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**C24**

Setter's name: Sina Ober-Blobaum

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Lecture title: Dynamical Systems

Question no: 1

## C 24 Dynamical Systems

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### Answers to Examination Question 2018

#### Question 1

- 1) a) • A point  $p \in D$  is called an  $\omega$  limit point of the trajectory  $P \subset \phi(t, x)$  if there exists a sequence of times  $\{t_i\}$ ,  $t_i \rightarrow \infty$  such that

$$\lim_{i \rightarrow \infty} \phi(t_i, x) = p$$

This point is called  $\omega(x)$ .

- $\alpha$  limit points are defined in the same way, but with  $t \rightarrow -\infty$ . This point is called  $\alpha(x)$
- $\alpha(\Gamma)$  and  $\omega(\Gamma)$  are called the  $\alpha$ -limit set and  $\omega$ -limit set respectively, and they are the set of all  $\alpha$  limit points and  $\omega$  limit points for the trajectory  $\Gamma$ , i.e. the set of points from which the trajectory could have started and the set of points at which it ends.

- b) (i)  $\omega(x) = x$   
(ii)  $\omega(x)$  is the periodic orbit  
(iii)  $\omega(x_0) = x_0$ ,  $\omega(y_0) = x_0$   
 $\omega(x_1) = x_1$ ,  $\omega(y_1) = \emptyset$   
 $\omega(y_2) = \{x_0\} \cup \{\text{homoclinic orbit}\}$

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Lecture title: Dynamical Systems

Question no: **1**

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1) c) (i) eigenvalues  $\lambda_{1,2}^c = \pm j$ , eigenvectors  $v^c = \begin{pmatrix} 1 \\ \pm j \\ 0 \end{pmatrix}$   
 $E^c = \text{span} \left\{ \begin{pmatrix} 1 \\ 1 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 \\ -1 \\ 0 \end{pmatrix} \right\}$

eigenvalue  $\lambda_3^s = -2$ , eigenvector  $v^s = \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix}$   
 $E^s = \text{span} \left\{ \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix} \right\}$

$E^u = \emptyset$

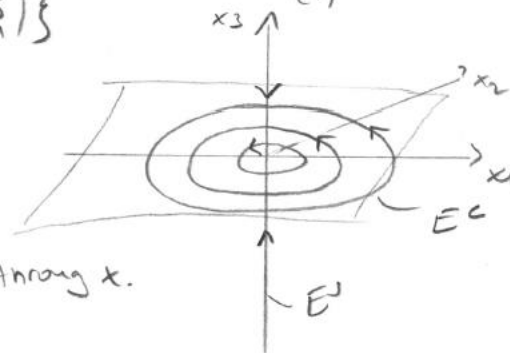
(ii) - for  $x$  on the  $\begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}$ -axis:

$w(x)$  is the periodic orbit  
in the  $x_1$ - $x_2$ -plane going through  $x$ .

- for  $x$  on the  $\begin{pmatrix} 0 \\ 1 \\ 0 \end{pmatrix}$ -axis:

$w(x)$  is the periodic orbit  
in the  $x_1$ - $x_2$ -plane going through  $x$ .

- for  $x$  on the  $\begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix}$ -axis:  $w(x) = (0, 0, 0)$



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Lecture title: Dynamical Systems

Question no: 2

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Question 2

2) a) (i) With  $H(x, y) = \frac{1}{2}y^2 + x^3 - 2x^2 + x$

we obtain  $\dot{x} = \frac{\partial H}{\partial y} = y$

$\dot{y} = -\frac{\partial H}{\partial x} = -3x^2 + 4x - 1$

(ii) equilibria  $(1, 0)$  and  $(\frac{1}{3}, 0)$

Jacobian:  $J = \begin{pmatrix} 0 & 1 \\ -6x+4 & 0 \end{pmatrix}$

$J(1, 0) = \begin{pmatrix} 0 & 1 \\ -2 & 0 \end{pmatrix} \Rightarrow$  eigenvalues  $\lambda_{1,2} = \pm j\sqrt{2}$   
 $\Rightarrow$  linear centre (non-hyperbolic)

$J(\frac{1}{3}, 0) = \begin{pmatrix} 0 & 1 \\ 2 & 0 \end{pmatrix} \Rightarrow$  eigenvalues  $\lambda_{1,2} = \pm\sqrt{2}$   
 $\Rightarrow$  saddle (hyperbolic)  
unstable

by Hartman-Grobman: the saddle  $(\frac{1}{3}, 0)$  is also a non-linear saddle but we do not know about  $(1, 0)$  (because non-hyperbolic)

(iii) A natural Lyapunov function candidate is the Hamiltonian function

$V(x, y) = \frac{1}{2}y^2 + x^3 - 2x^2 + x$

a)  $V(1, 0) = 0$  ✓

b)  $\dot{V}(x, y) = \nabla V(x, y) \cdot \begin{pmatrix} \dot{x} \\ \dot{y} \end{pmatrix} = 0$  ✓

(either by computing or arguing that  $V=H$  is an invariant of the system)

c)  $(1, 0)$  is minimum of  $V$  because

$\nabla V(x, y) = \begin{pmatrix} 3x^2 - 4x + 1 \\ y \end{pmatrix}$ ,  $\nabla^2 V(x, y) = \begin{pmatrix} 6x - 4 & 0 \\ 0 & 1 \end{pmatrix}$

$\Rightarrow \nabla V(1, 0) = 0$ ,  $\nabla^2 V(1, 0) > 0$  positive definite

$\Rightarrow V(x, y) > 0$  in a neighborhood of  $(1, 0)$  ✓

$\Rightarrow (1, 0)$  is stable

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Question no: 2

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2) a) (iv) NO, because trajectories of Hamiltonian systems always evolve along level sets of the Hamiltonian which are closed curves. or:

Since Hamiltonian systems are conservative they cannot have attracting equilibrium points.

b) (i) A Hamilton system  $\dot{x} = f(x, y) = -\frac{\partial H}{\partial y}$   
 $\dot{y} = g(x, y) = \frac{\partial H}{\partial x}$

is orthogonal to the gradient system

$$\dot{x} = g(x, y), \quad \dot{y} = -f(x, y)$$

in the sense that trajectories of one system are orthogonal to trajectories of the other system

(ii)  $\dot{x} = -3x^2 + 4x - 1$   
 $\dot{y} = -y$

(iii) Hamiltonian and gradient systems have the same equilibria, centres map to nodes, saddles to saddles.

$\Rightarrow$  equilibria  $(1, 0)$  and  $(\frac{1}{3}, 0)$

$$\text{Jacobian } J(x, y) = \begin{pmatrix} 6x+4 & 0 \\ 0 & -1 \end{pmatrix}$$

$$J(1, 0) = \begin{pmatrix} 2 & 0 \\ 0 & -1 \end{pmatrix} \Rightarrow \text{ev } \lambda_1 = -2, \lambda_2 = -1 \Rightarrow \text{stable focus}$$

$$J(\frac{1}{3}, 0) = \begin{pmatrix} 2 & 0 \\ 0 & -1 \end{pmatrix} \Rightarrow \text{ev } \lambda_1 = 2, \lambda_2 = -1 \Rightarrow \text{unstable saddle}$$

(iv) Gradient system cannot have periodic solutions

[Proof from lecture (not mandatory):

$$\dot{x} = -\nabla V; \quad \dot{V} = \nabla V \cdot \dot{x} = -\nabla V \cdot \nabla V = -|\dot{x}|^2$$

if  $x(t)$  is closed orbit of period  $T$ , then

$$0 = V(x(t)) - V(x(0)) = -\int_0^T |\dot{x}|^2 dt \neq 0 \quad \checkmark$$

**Paper: C24** | Setter's name: **Stephen Payne**

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Lecture title: **Perturbation Methods**

Question no: **3**

a. Using multiple scales, with  $t_1 = t$  and  $t_2 = \varepsilon t$  yields:

$$\frac{d}{dt} \rightarrow \frac{dt_1}{dt} \frac{\partial}{\partial t_1} + \frac{dt_2}{dt} \frac{\partial}{\partial t_2} = \frac{\partial}{\partial t_1} + \varepsilon \frac{\partial}{\partial t_2}$$

Now inserting a perturbation series of the form:

$$y = y_0 + \varepsilon y_1 + \dots$$

gives:

$$\left( \frac{\partial}{\partial t_1} + \varepsilon \frac{\partial}{\partial t_2} \right) \left( \frac{\partial}{\partial t_1} + \varepsilon \frac{\partial}{\partial t_2} \right) (y_0 + \varepsilon y_1 + \dots) - \varepsilon (1 - (y_0 + \varepsilon y_1 + \dots)^2) \left( \frac{\partial}{\partial t_1} + \varepsilon \frac{\partial}{\partial t_2} \right) (y_0 + \varepsilon y_1 + \dots) + (y_0 + \varepsilon y_1 + \dots) = 0$$

Collecting terms in  $\varepsilon^0$  gives:

$$\frac{\partial^2 y_0}{\partial t_1^2} + y_0 = 0$$

hence the solution:

$$y_0 = a_0(t_2)e^{it_1} + b_0(t_2)e^{-it_1}$$

b. Collecting terms in  $\varepsilon^1$  gives:

$$\frac{\partial^2 y_1}{\partial t_1^2} + y_1 = (1 - y_0^2) \frac{\partial y_0}{\partial t_1} - 2 \frac{\partial^2 y_0}{\partial t_1 \partial t_2}$$

Substituting the answer from part (a) into the RHS then gives:

$$\frac{\partial^2 y_1}{\partial t_1^2} + y_1 = e^{it_1} \left[ ia_0(1 - 2a_0b_0) + ia_0^2b_0 - 2i \frac{da_0}{dt_2} \right] + e^{-it_1} \left[ -ib_0(1 - 2a_0b_0) - ia_0b_0^2 + 2i \frac{db_0}{dt_2} \right] + \dots$$

The secular terms, i.e. the square brackets on the RHS, must be zero for the solution to be bounded:

$$2 \frac{da_0}{dt_2} = a_0(1 - a_0b_0)$$

$$2 \frac{db_0}{dt_2} = b_0(1 - a_0b_0)$$

The initial conditions come from the solution to part (a) and  $y(0) = 1$  and  $\frac{dy}{dt}(0) = 0$ . Hence:

$$a_0(0) + b_0(0) = 1$$

$$ia_0(0) - ib_0(0) = 0$$

and thus:  $a_0(0) = b_0(0) = 1/2$ . Note that the question does not ask for a solution.

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Lecture title: Advanced Probability

Question no: **4***To be handwritten. Please include question sections (e.g. a, b, c) and the marks attributed to each section.*Consider the following dataset  $\mathcal{D}$ , tabulated as

$x$	$y(x)$
2	2
5	1.

Our goal is to model the function  $y(x)$ , where the independent variable  $x$  is positive and real. Define a model  $\mathcal{M}$  as

$$p(y | x, \theta, \mathcal{M}) = \begin{cases} xy\theta & 0 \leq y < A \\ 0 & \text{otherwise} \end{cases}$$

$$p(\theta | \mathcal{M}) = \begin{cases} \frac{1}{2} \sin(\theta) & 0 \leq \theta < \pi \\ 0 & \text{otherwise.} \end{cases}$$

Observations  $y$  are identically and independently distributed given  $x$ ,  $\theta$  and  $\mathcal{M}$ .

- (a) Determine
- $A$
- .

[3 marks]

$A$  can be determined by noting that  $p(y | x, \theta, \mathcal{M})$  must be normalised over  $y$ . That is,

$$\begin{aligned} 1 &= \int p(y | x, \theta, \mathcal{M}) \, dy \\ &= \int_0^A xy\theta \, dy \\ &= \left[ \frac{1}{2}xy^2\theta \right]_0^A \\ &= \frac{1}{2}xA^2\theta \\ A &= \sqrt{\frac{2}{x\theta}}. \end{aligned}$$

Only the positive root is consistent with the question.

- (b) Determine the model evidence for
- $\mathcal{M}$
- given
- $\mathcal{D}$
- .

[8 marks]

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Lecture title: Advanced Probability

Question no: **4***To be handwritten. Please include question sections (e.g. a, b, c) and the marks attributed to each section.**Draft Only – 12th January 2018*

Given that the two observations are IID, the model evidence is

$$\begin{aligned} p(\mathcal{D} | \mathcal{M}) &= \int p(y = 2 | x = 2, \theta, \mathcal{M}) p(y = 1 | x = 5, \theta, \mathcal{M}) p(\theta | \mathcal{M}) d\theta \\ &= \int_0^L (2 \times 2) \theta (5 \times 1) \theta \frac{1}{2} \sin(\theta) d\theta. \end{aligned}$$

 $L$  is determined by recognising that  $p(y | x, \theta, \mathcal{M}) = 0$  if

$$\begin{aligned} y &\geq A \\ y &\geq \sqrt{\frac{2}{x\theta}} \\ \frac{1}{2}y^2x &\geq \frac{1}{\theta} \\ \frac{2}{y^2x} &\leq \theta. \end{aligned}$$

There are two such terms in the integrand ( $p(y = 2 | x = 2, \theta, \mathcal{M})$  and  $p(y = 1 | x = 5, \theta, \mathcal{M})$ ): The first term is zero for  $\theta \geq \frac{2}{y^2x} = \frac{2}{2^2 \times 2} = \frac{1}{4}$ . The second term is zero for  $\theta \geq \frac{2}{y^2x} = \frac{2}{1^2 \times 5} = \frac{2}{5}$ .  $p(\theta | \mathcal{M})$  is zero for  $\theta \geq \pi$ .  $L$  is given by the lowest of the three limits, that is,  $L = \frac{1}{4}$ .

Returning to the model evidence,

$$p(\mathcal{D} | \mathcal{M}) = 10 \int_0^{\frac{1}{4}} \theta^2 \sin(\theta) d\theta.$$

Recalling integration by parts (which we'll use twice):

$$\begin{aligned} (uv)' &= u'v + v'u \\ uv - \int v'u d &= \int u'v. \end{aligned}$$

Hence

$$\begin{aligned} p(\mathcal{D} | \mathcal{M}) &= 10 \left[ \theta^2 (-\cos(\theta)) \right]_0^{\frac{1}{4}} - 10 \int_0^{\frac{1}{4}} 2\theta (-\cos(\theta)) d\theta \\ &= 10 \left[ \theta^2 (-\cos(\theta)) \right]_0^{\frac{1}{4}} + 20 \int_0^{\frac{1}{4}} \theta \cos(\theta) d\theta \\ &= -\frac{5}{8} \cos\left(\frac{1}{4}\right) + 20 \left( \left[ \theta \sin(\theta) \right]_0^{\frac{1}{4}} - \int_0^{\frac{1}{4}} \sin(\theta) d\theta \right) \\ &= -\frac{5}{8} \cos\left(\frac{1}{4}\right) + 5 \sin\left(\frac{1}{4}\right) - 20 \left[ -\cos(\theta) \right]_0^{\frac{1}{4}} \\ &= -\frac{5}{8} \cos\left(\frac{1}{4}\right) + 5 \sin\left(\frac{1}{4}\right) + 20 \cos\left(\frac{1}{4}\right) - 20 \\ &= \frac{155}{8} \cos\left(\frac{1}{4}\right) + 5 \sin\left(\frac{1}{4}\right) - 20 \approx 0.00970. \end{aligned}$$

) Describe the model by interpreting  $p(y | x, \theta, \mathcal{M})$  and  $p(\theta | \mathcal{M})$ . Characterise the functions

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[5 marks]

- $p(y | x, \theta, \mathcal{M})$  is the likelihood (connecting the parameter  $\theta$  to data) and  $p(\theta | \mathcal{M})$  is the prior for the parameter.
- $\mathcal{M}$  is a parametric model: it has only the single parameter  $\theta$ . It is hence likely to be far less flexible than a non-parametric model, like a Gaussian process.
- $p(\theta | \mathcal{M})$  is a fairly typical unimodal, bounded-support, prior, with a mean and mode of  $\frac{\pi}{2}$ .
- $p(y | x, \theta, \mathcal{M})$  is a slightly unusual likelihood. For a given  $x$  and  $\theta$ , the probability of  $y$  is linearly related to the value of  $y$ : the most probable value is just less than  $A$ .
- According to the likelihood,  $0 \leq y(x) < \sqrt{\frac{2}{x\theta}}$ . As such, the maximum possible value of  $y(x)$  *decreases* with increasing  $x$  and  $\theta$ . However, within the envelope of possible values for  $y(x)$ , the weighting towards higher values linearly *increases* with increasing  $x$  and  $\theta$ .