2$$

$$\Rightarrow \theta_1 \|\bar{x}_1\| + (1-\theta_1) \|\bar{x}_2\| \leq r_1 + r_2$$

$$\therefore \|\theta_1 \bar{x}_1 + (1-\theta_1) \bar{x}_2\| \leq \theta_1 \|\bar{x}_1\| + (1-\theta_1) \|\bar{x}_2\|$$

$$\therefore \|\theta_1 \bar{x}_1 + (1-\theta_1) \bar{x}_2\| \leq r_1 + r_2.$$

Thus, $B(x_1, r_1) \cap B(x_2, r_2) \subseteq B(x_1, r_1 + r_2)$.

Hence proved that $B(x_1, r_1) \cap B(x_2, r_2) \subseteq B(x_1, r_1 + r_2)$.

Thus, $B(x_1, r_1) \cap B(x_2, r_2) \subseteq B(x_1, r_1 + r_2)$.

$$\underline{\underline{B(x_1, r_1)}}$$

3) Let $x(t)$ be a zero mean Gaussian random process with covariance function given by $C_x(t_1, t_2)$
 where $C_x(t_1, t_2) = \sigma^2 e^{-|t_1 - t_2|}$,
 find the joint pdf of $x(t)$ and $x(t+s)$

A) When $X_1 = x(t_1), X_2 = x(t_2), \dots, X_k = x(t_k)$ are samples of a ~~Gaussian~~ random process $x(t_k)$, then that is called a Gaussian random process.

The joint pdf of jointly Gaussian random variables is determined by the vector of means (m) and the covariance matrix Σ :

$$f_{X_1, X_2, \dots, X_k}(x_1, x_2, \dots, x_k) = \frac{1}{(2\pi)^{k/2} \sqrt{|\Sigma|}} \exp\left(-\frac{1}{2} (x - m)^\top \Sigma^{-1} (x - m)\right)$$

where $X = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_k \end{bmatrix}$ $m = \begin{bmatrix} m_x(t_1) \\ m_x(t_2) \\ \vdots \\ m_x(t_k) \end{bmatrix}$ $\Sigma_X = \begin{bmatrix} C_x(t_1, t_1) & C_x(t_1, t_2) & \dots \\ \vdots & \ddots & \vdots \\ C_x(t_k, t_1) & \dots & C_x(t_k, t_k) \end{bmatrix}$

$\Rightarrow k = n$ (dimension of X)

$$\Rightarrow m_x = E(X)$$

$$\Rightarrow \Sigma_X = E[(X - m_x)(X - m_x)^\top]$$

$$= E[(x(t_i) - m_x(t_i))(x(t_j) - m_x(t_j))]$$

$$\Rightarrow C_x(t_i, t_j) = E[x(t_i)x(t_j)] - m_x(t_i)m_x(t_j)$$

$C_x(t_i, t_j)$ is a covariance function of Σ .

assuming $C_x(t_1, t_2) = \sigma^2 e^{-|t_1 - t_2|}$ & given $t_1 = t$
 $(x(t), X)$ pd mpm (stationary, so assume $t_2 = t+s$)

$$\cdot X = \begin{bmatrix} x(t) \\ x(t+s) \end{bmatrix} \text{ column} = \begin{bmatrix} m_x(t) \\ m_x(t+s) \end{bmatrix}$$

$$1-df X - \Sigma_X = \begin{bmatrix} C_x(t, t) & C_x(t, t+s) \\ C_x(t+s, t) & C_x(t+s, t+s) \end{bmatrix} \text{ matrix} \quad (A)$$

mean mpm \rightarrow no change in $m_x(t)$ & $m_x(t+s)$

where

$$C_x(t, t) = \sigma^2 e^0 = \sigma^2$$

multivariate mpm $C_x(t, t+s) = \sigma^2 e^{-s}$ since $s \neq 0$

similarly $C_x(t+s, t) = \sigma^2 e^{-s}$ by symmetry

$$\therefore \Sigma_X C_x(t+s, t+s) = \sigma^2 e^0 = \sigma^2 \text{ mpm} \quad (M)$$

$$(m-X)^T (m-X) \Sigma_X = \begin{bmatrix} -\sigma^2 & (\sigma^2 e^{-s}) \\ (\sigma^2 e^{-s}) & \sigma^2 \end{bmatrix} \begin{bmatrix} 1 & -e^{-s} \\ -e^{-s} & 1 \end{bmatrix} = \cancel{\begin{bmatrix} 1 & -e^{-s} \\ -e^{-s} & 1 \end{bmatrix}}$$

$$\Sigma_X^{-1} = \frac{1}{\sigma^2} \begin{bmatrix} 1 & -e^{-s} \\ -e^{-s} & 1 \end{bmatrix} \quad \text{mpm} \quad 1 \Sigma 1 = \frac{1}{\sigma^2} (1 - e^{-2s})$$

The joint pdf r (for a zero mean process) $\{m_x = 0\}$

$$[C((if)_{X_1, X_2}(x_1, x_2) = x)] = \frac{1}{2\pi \sigma^2 \sqrt{1-e^{-2s}}} \exp\left(\frac{-1}{2\sigma^2} [x_1(t)x_2(t+s)]\right) \sum_X \begin{bmatrix} x_1(t) \\ x_2(t+s) \end{bmatrix}$$

$$(if)_{X_1} (if)_{X_2} = [C(if)X(if)X] = \text{fddm}$$

$\therefore \Sigma_X$ is ordinary covariance $\Rightarrow (if)_{X_1, X_2}$

$$f_{X_1 X_2}(x_1, x_2) = \frac{1}{2\pi\sigma^2\sqrt{1-e^{2s}}} \exp\left(\frac{-1}{2\sigma^2\sqrt{1-e^{2s}}}[x_1(t)x_2(t+s)]\begin{bmatrix} x_1(t)-x_1(t+s)e^s \\ -e^s x_1(t)+x_1(t+s) \end{bmatrix}\right)$$

$$= \frac{1}{2\pi\sigma^2\sqrt{1-e^{2s}}} \exp\left(\frac{-1}{2\sigma^2\sqrt{1-e^{2s}}}\left[(x_1(t))^2 - 2e^s x_1(t)x_1(t+s) + (x_1(t+s))^2\right]\right)$$

Point pdf =

$$\frac{1}{2\pi\sigma^2\sqrt{1-e^{2s}}} \exp\left(\frac{-1}{2\sigma^2\sqrt{1-e^{2s}}}\left[(x_1(t))^2 - 2e^s x_1(t)x_1(t+s) + (x_1(t+s))^2\right]\right)$$

Sorry for cramming everything into 1 line.

4) Consider the following state space eqn:

$$\dot{x}(t) = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}x(t) + \begin{bmatrix} 0 \\ 1 \end{bmatrix}u(t)$$

Consider the following cost function

$$J = \int_0^\infty (x^T Q + u^2) dt \text{ where } Q \text{ is}$$

given by $Q = \begin{bmatrix} 1 & 0 \\ 0 & 2 \end{bmatrix}$

Design an LQR and then provide a state feedback of $u = Kx$.

A) $A = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}, B = \begin{bmatrix} 0 \\ 1 \end{bmatrix}, Q = \begin{bmatrix} 1 & 0 \\ 0 & 2 \end{bmatrix}$

We know that the gain matrix can be represented as $K = -R^{-1}B_K^T P$ which is the optimal feedback solution.

Here P is the solution of the Riccati equation $A^T P + PA - PB_K R^{-1} B_K^T P = -Q$

The general cost function is

$$J(K, \vec{x}(0)) = \int_0^\infty \vec{x}^T(t) Q \vec{x}(t) + \vec{U}_K^T(t) R \vec{U}_K(t) dt$$

Comparing the general cost function with the given cost function.

We can see that $R \neq P$.

$$\text{Riccati Eqn} + A^T P + PA - PB_K R^{-1} B^T P = -Q.$$

substituting the known matrices in the Riccati Eqn:

$$\begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} P_{11} & P_{12} \\ P_{12} & P_{22} \end{bmatrix} + \begin{bmatrix} P_{11} & P_{12} \\ P_{12} & P_{22} \end{bmatrix} \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} - \begin{bmatrix} P_{11} & P_{12} \\ P_{12} & P_{22} \end{bmatrix} \begin{bmatrix} 0 \\ 1 \end{bmatrix} \mathbb{I} \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} P_{11} & P_{12} \\ P_{12} & P_{22} \end{bmatrix} = -Q$$

$$\Rightarrow \begin{bmatrix} 0 & 0 \\ P_{11} & P_{12} \end{bmatrix} + \begin{bmatrix} 0 & P_{11} \\ 0 & P_{12} \end{bmatrix} - \begin{bmatrix} P_{12} \\ P_{22} \end{bmatrix} \begin{bmatrix} P_{12} & P_{22} \end{bmatrix} = -\begin{bmatrix} 1 & 0 \\ 0 & -2 \end{bmatrix}$$

$$\Rightarrow \begin{bmatrix} 0 & P_{11} \\ P_{11} & 2P_{12} \end{bmatrix} - \begin{bmatrix} P_{12}^2 & P_{12}P_{22} \\ P_{12}P_{22} & P_{22}^2 \end{bmatrix} = \begin{bmatrix} -1 & 0 \\ 0 & -2 \end{bmatrix}$$

$$\Rightarrow \begin{bmatrix} -P_{12}^2 & P_{11} - P_{12}P_{22} \\ P_{11} - P_{12}P_{22} & 2P_{12} - P_{22}^2 \end{bmatrix} = \begin{bmatrix} -1 & 0 \\ 0 & -2 \end{bmatrix}$$

$$P_{11} = P_{12}P_{22} \quad -P_{12}^2 = -1 \quad \Rightarrow P_{12} = \pm 1$$

Now when $P_{12} = 1$

Case 1

$$\Rightarrow P_{11} = P_{22}$$

$$\text{essentially } 2P_{12} - P_{22}^2 = -2$$

$$\Rightarrow P_{22} = \pm \sqrt{1+2}$$

when $P_{12} = -1 \Rightarrow P_{11} = -P_{22}$ Case 2

$$\text{essentially } -2P_{12} - P_{22}^2 = -2 \Rightarrow P_{22} = \pm \sqrt{2-2}$$

when we look at case 2, there is a clear possibility for P_{22} to be complex when $\gamma > 0$ which is not desirable.

So we consider only case 1:

In case 1 we will have 2 sub cases

case 1.1 \Rightarrow when $P_{22} = +\sqrt{\gamma+2}$

case 1.2 \Rightarrow when $P_{22} = -\sqrt{\gamma+2}$.

$$\rightarrow 1.1 \quad P_{22} = +\sqrt{\gamma+2}$$

$$\therefore P = \begin{bmatrix} \sqrt{\gamma+2} & 1 \\ 0, 1 - \sqrt{\gamma+2} & \end{bmatrix} \text{ since } P \text{ should always be the definite matrix.}$$

The eigen values of P are

$$-1 + ((\sqrt{\gamma+2}) - \lambda)((\sqrt{\gamma+2}) - \lambda) = 0$$

$$-1 + (\sqrt{\gamma+2} - \lambda)^2 = 0$$

$$\lambda = \sqrt{\gamma+2} \pm 1$$

$$\rightarrow 1.2 \quad P_{22} = -\sqrt{\gamma+2}$$

$$\therefore P = \begin{bmatrix} -\sqrt{\gamma+2} & 1 \\ -1 & -\sqrt{\gamma+2} \end{bmatrix}$$

The eigen values are

$$(\lambda + \sqrt{\gamma+2})^2 = 1 \Rightarrow \lambda = \pm 1 - \sqrt{\gamma+2}$$

In case 1.2, there is a chance that upon choosing certain values, the value of P will be negative definite which is not desirable so we move ahead with case 1.1

In case 1.1 $\lambda_1, \lambda_2 > 0$, $\therefore P$ is the definite.

$$P = \begin{bmatrix} \sqrt{\gamma+2} & 1 \\ 1 & \sqrt{\gamma+2} \end{bmatrix}$$

Now we can compute 'Gain matrix K'

$$K = -R^{-1}B^T P$$

~~$$K = -P^{-1} \begin{bmatrix} 0 \\ 1 \end{bmatrix}^T \begin{bmatrix} \sqrt{\gamma+2} & 1 \\ 1 & \sqrt{\gamma+2} \end{bmatrix}$$~~

$$K = - \begin{bmatrix} 0 & 1 \end{bmatrix} \begin{bmatrix} \sqrt{\gamma+2} & 1 \\ 1 & \sqrt{\gamma+2} \end{bmatrix}$$

$$K = -[1 \quad \sqrt{\gamma+2}]$$

providing state feed back of $u = kx$

$$\dot{x} = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}x + \begin{bmatrix} 0 \\ 1 \end{bmatrix}[-1 - \sqrt{\gamma+2}]x$$

$$= \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}x + \begin{bmatrix} 0 & 0 \\ -1 & -\sqrt{\gamma+2} \end{bmatrix}x$$

$\dot{x} = \begin{bmatrix} 0 & 1 \\ -1 & -\sqrt{s+2} \end{bmatrix} x$ is the required state eqn with LQR controller provided with a state feedback $u = kx$

0

5) Consider the following state space representation

$$\dot{x}(t) = \begin{bmatrix} 1 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & 1 \end{bmatrix} x(t) + \begin{bmatrix} 0 & 1 \\ 1 & 0 \\ 0 & 1 \end{bmatrix} u(t)$$

The order of A matrix is $n \times n = 3 \times 3$

The order of B matrix is $n \times m = 3 \times 2$

w.k.t

the order of controllability Matrix C is $n \times nm = 3 \times 6$

and we know $C = [B \mid AB \mid A^2B]$

$$B = \begin{bmatrix} 0 & 1 \\ 1 & 0 \\ 0 & 1 \end{bmatrix} \quad AB = \begin{bmatrix} 1 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & 1 \end{bmatrix} \begin{bmatrix} 0 & 1 \\ 1 & 0 \\ 0 & 1 \end{bmatrix}$$

$$A^2 = \begin{bmatrix} 1 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 0 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 2 & 0 \\ 0 & 1 & 0 \\ 0 & -2 & 1 \end{bmatrix}$$

$$A^2B = \begin{bmatrix} 1 & 2 & 0 \\ 0 & 1 & 0 \\ 0 & 2 & 1 \end{bmatrix} \begin{bmatrix} 0 & 1 \\ 1 & 0 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 2 & 1 \\ 1 & 0 \\ 2 & 1 \end{bmatrix}$$

$$C = \begin{bmatrix} 0 & 1 & 1 & 2 & 1 \\ 1 & 0 & 1 & 0 & 1 \\ 0 & 1 & 1 & 2 & 1 \end{bmatrix}$$

f. used. }
{ Symbolab

We can manually turn the matrix to echelon form too.

Now the rank of C after comparing some rows and some manipulation turned out to be 2

$$\text{rank}(C) = 2 \Rightarrow 2 \leq n \Rightarrow 2 \leq 3$$

It shows that the system is uncontrollable

Now doing Similarity Transformation

$$S_{n \times n} = \begin{bmatrix} 1 & 0 & 1 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \Rightarrow S = \begin{bmatrix} 0 & 1 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix}$$

$$\Rightarrow S^{-1} = \frac{1}{|S|} \text{Adj}(S) = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 1 & 0 \\ 1 & 0 & 1 \end{bmatrix}$$

$$\hat{A} = S^{-1}AS = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & -1 \end{bmatrix} \begin{bmatrix} 1 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & 1 \end{bmatrix} \begin{bmatrix} 0 & 1 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix}$$

$$= \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & -1 \end{bmatrix} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 0 & 0 \\ 1 & 1 & 0 \end{bmatrix} = A_{22}$$

$$\hat{A} = \begin{bmatrix} 1 & 0 & 0 \\ 1 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} = \begin{bmatrix} A_{11} & A_{12} \\ 0 & A_{22} \end{bmatrix}$$

since $A_{11} = n_r \times n_r = 2 \times 2 = \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix}$

$$\hat{B} = \hat{S}^T B_K = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & -1 \end{bmatrix} \begin{bmatrix} 0 & 1 \\ 1 & 0 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix} = \begin{bmatrix} B_1 \\ B_2 \\ 0 \end{bmatrix}$$

$B_1 = n_r \times n_r = 2 \times 2$

$$\Rightarrow B_1 = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

The standard form of uncontrollable systems is given by

$$\dot{x} = \hat{A}x + \hat{B}v \quad \text{①}$$

$$\dot{x} = \begin{bmatrix} 1 & 0 & 0 \\ 1 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} x + \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix} v$$

Here, the uncontrollable part is given by (A_{11}, B_1)

State space form of that

$$\dot{x} = \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix} x + \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} v$$

b) Consider the system $\dot{x} = \begin{bmatrix} -3 & 2 \\ -1 & -1 \end{bmatrix} x$. Investigate the

stability of the system using the Lyapunov equation

$$A^T P + P A = -Q$$

$$Q = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

A). Lyapunov stability theorem states that, a system is stable iff, for any symmetric and definite matrix Q , there exists a symmetric and definite matrix P such that

$$A^T P + P A = -Q$$

Assumption:-

$$P = \begin{bmatrix} P_{11} & P_{12} \\ P_{12} & P_{22} \end{bmatrix} \Rightarrow (P_{11} - \lambda)(P_{22} - \lambda) = P_{12}^2$$

$$A = \begin{bmatrix} -3 & 2 \\ -1 & -1 \end{bmatrix} \quad A^T = \begin{bmatrix} -3 & -1 \\ 2 & -1 \end{bmatrix}$$

$$A^T P = \begin{bmatrix} -3 & -1 \\ 2 & -1 \end{bmatrix} \begin{bmatrix} P_{11} & P_{12} \\ P_{12} & P_{22} \end{bmatrix} = \begin{bmatrix} -3P_{11} - P_{12} & -3P_{12} - P_{22} \\ 2P_{11} - P_{12} & 2P_{12} - P_{22} \end{bmatrix}$$

$$\boxed{\begin{bmatrix} P_{11} & P_{12} \\ P_{12} & P_{22} \end{bmatrix}} = \boxed{\begin{bmatrix} -3P_{11} - P_{12} & -2 \\ 2P_{11} - P_{12} & 2P_{12} - P_{22} \end{bmatrix}}$$

$$P A = \begin{bmatrix} P_{11} & P_{12} \\ P_{12} & P_{22} \end{bmatrix} \begin{bmatrix} -3 & 2 \\ -1 & -1 \end{bmatrix} = \begin{bmatrix} -3P_{11} - P_{12} & 2P_{11} - P_{12} \\ -3P_{12} - P_{22} & 2P_{12} - P_{22} \end{bmatrix}$$

$$A^T P + P A = \begin{bmatrix} -6P_{11} - 2P_{12} & 2P_{11} - 4P_{12} - P_{22} \\ 2P_{11} - 4P_{12} - P_{22} & 4P_{12} - 2P_{22} \end{bmatrix} = \begin{bmatrix} -1 & 0 \\ 0 & -1 \end{bmatrix}$$

at step we get $\begin{bmatrix} 3 \text{ eqns} \\ -1 \end{bmatrix}$ (eqns with unknown)

method we get $-6P_{11} - 2P_{12} = -12$ \dots (1) plus we can solve
 $2P_{11} - 4P_{12} + P_{22} = 0$ \dots (2) manually or
 $4P_{12} - 2P_{22} = -1$ \dots (3) use cramer's rule

simply. Upon solving we get (I did it manually)

which gives us $P_{11} = \frac{1}{40}$, $P_{12} = -\frac{1}{40}$, $P_{22} = \frac{18}{40}$

straight out $P_{11} = \frac{1}{40}$, $P_{12} = -\frac{1}{40}$, $P_{22} = \frac{18}{40}$

$$A = 49 + 9\lambda$$

$$\therefore P = \frac{1}{40} \begin{bmatrix} 7 & -1 \\ -1 & 18 \end{bmatrix} \quad \text{[matrix]} = 9$$

finding eigen values of P .

$$\begin{bmatrix} -8 & -1 \\ -1 & 18 \end{bmatrix} = \lambda$$

$$(7-\lambda)(18-\lambda) - 1 = 0$$

$$126 - 25\lambda + \lambda^2 - 1 = 0$$

$$\lambda^2 - 25\lambda + 125 = 0 \quad \text{[square]} = 9\lambda$$

$$\lambda = \frac{25 \pm \sqrt{625 - 500}}{2} = \frac{25 \pm 5\sqrt{5}}{2}$$

$$\lambda = \frac{25 \pm 5\sqrt{5}}{2}$$

$\lambda_1 = 17.5$, $\lambda_2 = 11.25$ is evident that $\lambda_1, \lambda_2 > 0$

\therefore The system is stable.

$$\begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} = \begin{bmatrix} 9 & -11.25 \\ -11.25 & 9 \end{bmatrix} = A + 9\lambda$$