

# Computational Methods in Dynamical Systems and Advanced Examples

*FisMat 2015*

*Obverse and reverse of the same coin [head and tails]*

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July 2015

- Lecture 1. Simulation vs Continuation.  
How do we compute the bifurcation diagrams?  
IFT + Newton

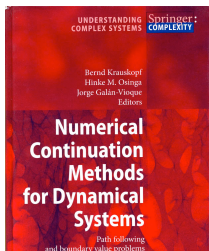
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- Lecture 4. Advanced Examples from Celestial Mechanics.
- Workshop. Application to a Mean Field problem in Quantum Mechanics.

- Lecture Notes: Numerical Analysis of Nonlinear Equations. E. J. Doedel.
- Chapter 10: Elements of Applied Bifurcation Theory. Y.A. Kuznetsov.
- Chapter 1: Numerical Continuation Methods for Dynamical systems. Path Following and boundary value problems. B. Krauskopf, H. Osinga and J. Galán-Vioque.



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- A. Vanderbauwhede (Ghent)
- F. J. Muñoz Almaraz  
(Cardenal Herrera CEU Valencia)

Find all the solutions of:

- $f(x, \lambda) = \lambda + x^2$
- $f(x, \lambda) = (x - \lambda)x$
- $f(x, \lambda) = \lambda x - x^3$

for all values of  $x$  and  $\lambda$ .



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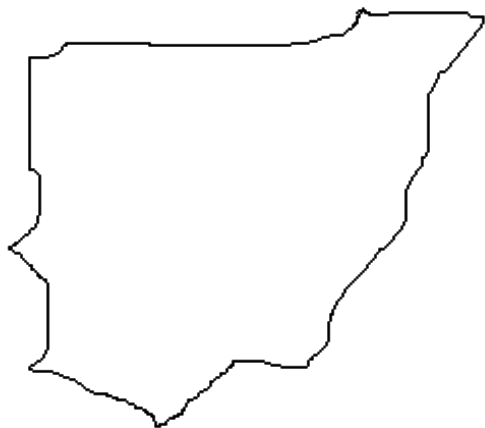
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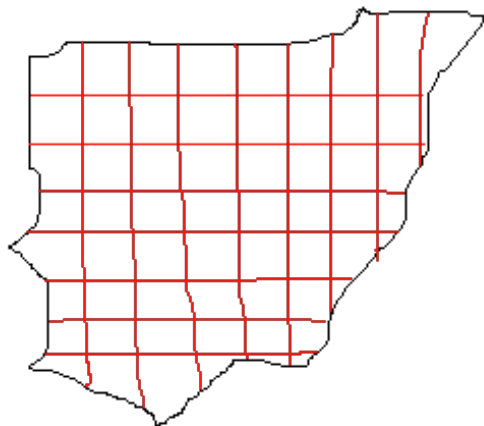
How do we get the answer with the computer?

or, how do we proceed in realistic examples?

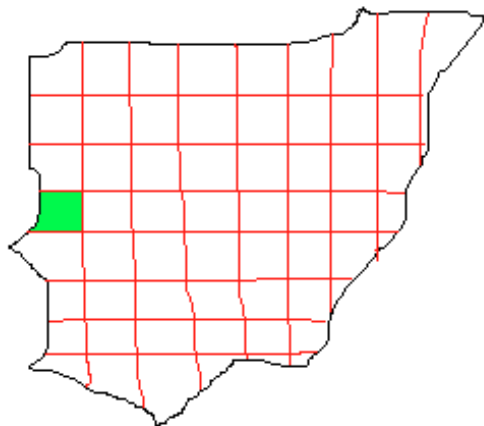
# Simulation vs continuation



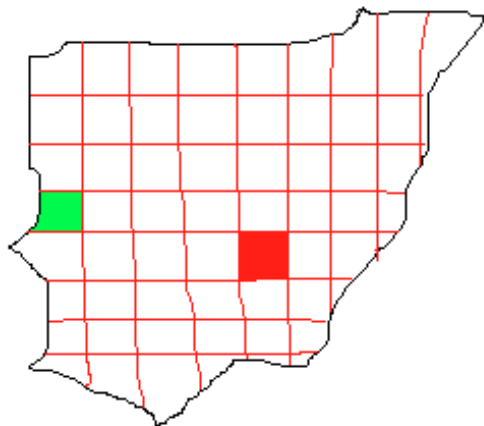
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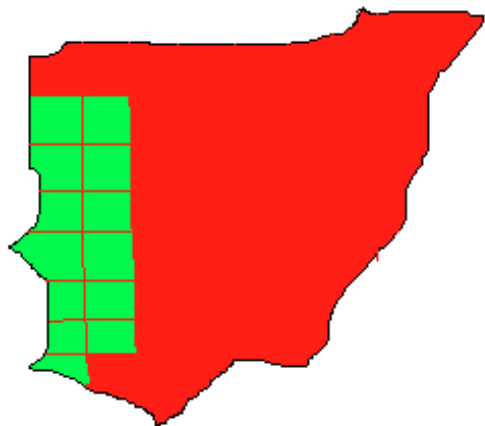
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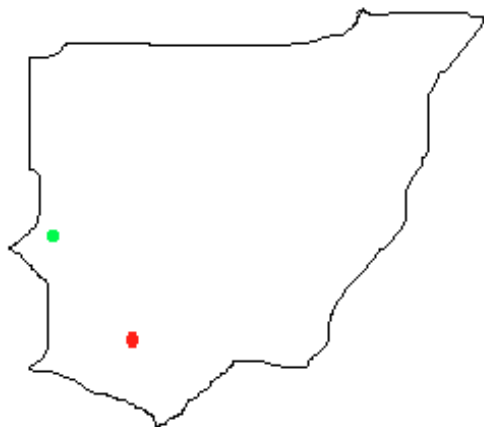


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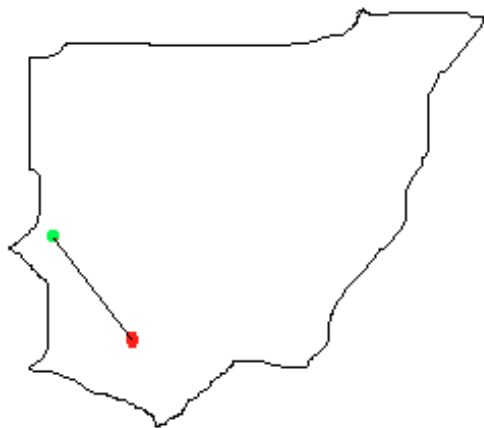




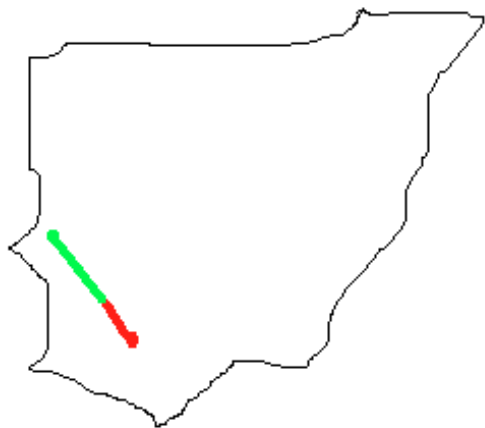
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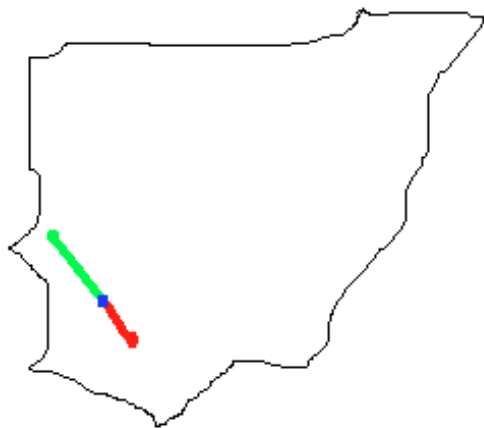
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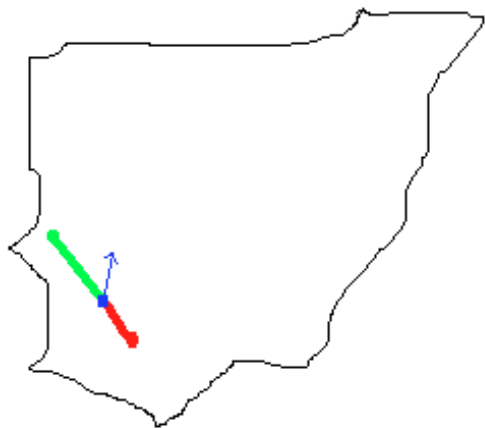
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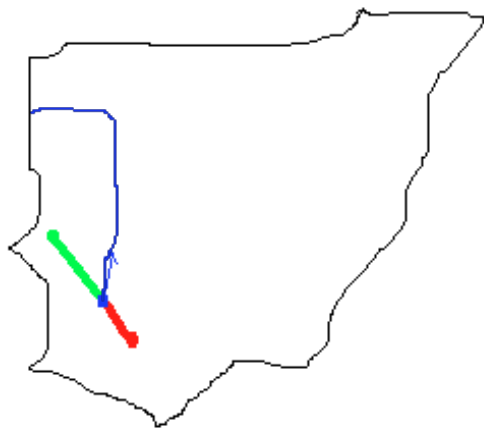
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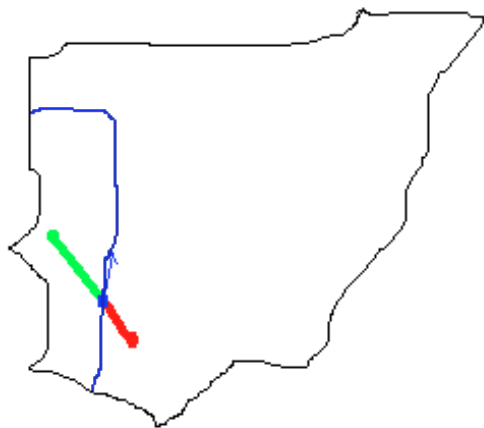
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# Simulation vs continuation



## Goal:

Characterize the solutions for all value of the initial conditions, parameter values and even "nearby" systems for the ODE:

$$\begin{cases} u'(t) = G(u, \lambda), & G : \Omega \subset \mathbb{R}^n \times \mathbb{R} \rightarrow \mathbb{R}^n, \\ u(0) = u_0, & u \in \mathbb{R}^n, \lambda \in \mathbb{R}. \end{cases}$$

- Why looking for zeros?
  - Equilibria, periodic orbits, stability, bifurcations. . .
- **Qualitative** vs **quantitative** analysis of differential equations.
- From **local** analysis to a **global** understanding of the system via the continuation of *special* solutions.



# What is the best computational approach?

Skilled programmer and/or long term project

Be a man and write your own code!

or

The wimpy approach

Use a (good) black box code, but  
**understand** what you are doing and be careful.

In this course we will follow the second path with a glance at the first. (AUTO and MATLAB).

- Taylor's theorem.
- Locating zeros: The elevator's theorem and Newton's method.
- Implicit function theorem.

# Elevator's theorem

This elevator takes you to the second floor without passing through the first floor.

This is imposible signed: **Bolzano**.



# Newton's method

Suppose  $u^0$  is close to a zero of

$$G(u) = 0.$$

How do we compute a  $u^1$  even closer to the zero?  
Replace the left hand side by its linear part

$$G(u^1) \simeq G(u^0) + J(u^1 - u^0) \simeq 0,$$

where  $J = G_u(u^0)$  is the Jacobian.

$$u^1 = u^0 - J^{-1}G(u^0).$$

In practice, solve

$$J\Delta u = -G(u^0),$$

and

$$u^1 = u^0 + \Delta u$$

and iterate up to convergence. (see Ch. 10 Kuznetsov)

## The Implicit Function Theorem

Let  $\mathbf{G} : \mathbb{R}^n \times \mathbb{R} \rightarrow \mathbb{R}^n$  satisfy

(i)  $\mathbf{G}(\mathbf{u}_0, \lambda_0) = \mathbf{0}$ ,  $\mathbf{u}_0 \in \mathbb{R}^n$ ,  $\lambda_0 \in \mathbb{R}$ .

(ii)  $\mathbf{G}_{\mathbf{u}}(\mathbf{u}_0, \lambda_0)$  is nonsingular (i.e.,  $\mathbf{u}_0$  is an *isolated solution*),

(iii)  $\mathbf{G}$  and  $\mathbf{G}_{\mathbf{u}}$  are smooth near  $\mathbf{u}_0$ .

Then there exists a unique, smooth *solution family*  $\mathbf{u}(\lambda)$  such that

- $\mathbf{G}(\mathbf{u}(\lambda), \lambda) = \mathbf{0}$ , for all  $\lambda$  near  $\lambda_0$ ,
- $\mathbf{u}(\lambda_0) = \mathbf{u}_0$ .

PROOF : See a good Analysis book ...

# Persistence of solutions

Consider the equation

$$\mathbf{G}(\mathbf{u}, \lambda) = \mathbf{0}, \quad \mathbf{u}, \mathbf{G}(\cdot, \cdot) \in \mathbb{R}^n, \quad \lambda \in \mathbb{R}.$$

Let

$$\mathbf{x} \equiv (\mathbf{u}, \lambda).$$

Then the equation can be written

$$\mathbf{G}(\mathbf{x}) = \mathbf{0}, \quad \mathbf{G} : \mathbb{R}^{n+1} \rightarrow \mathbb{R}^n.$$

DEFINITION.

A solution  $\mathbf{x}_0$  of  $\mathbf{G}(\mathbf{x}) = \mathbf{0}$  is *regular* if the matrix

$$\mathbf{G}_{\mathbf{x}}^0 \equiv \mathbf{G}_{\mathbf{x}}(\mathbf{x}_0), \quad (\text{with } n \text{ rows and } n + 1 \text{ columns})$$

has maximal rank, *i.e.*, if

$$\text{Rank}(\mathbf{G}_{\mathbf{x}}^0) = n.$$



In the parameter formulation,

$$\mathbf{G}(\mathbf{u}, \lambda) = \mathbf{0} ,$$

we have

$$\text{Rank}(\mathbf{G}_x^0) = \text{Rank}(\mathbf{G}_u^0 \mid \mathbf{G}_\lambda^0) = n \iff \begin{cases} \text{(i) } \mathbf{G}_u^0 \text{ is nonsingular,} \\ \text{or} \\ \text{(ii) } \begin{cases} \dim \mathcal{N}(\mathbf{G}_u^0) = 1 , \\ \text{and} \\ \mathbf{G}_\lambda^0 \notin \mathcal{R}(\mathbf{G}_u^0) . \end{cases} \end{cases}$$

Above,

$\mathcal{N}(\mathbf{G}_u^0)$  denotes the *null space* of  $\mathbf{G}_u^0$  ,

and

$\mathcal{R}(\mathbf{G}_u^0)$  denotes the *range* of  $\mathbf{G}_u^0$  ,

*i.e.*, the linear space spanned by the  $n$  columns of  $\mathbf{G}_u^0$  .

THEOREM. Let

$$\mathbf{x}_0 \equiv (\mathbf{u}_0, \lambda_0)$$

be a regular solution of

$$\mathbf{G}(\mathbf{x}) = \mathbf{0}.$$

Then, near  $\mathbf{x}_0$ , there exists a unique one-dimensional *solution family*

$$\mathbf{x}(s) \quad \text{with} \quad \mathbf{x}(0) = \mathbf{x}_0.$$

PROOF. Since

$$\text{Rank}(\mathbf{G}_x^0) = \text{Rank}(\mathbf{G}_u^0 \mid \mathbf{G}_\lambda^0) = n,$$

then either  $\mathbf{G}_u^0$  is nonsingular and by the IFT we have

$$\mathbf{u} = \mathbf{u}(\lambda) \quad \text{near} \quad \mathbf{x}_0,$$

or else we can interchange columns in the Jacobian  $\mathbf{G}_x^0$  to see that the solution can locally be parametrized by one of the components of  $\mathbf{u}$ .

Thus a unique solution family passes through a regular solution. •



NOTE:

- Such a *solution family* is sometimes also called a *solution branch* .
- Case (ii) above is that of a *simple fold* , to be discussed later.
- Thus even near a simple fold there is a unique solution family.
- However, near such a fold, the family can not be parametrized by  $\lambda$ .

## Parameter Continuation

Here the continuation parameter is taken to be  $\lambda$ .

Suppose we have a solution  $(\mathbf{u}_0, \lambda_0)$  of

$$\mathbf{G}(\mathbf{u}, \lambda) = \mathbf{0},$$

as well as the direction vector  $\dot{\mathbf{u}}_0$ .

Here

$$\dot{\mathbf{u}} \equiv \frac{d\mathbf{u}}{d\lambda}.$$

We want to compute the solution  $\mathbf{u}_1$  at  $\lambda_1 \equiv \lambda_0 + \Delta\lambda$ .

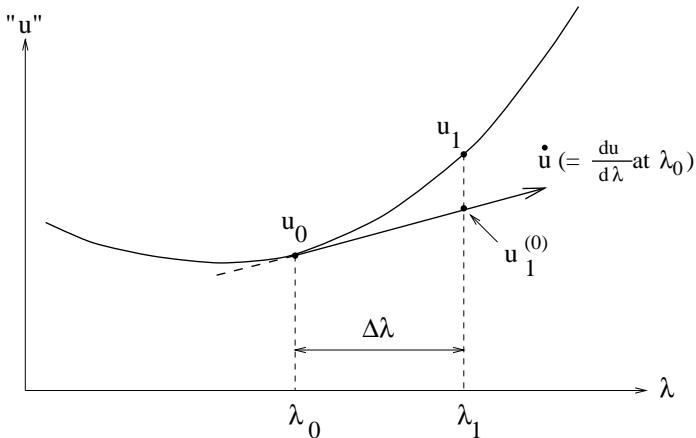


Figure 10: Graphical interpretation of parameter-continuation.

To solve the equation

$$\mathbf{G}(\mathbf{u}_1, \lambda_1) = \mathbf{0},$$

for  $\mathbf{u}_1$  (with  $\lambda = \lambda_1$  fixed) we use Newton's method

$$\begin{aligned} \mathbf{G}_{\mathbf{u}}(\mathbf{u}_1^{(\nu)}, \lambda_1) \Delta \mathbf{u}_1^{(\nu)} &= -\mathbf{G}(\mathbf{u}_1^{(\nu)}, \lambda_1), \\ \mathbf{u}_1^{(\nu+1)} &= \mathbf{u}_1^{(\nu)} + \Delta \mathbf{u}_1^{(\nu)}. \end{aligned} \quad \nu = 0, 1, 2, \dots$$

As initial approximation use

$$\mathbf{u}_1^{(0)} = \mathbf{u}_0 + \Delta \lambda \dot{\mathbf{u}}_0.$$

If

$$\mathbf{G}_{\mathbf{u}}(\mathbf{u}_1, \lambda_1) \text{ is nonsingular,}$$

and  $\Delta \lambda$  sufficiently small, then the Newton convergence theory guarantees that this iteration will converge.

After convergence, the new direction vector  $\dot{\mathbf{u}}_1$  can be computed by solving

$$\mathbf{G}_{\mathbf{u}}(\mathbf{u}_1, \lambda_1) \dot{\mathbf{u}}_1 = -\mathbf{G}_{\lambda}(\mathbf{u}_1, \lambda_1) .$$

This equation follows from differentiating

$$\mathbf{G}(\mathbf{u}(\lambda), \lambda) = \mathbf{0} ,$$

with respect to  $\lambda$  at  $\lambda = \lambda_1$  .

NOTE:

- $\dot{\mathbf{u}}_1$  can be computed without another *LU*-factorization of  $\mathbf{G}_{\mathbf{u}}(\mathbf{u}_1, \lambda_1)$  .
- Thus the extra work to find  $\dot{\mathbf{u}}_1$  is negligible.

## Excercise for Lecture 1

When will the parameter continuation fail?

## Keller's Pseudo-Arclength Continuation

This method allows continuation of a solution family past a fold.

Suppose we have a solution  $(\mathbf{u}_0, \lambda_0)$  of

$$\mathbf{G}(\mathbf{u}, \lambda) = \mathbf{0},$$

as well as the direction vector  $(\dot{\mathbf{u}}_0, \dot{\lambda}_0)$  of the solution branch.

Pseudo-arclength continuation solves the following equations for  $(\mathbf{u}_1, \lambda_1)$ :

$$\mathbf{G}(\mathbf{u}_1, \lambda_1) = \mathbf{0},$$

$$(\mathbf{u}_1 - \mathbf{u}_0)^* \dot{\mathbf{u}}_0 + (\lambda_1 - \lambda_0) \dot{\lambda}_0 - \Delta s = 0.$$

See Figure 11 for a graphical interpretation.

# Pseudoarclength continuation

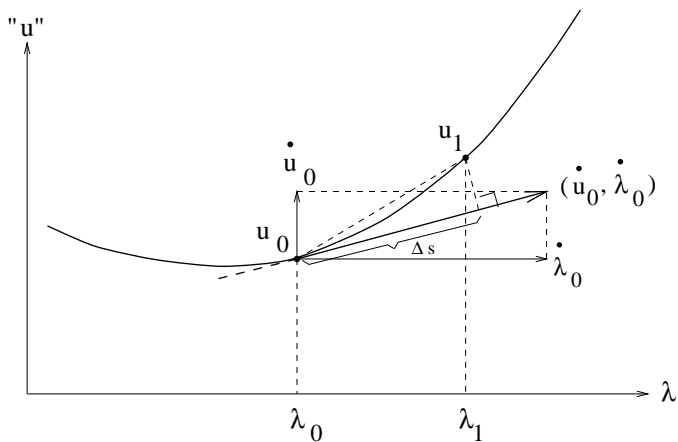


Figure 11: Graphical interpretation of pseudo-arclength continuation.



# Pseudoarclength continuation

Solve the equations

$$\mathbf{G}(\mathbf{u}_1, \lambda_1) = \mathbf{0},$$

$$(\mathbf{u}_1 - \mathbf{u}_0)^* \dot{\mathbf{u}}_0 + (\lambda_1 - \lambda_0) \dot{\lambda}_0 - \Delta s = 0.$$

for  $(\mathbf{u}_1, \lambda_1)$  by Newton's method:

$$\begin{pmatrix} (\mathbf{G}_{\mathbf{u}}^1)^{(\nu)} & (\mathbf{G}_{\lambda}^1)^{(\nu)} \\ \dot{\mathbf{u}}_0^* & \dot{\lambda}_0 \end{pmatrix} \begin{pmatrix} \Delta \mathbf{u}_1^{(\nu)} \\ \Delta \lambda_1^{(\nu)} \end{pmatrix} = - \begin{pmatrix} \mathbf{G}(\mathbf{u}_1^{(\nu)}, \lambda_1^{(\nu)}) \\ (\mathbf{u}_1^{(\nu)} - \mathbf{u}_0)^* \dot{\mathbf{u}}_0 + (\lambda_1^{(\nu)} - \lambda_0) \dot{\lambda}_0 - \Delta s \end{pmatrix}.$$

Next direction vector :

$$\begin{pmatrix} \mathbf{G}_{\mathbf{u}}^1 & \mathbf{G}_{\lambda}^1 \\ \dot{\mathbf{u}}_0^* & \dot{\lambda}_0 \end{pmatrix} \begin{pmatrix} \dot{\mathbf{u}}_1 \\ \dot{\lambda}_1 \end{pmatrix} = \begin{pmatrix} \mathbf{0} \\ 1 \end{pmatrix}.$$

# Pseudoarclength continuation

NOTE:

- In practice  $(\dot{\mathbf{u}}_1, \dot{\lambda}_1)$  can be computed with one extra backsubstitution.
- The orientation of the branch is preserved if  $\Delta s$  is sufficiently small.
- The direction vector must be rescaled, so that indeed  $\|\dot{\mathbf{u}}_1\|^2 + \dot{\lambda}_1^2 = 1$ .

# Pseudoarclength continuation

THEOREM.

The *Jacobian* of the pseudo-arclength system is *nonsingular* at a *regular* solution point.

PROOF. Let

$$\mathbf{x} \equiv (\mathbf{u}, \lambda) \in \mathbb{R}^{n+1}.$$

Then pseudo-arclength continuation can be written as

$$\mathbf{G}(\mathbf{x}_1) = 0,$$

$$(\mathbf{x}_1 - \mathbf{x}_0)^* \dot{\mathbf{x}}_0 - \Delta s = 0, \quad (\|\dot{\mathbf{x}}_0\| = 1).$$

(See Figure 12 for a graphical interpretation.)

# Pseudoarclength continuation

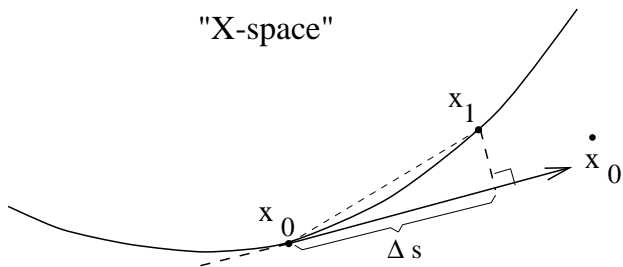


Figure 12: Parameter-independent pseudo-arclength continuation.

# Pseudoarclength continuation

The matrix in Newton's method at  $\Delta s = 0$  is

$$\begin{pmatrix} \mathbf{G}_x^0 \\ \dot{\mathbf{x}}_0^* \end{pmatrix}.$$

At a regular solution we have

$$\mathcal{N}(\mathbf{G}_x^0) = \text{Span}\{\dot{\mathbf{x}}_0^*\}.$$

We must show that

$$\begin{pmatrix} \mathbf{G}_x^0 \\ \dot{\mathbf{x}}_0^* \end{pmatrix}$$

is nonsingular at a regular solution.

# Pseudoarclength continuation

If on the contrary

$$\begin{pmatrix} \mathbf{G}_x^0 \\ \dot{\mathbf{x}}_0^* \end{pmatrix}$$

is singular then

$$\mathbf{G}_x^0 \mathbf{z} = 0 \quad \text{and} \quad \dot{\mathbf{x}}_0^* \mathbf{z} = 0 ,$$

for some vector  $\mathbf{z} \neq \mathbf{0}$ .

Thus

$$\mathbf{z} = c \dot{\mathbf{x}}_0 , \quad \text{for some constant } c .$$

But then

$$0 = \dot{\mathbf{x}}_0^* \mathbf{z} = c \dot{\mathbf{x}}_0^* \dot{\mathbf{x}}_0 = c \|\dot{\mathbf{x}}_0\|^2 = c ,$$

so that  $\mathbf{z} = \mathbf{0}$ , which is a contradiction. •

# Recall the ingredients

The building blocks for the continuation of solutions are:

- Newton's method of the properly chosen function  $G(x)$ .
- Pseudoarclength continuation.
- Convergence, step control and accuracy.
- Appropriate test function.
- Data handling and representation.

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All these in an efficient way.



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All these in an efficient way.

Extensions:

- detect and identify bifurcation points
- branch switching
- homo- and heteroclinic orbits

Compute the bifurcation diagram of

- $f(x, \lambda) = \lambda + x^2$
- $f(x, \lambda) = (x - \lambda)x$
- $f(x, \lambda) = \lambda x - x^3$

for all values of  $x$  and  $\lambda$ .

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for all values of  $x$  and  $\lambda$ .

**Exercise** Continue the perturbed pitchfork case. (add a  $+\epsilon$  term, and continue in  $\epsilon$ .)

## A Predator-Prey Model

(AUTO demo pp2.)

$$\begin{cases} u_1' = 3u_1(1 - u_1) - u_1u_2 - \lambda(1 - e^{-5u_1}), \\ u_2' = -u_2 + 3u_1u_2. \end{cases}$$

Here  $u_1$  may be thought of as “fish” and  $u_2$  as “sharks”, while the term

$$\lambda(1 - e^{-5u_1}),$$

represents “fishing”, with “fishing-quota”  $\lambda$ .

When  $\lambda = 0$  the *stationary solutions* are

$$\begin{cases} 3u_1(1 - u_1) - u_1u_2 = 0 \\ -u_2 + 3u_1u_2 = 0 \end{cases} \Rightarrow (u_1, u_2) = (0, 0), (1, 0), \left(\frac{1}{3}, 2\right).$$

The Jacobian matrix is

$$\mathbf{G}_{\mathbf{u}} = \begin{pmatrix} 3 - 6u_1 - u_2 - 5\lambda e^{-5u_1} & -u_1 \\ 3u_2 & -1 + 3u_1 \end{pmatrix} = \mathbf{G}_{\mathbf{u}}(u_1, u_2; \lambda).$$

$$\mathbf{G}_{\mathbf{u}}(0, 0; 0) = \begin{pmatrix} 3 & 0 \\ 0 & -1 \end{pmatrix}; \text{ eigenvalues } 3, -1 \text{ (unstable)}.$$

$$\mathbf{G}_{\mathbf{u}}(1, 0; 0) = \begin{pmatrix} -3 & -1 \\ 0 & 2 \end{pmatrix}; \text{ eigenvalues } -3, 2 \text{ (unstable)}.$$

$$\mathbf{G}_{\mathbf{u}}\left(\frac{1}{3}, 2; 0\right) = \begin{pmatrix} -1 & -\frac{1}{3} \\ 6 & 0 \end{pmatrix}; \text{ eigenvalues } \begin{cases} (-1 - \mu)(-\mu) + 2 = 0 \\ \mu^2 + \mu + 2 = 0 \\ \mu_{\pm} = \frac{-1 \pm \sqrt{-7}}{2} \\ \text{Re}(\mu_{\pm}) < 0 \text{ (stable)}. \end{cases}$$

All three Jacobians at  $\lambda = 0$  are nonsingular.

Thus, by the IFT, all three stationary points persist for (small)  $\lambda \neq 0$ .

In this problem we can *explicitly* find all solutions (see Figure 1) :

Branch I :

$$(u_1, u_2) = (0, 0) .$$

Branch II :

$$u_2 = 0 , \quad \lambda = \frac{3u_1(1-u_1)}{1-e^{-5u_1}} .$$

$$\text{(Note that } \lim_{u_1 \rightarrow 0} \lambda = \lim_{u_1 \rightarrow 0} \frac{3(1-2u_1)}{5e^{-5u_1}} = \frac{3}{5} \text{.)}$$

Branch III :

$$u_1 = \frac{1}{3}, \quad \frac{2}{3} - \frac{1}{3} u_2 - \lambda(1 - e^{-5/3}) = 0 \Rightarrow u_2 = 2 - 3\lambda(1 - e^{-5/3}) .$$

These solution families intersect at two *branch points*, one of which is

$$(u_1, u_2, \lambda) = (0, 0, 3/5) .$$

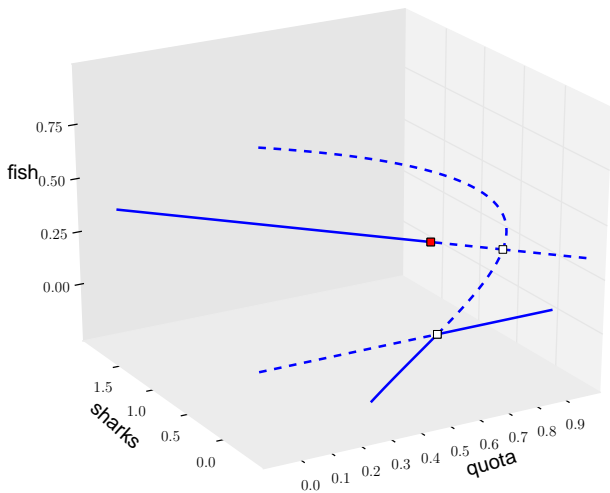


Figure 1: Stationary solution families of the predator-prey model. Solid/dashed lines denote stable/unstable solutions. Note the *fold*, the *bifurcations* (open squares), and the *Hopf bifurcation* (red square).

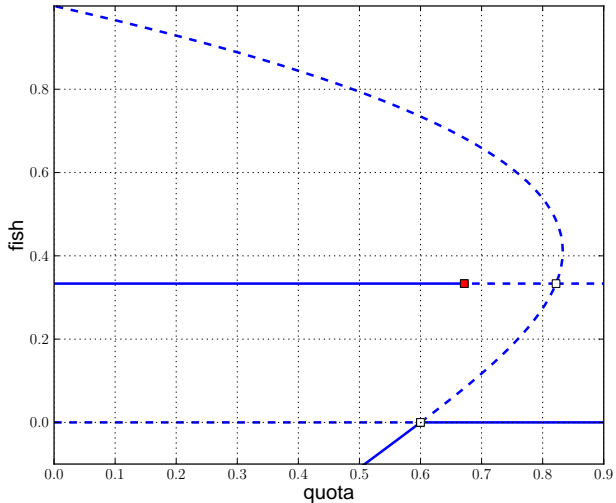


Figure 2: Stationary solution families of the predator-prey model, showing *fish* versus *quota*. Solid/dashed lines denote stable/unstable solutions.



- Stability of branch I :

$$\mathbf{G}_{\mathbf{u}}((0,0); \lambda) = \begin{pmatrix} 3 - 5\lambda & 0 \\ 0 & -1 \end{pmatrix}; \quad \text{eigenvalues } 3 - 5\lambda, \quad -1 .$$

Hence the trivial solution is :

unstable if  $\lambda < 3/5$  ,

and

stable if  $\lambda > 3/5$  ,

as indicated in Figure 2.

- Stability of branch II :

This family has no stable positive solutions.

- Stability of branch III :

At  $\lambda_H \approx 0.67$ ,

(the red square in Figure 2) the complex eigenvalues cross the imaginary axis.

This crossing is a *Hopf bifurcation*, a topic to be discussed later.

Beyond  $\lambda_H$  there are *periodic solutions* whose period  $T$  increases as  $\lambda$  increases. (See Figure 4 for some representative periodic orbits.)

The period becomes infinite at  $\lambda = \lambda_\infty \approx 0.70$ .

This final orbit is called a *heteroclinic cycle*.

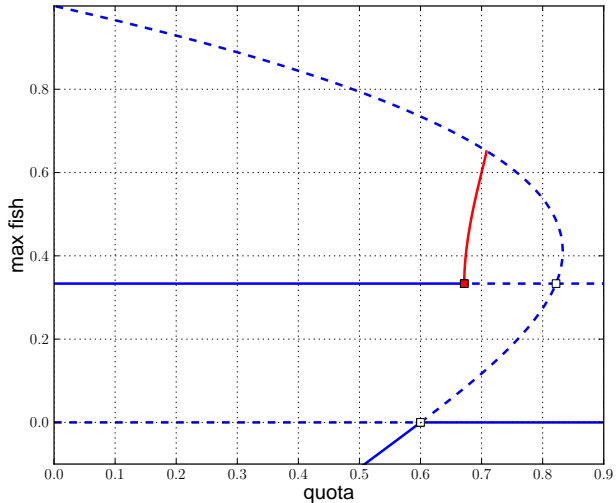


Figure 3: Stationary (blue) and periodic (red) solution families of the predator-prey model.

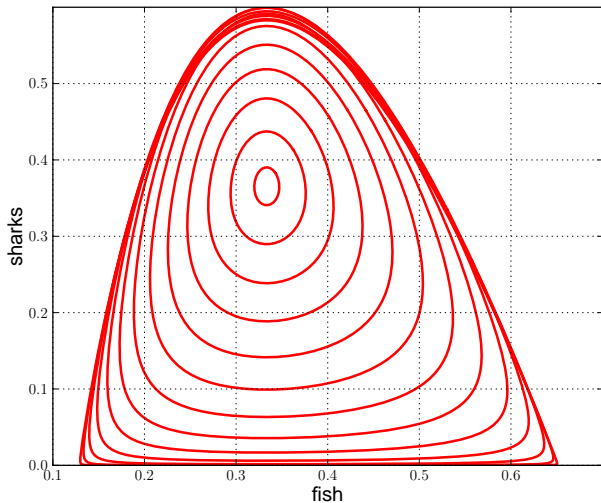


Figure 4: Some periodic solutions of the predator-prey model. The largest orbits are very close to a *heteroclinic cycle*.

From Figure 3 we can deduce the solution behavior for (slowly) increasing  $\lambda$  :

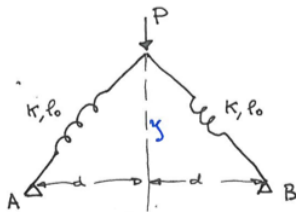
- Branch III is followed until  $\lambda_H \approx 0.67$  .
- Periodic solutions of increasing period until  $\lambda = \lambda_\infty \approx 0.70$  .
- Collapse to trivial solution (Branch I).

EXERCISE.

Use **AUTO** to repeat the numerical calculations (demo pp2) .

Sketch *phase plane diagrams* for  $\lambda = 0, 0.5, 0.68, 0.70, 0.71$  .

# Nontrivial example II: equilibria of the loaded arch



$$\frac{\partial \tilde{V}}{\partial \tilde{y}} = (\tilde{\ell}(y) - 1) \cdot \frac{d\tilde{\ell}}{d\tilde{y}} + \mu = (\tilde{\ell}(y) - 1) \frac{\tilde{y}}{\tilde{\ell}} + \mu = \tilde{y} - \frac{\tilde{y}}{\sqrt{\rho^2 + \tilde{y}^2}} + \mu$$

$$y'' = -y + \frac{y}{\sqrt{\rho^2 + y^2}} + \mu$$

# An example of oscillations: Hopf theorem

Analyze

$$\begin{aligned}\frac{du_1}{dt} &= \alpha u_1 - u_2 - \beta u_1(u_1^2 + u_2^2) \\ \frac{du_2}{dt} &= u_1 + \alpha u_2 - \beta u_2(u_1^2 + u_2^2)\end{aligned}\tag{1}$$

## The Hopf Bifurcation Theorem

THEOREM. Suppose that along a stationary solution family  $(\mathbf{u}(\lambda), \lambda)$ , of

$$\mathbf{u}' = \mathbf{f}(\mathbf{u}, \lambda),$$

a complex conjugate pair of eigenvalues

$$\alpha(\lambda) \pm i \beta(\lambda),$$

of  $f_{\mathbf{u}}(\mathbf{u}(\lambda), \lambda)$  crosses the imaginary axis transversally, *i.e.*, for some  $\lambda_0$ ,

$$\alpha(\lambda_0) = 0, \quad \beta(\lambda_0) \neq 0, \quad \text{and} \quad \dot{\alpha}(\lambda_0) \neq 0.$$

Also assume that there are no other eigenvalues on the imaginary axis.

Then there is a *Hopf bifurcation*, *i.e.*, a family of periodic solutions bifurcates from the stationary solution at  $(\mathbf{u}_0, \lambda_0)$ .  $\circ$

NOTE: The assumptions also imply that  $\mathbf{f}_{\mathbf{u}}^0$  is nonsingular, so that the stationary solution family can indeed be parametrized locally using  $\lambda$ .



## The BVP Approach.

Consider

$$\mathbf{u}'(t) = \mathbf{f}(\mathbf{u}(t), \lambda), \quad \mathbf{u}(\cdot), \mathbf{f}(\cdot) \in \mathbb{R}^n, \quad \lambda \in \mathbb{R}.$$

Fix the interval of periodicity by the transformation

$$t \rightarrow \frac{t}{T}.$$

Then the equation becomes

$$\boxed{\mathbf{u}'(t) = T \mathbf{f}(\mathbf{u}(t), \lambda)}, \quad \mathbf{u}(\cdot), \mathbf{f}(\cdot) \in \mathbb{R}^n, \quad T, \lambda \in \mathbb{R}.$$

and we seek solutions of period 1, *i.e.*,

$$\boxed{\mathbf{u}(0) = \mathbf{u}(1)}.$$

Note that the period  $T$  is one of the unknowns.

# Hopf theorem

The above equations do not uniquely specify  $\mathbf{u}$  and  $T$  :

Assume that we have computed

$$(\mathbf{u}_{k-1}(\cdot), T_{k-1}, \lambda_{k-1}),$$

and we want to compute the next solution

$$(\mathbf{u}_k(\cdot), T_k, \lambda_k).$$

Specifically,  $\mathbf{u}_k(t)$  can be translated freely in time:

If  $\mathbf{u}_k(t)$  is a periodic solution, then so is

$$\mathbf{u}_k(t + \sigma),$$

for any  $\sigma$ .

Thus, a “*phase condition*” is needed.

# Hopf theorem

An example is the Poincaré orthogonality condition

$$(\mathbf{u}_k(0) - \mathbf{u}_{k-1}(0))^* \mathbf{u}'_{k-1}(0) = 0 .$$

(Below we derive a numerically more suitable phase condition.)

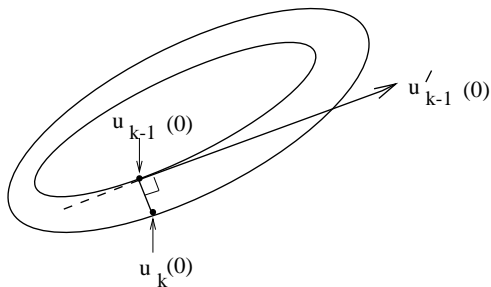


Figure 48: Graphical interpretation of the Poincaré phase condition.

## Integral Phase Condition

If  $\tilde{\mathbf{u}}_k(t)$  is a solution then so is

$$\tilde{\mathbf{u}}_k(t + \sigma) ,$$

for any  $\sigma$  .

We want the solution that minimizes

$$D(\sigma) \equiv \int_0^1 \|\tilde{\mathbf{u}}_k(t + \sigma) - \mathbf{u}_{k-1}(t)\|_2^2 dt .$$

The optimal solution

$$\tilde{\mathbf{u}}_k(t + \hat{\sigma}) ,$$

must satisfy the necessary condition

$$D'(\hat{\sigma}) = 0 .$$

# Hopf theorem

Differentiation gives the necessary condition

$$\int_0^1 (\tilde{\mathbf{u}}_k(t + \hat{\sigma}) - \mathbf{u}_{k-1}(t))^* \tilde{\mathbf{u}}_k'(t + \hat{\sigma}) dt = 0 .$$

Writing

$$\mathbf{u}_k(t) \equiv \tilde{\mathbf{u}}_k(t + \hat{\sigma}) ,$$

gives

$$\int_0^1 (\mathbf{u}_k(t) - \mathbf{u}_{k-1}(t))^* \mathbf{u}_k'(t) dt = 0 .$$

Integration by parts, using periodicity, gives

$$\boxed{\int_0^1 \mathbf{u}_k(t)^* \mathbf{u}_{k-1}'(t) dt = 0} .$$

This is the *integral phase condition*.

## Pseudo-Arclength Continuation

We use pseudo-arclength continuation to follow a family of periodic solutions.

This allows calculation past folds along a family of periodic solutions.

It also allows calculation of a “vertical family” of periodic solutions.

For periodic solutions the pseudo-arclength equation is

$$\int_0^1 (\mathbf{u}_k(t) - \mathbf{u}_{k-1}(t))^* \dot{\mathbf{u}}_{k-1}(t) dt + (T_k - T_{k-1})\dot{T}_{k-1} + (\lambda_k - \lambda_{k-1})\dot{\lambda}_{k-1} = \Delta s .$$

In summary, we have the following equations for continuing periodic solutions:

$$\mathbf{u}'_k(t) = T \mathbf{f}(\mathbf{u}_k(t), \lambda_k),$$

$$\mathbf{u}_k(0) = \mathbf{u}_k(1),$$

$$\int_0^1 \mathbf{u}_k(t)^* \mathbf{u}'_{k-1}(t) dt = 0,$$

with pseudo-arclength continuation equation

$$\int_0^1 (\mathbf{u}_k(t) - \mathbf{u}_{k-1}(t))^* \dot{\mathbf{u}}_{k-1}(t) dt + (T_k - T_{k-1})\dot{T}_{k-1} + (\lambda_k - \lambda_{k-1})\dot{\lambda}_{k-1} = \Delta s.$$

Here

$$\mathbf{u}(\cdot), \mathbf{f}(\cdot) \in \mathbb{R}^n, \quad \lambda, T \in \mathbb{R}.$$

## Starting at a Hopf Bifurcation

Let

$$(\mathbf{u}_0, \lambda_0),$$

be a Hopf bifurcation point, *i.e.*,

$$\mathbf{f}_{\mathbf{u}}(\mathbf{u}_0, \lambda_0),$$

has a simple conjugate pair of purely imaginary eigenvalues

$$\pm i \omega_0, \quad \omega_0 \neq 0,$$

and no other eigenvalues on the imaginary axis.

Also, the pair crosses the imaginary axis transversally with respect to  $\lambda$ .

By the Hopf Bifurcation Theorem, a family of periodic solutions bifurcates.



Asymptotic estimates for periodic solutions near the Hopf bifurcation :

$$\mathbf{u}(t; \epsilon) = \mathbf{u}_0 + \epsilon \phi(t) + \mathcal{O}(\epsilon^2),$$

$$T(\epsilon) = T_0 + \mathcal{O}(\epsilon^2),$$

$$\lambda(\epsilon) = \lambda_0 + \mathcal{O}(\epsilon^2).$$

Here  $\epsilon$  locally parametrizes the family of periodic solutions.

$T(\epsilon)$  denotes the period, and

$$T_0 = \frac{2\pi}{\omega_0}.$$

The function  $\phi(t)$  is the normalized nonzero periodic solution of the linearized, constant coefficient problem

$$\phi'(t) = \mathbf{f}_{\mathbf{u}}(\mathbf{u}_0, \lambda_0) \phi(t).$$

To compute a first periodic solution

$$(\mathbf{u}_1(\cdot), T_1, \lambda_1),$$

near a Hopf bifurcation  $(\mathbf{u}_0, \lambda_0)$ , we still have

$$\boxed{\mathbf{u}'_1(t) = T \mathbf{f}(\mathbf{u}_1(t), \lambda_1)}, \quad (10)$$

$$\boxed{\mathbf{u}_1(0) = \mathbf{u}_1(1)}. \quad (11)$$

Initial estimates for Newton's method are

$$\mathbf{u}_1^{(0)}(t) = \mathbf{u}_0 + \Delta s \phi(t), \quad T_1^{(0)} = T_0, \quad \lambda_1^{(0)} = \lambda_0.$$

# Hopf theorem

Above,  $\phi(t)$  is a nonzero solution of the time-scaled, linearized equations

$$\phi'(t) = T_0 \mathbf{f}_{\mathbf{u}}(\mathbf{u}_0, \lambda_0) \phi(t), \quad \phi(0) = \phi(1),$$

namely,

$$\phi(t) = \sin(2\pi t) \mathbf{w}_s + \cos(2\pi t) \mathbf{w}_c,$$

where

$$(\mathbf{w}_s, \mathbf{w}_c),$$

is a null vector in

$$\begin{pmatrix} -\omega_0 I & \mathbf{f}_{\mathbf{u}}(\mathbf{u}_0, \lambda_0) \\ \mathbf{f}_{\mathbf{u}}(\mathbf{u}_0, \lambda_0) & \omega_0 I \end{pmatrix} \begin{pmatrix} \mathbf{w}_s \\ \mathbf{w}_c \end{pmatrix} = \begin{pmatrix} \mathbf{0} \\ \mathbf{0} \end{pmatrix}, \quad \omega_0 = \frac{2\pi}{T_0}.$$

The nullspace is generically two-dimensional since

$$\begin{pmatrix} -\mathbf{w}_c \\ \mathbf{w}_s \end{pmatrix},$$

is also a null vector.

# Hopf theorem

For the phase equation we “align”  $\mathbf{u}_1$  with  $\phi(t)$ , *i.e.*,

$$\int_0^1 \mathbf{u}_1(t)^* \phi'(t) dt = 0 .$$

Since

$$\dot{\lambda}_0 = \dot{T}_0 = 0 ,$$

the pseudo-arclength equation for the first step reduces to

$$\int_0^1 (\mathbf{u}_1(t) - \mathbf{u}_0(t))^* \phi(t) dt = \Delta s .$$

- AUTO solves BVP with orthogonal collocation with adaptative mesh selection.
- Floquet multipliers are computed for free.
- The code is partially parallelized (openmp and mpi).
- AUTO can solve in a efficient way system of moderate to large dimensions.

# A difficult example: Bogdanov-Takens bifurcation

Analyze

$$\begin{aligned}\frac{du_1}{dt} &= u_2 \\ \frac{du_2}{dt} &= -n + bu_2 + u_1^2 + u_1 u_2\end{aligned}$$

*Some results on homoclinic and heteroclinic connections in planar systems*, A. Gasull, H. Giacomini and J. Torregrosa (Nonlinearity)

See also Kuznetsov's book.

Zeros, continuation and bifurcations.

# Unusual applications of continuation.

## Zeros, continuation and bifurcations.

Any problem that may be formulated as  $G(u, \lambda) = 0$  is suitable for continuation.



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- What about computing eigenvalues?

## Zeros, continuation and bifurcations.

Any problem that may be formulated as  $G(u, \lambda) = 0$  is suitable for continuation.

- What about computing eigenvalues?
- and initial value problems?

What are the eigenvalues of

$$\mathbf{A} = \begin{bmatrix} 8 & 1 & 6 \\ 3 & 5 & 7 \\ 4 & 9 & 2 \end{bmatrix} ?$$

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with Matlab,

$$\text{eig}(\mathbf{A}) = [15.0000 \quad 4.89990 \quad -4.89990]$$

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with Matlab,

$$\text{eig}(\mathbf{A}) = [15.0000 \quad 4.89990 \quad -4.89990]$$

with AUTO

$$(\mathbf{A} - \lambda I)\mathbf{v} = 0$$

## Example: The Lorenz Equations

(AUTO demos lor, lrz, man.)

$$x' = \sigma (y - x) ,$$

$$y' = \rho x - y - x z ,$$

$$z' = x y - \beta z ,$$

where

$$\sigma = 10 \quad \text{and} \quad \beta = 8/3 .$$

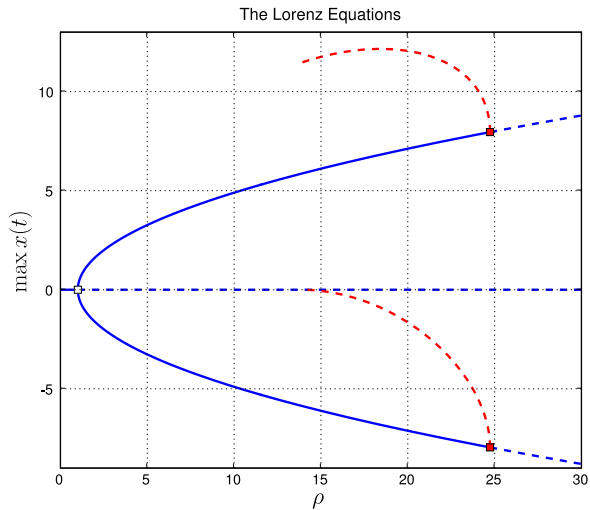


Figure 68: Bifurcation diagram of the Lorenz equations.



## NOTE:

- The zero solution is unstable for  $\rho > 1$ .
- Two nonzero stationary solutions bifurcate at  $\rho = 1$ .
- The nonzero stationary solutions become unstable for  $\rho > \rho_H$ .
- At  $\rho_H$  ( $\rho_H \approx 24.7$ ) there are Hopf bifurcations.
- Unstable periodic solutions emanate from each Hopf bifurcation.
- These families end in *homoclinic orbits* (infinite period) at  $\rho \approx 13.9$ .
- For  $\rho > \rho_H$  there is the famous *Lorenz attractor*.

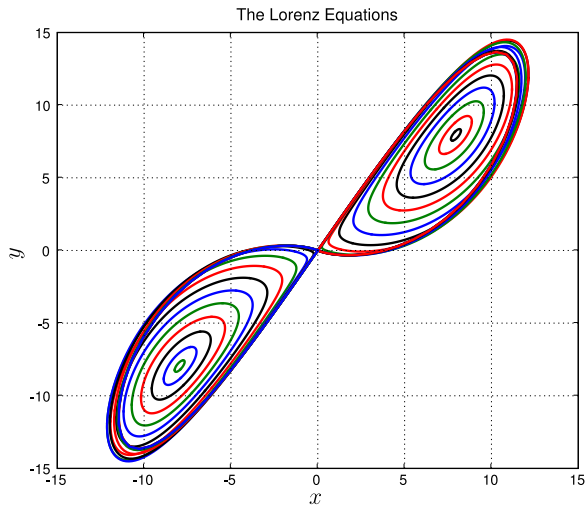


Figure 69: Unstable periodic orbits of the Lorenz equations.

# The Lorenz Manifold

- For  $\rho > 1$  the origin is a *saddle point*.
- The Jacobian has two negative eigenvalues and one positive eigenvalue.
- The two negative eigenvalues give rise to a 2D *stable manifold*.
- This manifold is known as as the *Lorenz Manifold*.
- The Lorenz Manifold helps us understand the *Lorenz attractor*.

Discrete and Continuous Dynamical Systems, 2010; (to appear).

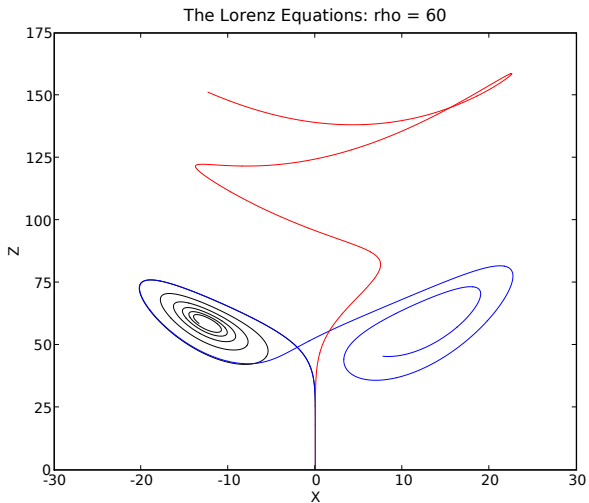


Figure 70: Three orbits whose initial conditions agree to  $>11$  decimal places !

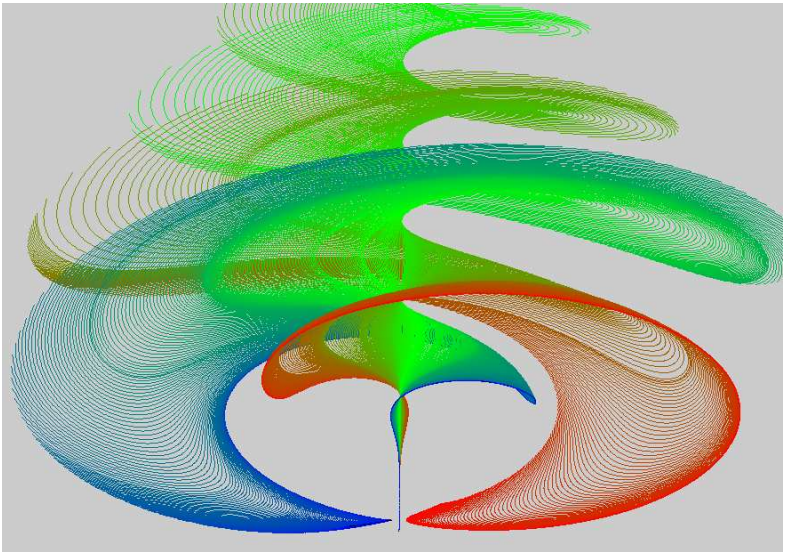


Figure 71: A small portion of a Lorenz Manifold ...

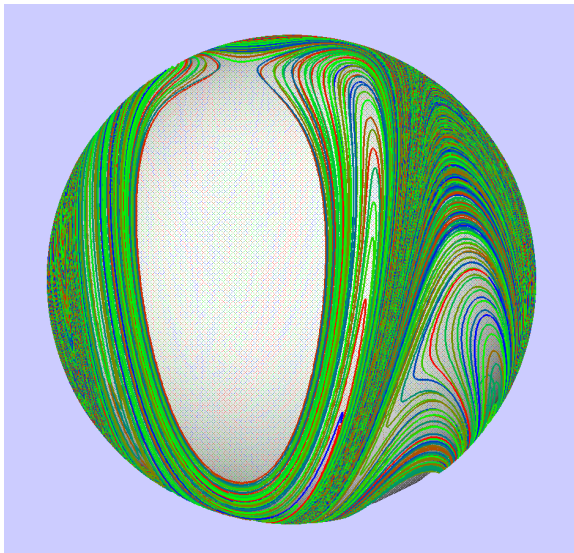


Figure 72: Intersection of a Lorenz Manifold with a sphere ( $\rho = 35$ ,  $R = 100$ ).

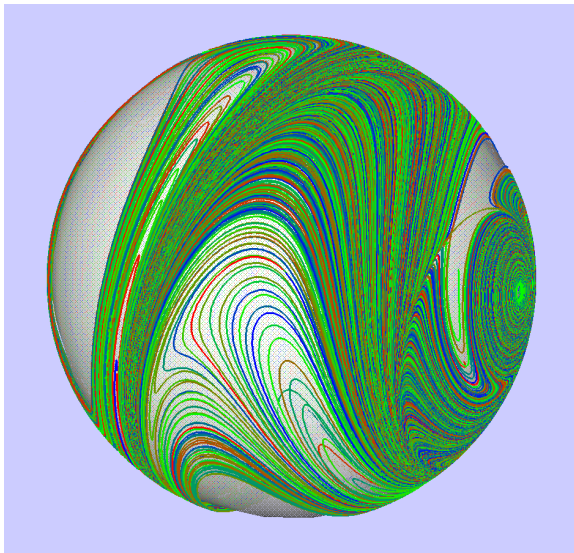


Figure 73: Intersection of a Lorenz Manifold with a sphere ( $\rho = 35$ ,  $R = 100$ ).

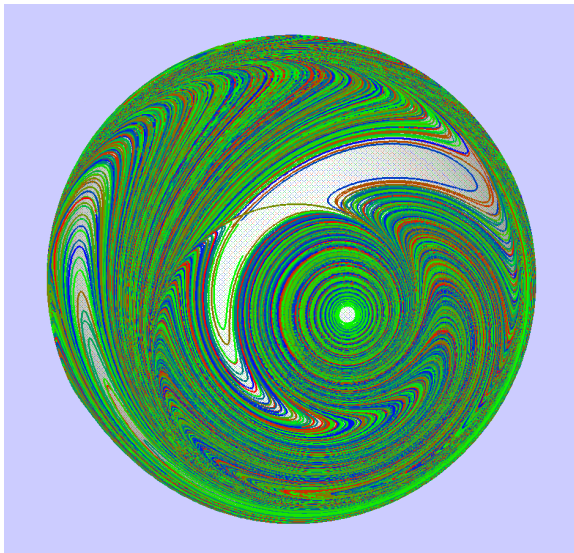


Figure 74: Intersection of a Lorenz Manifold with a sphere ( $\rho = 35$ ,  $R = 100$ ).



## NOTE:

- As shown, crossings of the Lorenz manifold with *a sphere* can be located.
- Crossings of the Lorenz manifold with *the plane*  $z = \rho - 1$  can be located.
- Connections between the origin and the nonzero equilibria can be located.
- There are subtle variations on the algorithm !

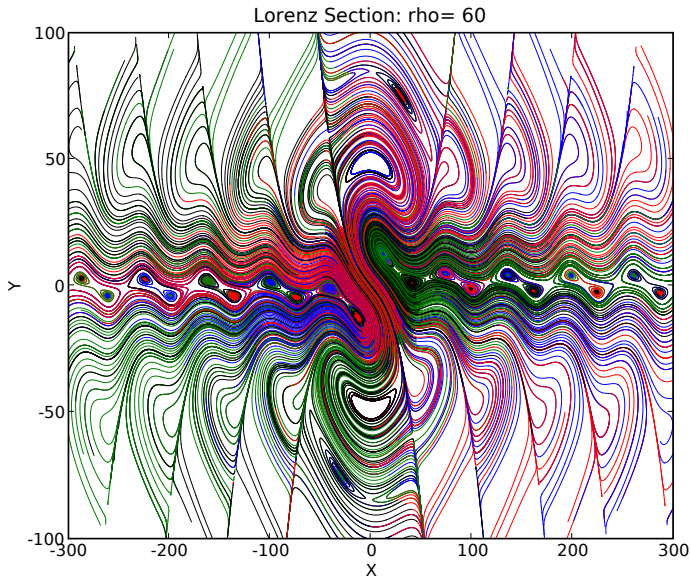


Figure 75: Crossings of the Lorenz Manifold with the plane  $z = \rho - 1$

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