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Classification of Autonomous Linear 2 × 2 Systems

Autonomore Linear Systems

A Digression

Math 286 Introduction to Differential Equations

Thomas Honold



ZJU-UIUC Institute



Fall Semester 2021

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of
Autonomous
Linear 2 × 2
Systems

Stability of Autonomou Linear Systems

A Digression

Outline

1 Classification of Autonomous Linear 2 × 2 Systems

2 Stability of Autonomous Linear Systems

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Today's Lecture:

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Classification

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The goal of this section is to examine the qualitative behaviour, including the asymptotics for $t \to \infty$ of solutions $\mathbf{y} \colon \mathbb{R} \to \mathbb{R}^2$, $t \mapsto \mathbf{y}(t) = (y_1(t), y_2(t))^\mathsf{T}$, of ODE systems of the form

 $\mathbf{v}' = \mathbf{A}\mathbf{v} + \mathbf{b}$ with $\mathbf{A} \in \mathbb{R}^{2 \times 2}$, $\mathbf{b} \in \mathbb{R}^2$.

and corresponding IVP's $\mathbf{y}' = \mathbf{A}\mathbf{y} + \mathbf{b}$, $y(t_0) = \mathbf{y}_0$.

Facts already known

- 1 All maximal solutions are parametric plane curves with domain \mathbb{R} .
 - 2 The corresponding non-parametric curves $\{y(t); t \in \mathbb{R}\}$ (orbits, trajectories) partition \mathbb{R}^2 (the phase plane).
- 3 Solutions $\mathbf{y}_1(t)$, $\mathbf{y}_2(t)$ determine the same orbit iff

 $\mathbf{y}_2(t) = \mathbf{y}_1(t+t_0)$ for some $t_0 \in \mathbb{R}$. These hold, mutatis mutandis, also for higher-dimensional autonomous linear systems and are consequences of the

sharpened version of the EUT in the linear case. In view of (3) we only need to consider IVP's with $t_0 = 0$.

Systems

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Definition

A point $\mathbf{y}_0 \in \mathbb{R}^2$ is said to be a *critical point* of $\mathbf{y}' = \mathbf{A}\mathbf{y} + \mathbf{b}$ if there is the constant solution $\mathbf{y}(t) \equiv \mathbf{y}_0$; equivalently, $\{\mathbf{y}_0\}$ is an orbit.

Clearly this equivalent to $\mathbf{A}\mathbf{y}_0 + \mathbf{b} = \mathbf{0}$.

Non-constant solutions $\mathbf{y}(t)$ satisfy $\mathbf{y}'(t) \neq \mathbf{0}$ for all $t \in \mathbb{R}$ and hence are smooth.

Tangent vectors (velocity vectors) at non-critical points are uniquely determined (from Property (3) or directly from $\mathbf{y}' = \mathbf{A}\mathbf{y} + \mathbf{b}$).

 \Longrightarrow Orbits have a direction of traverse at each of their points. This is indicated in a plot of the *direction field* (the vector field $\mathbb{R}^2 \to \mathbb{R}^2$, $\mathbf{x} \mapsto \mathbf{A}\mathbf{x} + \mathbf{b}$) and in a *phase portrait* (representative collection of orbits) by corresponding arrows.

Since the critical points of $\mathbf{y}' = \mathbf{A}\mathbf{y} + \mathbf{b}$ are the solutions of $\mathbf{A}\mathbf{x} = -\mathbf{b}$, they form an affine subspace of \mathbb{R}^2 . The possible cases are:

- 1 No critical point (\iff rk $\mathbf{A} \le 1 \land \mathbf{b} \notin \operatorname{csp} \mathbf{A}$);
- 2 exactly one critical point (\iff rk $\mathbf{A} = 2$);
- 3 a critical line (\iff rk $\mathbf{A} = 1 \land \mathbf{b} \in \operatorname{csp} \mathbf{A}$).
- 4 All points of \mathbb{R}^2 are critical ($\iff \mathbf{A} = \mathbf{0} \land \mathbf{b} = \mathbf{0}$).

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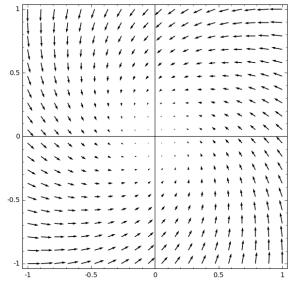


Figure: Direction field of $\mathbf{y}' = \begin{pmatrix} -1 & -1 \\ 1 & -1 \end{pmatrix} \mathbf{y}$

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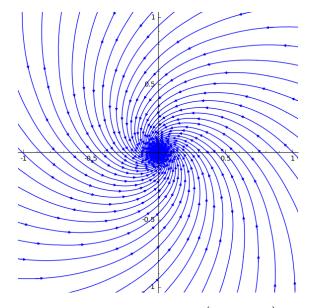


Figure: Phase portrait of $\mathbf{y}' = \begin{pmatrix} -1 & -1 \\ 1 & -1 \end{pmatrix} \mathbf{y}$

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Observation

An affine coordinate change $\mathbf{y} = \mathbf{Sz} + \mathbf{v}$ ($\mathbf{S} \in \mathbb{R}^{2 \times 2}$ invertible, $\mathbf{v} \in \mathbb{R}^2$) preserves most of the qualitative properties of the solutions (and of a phase portrait). If \mathbf{S} is not orthogonal, however, it may distort angles and distances.

The effect on the ODE of such a coordinate transformation is:

$$\begin{split} & z = S^{-1}(y-v) = S^{-1}y - S^{-1}v, \\ & z' = S^{-1}y' = S^{-1}(Ay+b) = S^{-1}ASz + S^{-1}(Av+b), \end{split}$$

i.e., the transformed system is $\mathbf{z}' = \widehat{\mathbf{A}}\mathbf{z} + \widehat{\mathbf{b}}$ with $\widehat{\mathbf{A}} = \mathbf{S}^{-1}\mathbf{A}\mathbf{S}$ and $\widehat{\mathbf{b}} = \mathbf{S}^{-1}(\mathbf{A}\mathbf{v} + \mathbf{b})$.

Consequences

- If there are critical points (\iff there exists $\mathbf{v} \in \mathbb{R}^2$ such that $\mathbf{A}\mathbf{v} + \mathbf{b} = \mathbf{0}$), we can transform the system into a homogeneous system $\mathbf{z}' = \widehat{\mathbf{A}}\mathbf{z}$ (which has at least one critical point, viz. the origin $\mathbf{0}$). The critical points of $\mathbf{z}' = \widehat{\mathbf{A}}\mathbf{z}$ are those in $\text{rker}(\widehat{\mathbf{A}})$.
 - When classifying homogeneous systems y' = Ay, we only need to consider one matrix from each complex similarity class that contains a real matrix.

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Consequences cont'd

Reason: If **A**, **B** are real and similar over \mathbb{C} , they must be similar over \mathbb{R} ; see subsequent exercise. Thus we can find a linear coordinate transformation $\mathbf{y} = \mathbf{Sz}$, $\mathbf{S} \in \mathbb{R}^{2 \times 2}$, which transforms $\mathbf{y}' = \mathbf{Ay}$ into $\mathbf{z}' = \mathbf{Bz}$.

Exercise

Suppose that $\mathbf{A}, \mathbf{B} \in \mathbb{R}^{n \times n}$ and $\mathbf{T} \in \mathbb{C}^{n \times n}$ satisfy $\mathbf{B} = \mathbf{T}^{-1}\mathbf{A}\mathbf{T}$.

- a) Setting $\mathbf{T} = \mathbf{P} + i\mathbf{Q}$ with $\mathbf{P}, \mathbf{Q} \in \mathbb{R}^{n \times n}$, show that \mathbf{P}, \mathbf{Q} satisfy the matrix equation $\mathbf{AX} = \mathbf{XB}$.
- b) Show that any matrix $\mathbf{S} = \mathbf{P} + \lambda \mathbf{Q}$, $\lambda \in \mathbb{R}$, satisfies this matrix equation as well.
- c) Show that that there exists $\lambda \in \mathbb{R}$ such that $\mathbf{P} + \lambda \mathbf{Q}$ is invertible.
 - *Hint:* Show that $\lambda \mapsto \det(\mathbf{P} + \lambda \mathbf{Q})$ is a polynomial function.
- d) Use a), b), c) to show that there exists $\mathbf{S} \in \mathbb{R}^{n \times n}$ such that $\mathbf{B} = \mathbf{S}^{-1} \mathbf{A} \mathbf{S}$.

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The Classification

First we consider the genuinely inhomogeneous systems $\mathbf{y}' = \mathbf{A}\mathbf{y} + \mathbf{b}$, i.e., those with $\mathbf{b} \notin \operatorname{csp}(\mathbf{A})$ and hence without a critical point/stationary solution.

Up to similarity, there are three cases to consider: (1) $\mathbf{A} = \mathbf{0}$; (2) $\operatorname{rk} \mathbf{A} = 1$ and \mathbf{A} is diagonalisable, i.e., similar to $\begin{pmatrix} 0 & 0 \\ 0 & \lambda \end{pmatrix}$ for some $\lambda \in \mathbb{R} \setminus \{0\}$; (3) $\operatorname{rk} \mathbf{A} = 1$ and \mathbf{A} is not diagonalisable, i.e., \mathbf{A} has the eigenvalue 0 with algebraic multiplicity 2 and geometric multiplicity 1, and hence is similar to $\begin{pmatrix} 0 & 0 \\ 1 & 0 \end{pmatrix}$.

Case 1:
$$\mathbf{A} = \begin{pmatrix} 0 & 0 \\ 0 & 0 \end{pmatrix}$$
, $\mathbf{b} = \begin{pmatrix} b_1 \\ b_2 \end{pmatrix} \neq \begin{pmatrix} 0 \\ 0 \end{pmatrix}$.

The general solution is $\mathbf{y}(t) = t \, \mathbf{b} + \mathbf{c}$, i.e., parallel lines with direction vector \mathbf{b} parametrized in the usual way.

A linear coordinate transformation $\mathbf{y} = \mathbf{Sz}$ (which doesn't change \mathbf{A}) could be applied to move \mathbf{b} to any fixed nonzero vector, e.g., $\mathbf{e}_1 = (1,0)^T$, but this is hardly necessary in this case.

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Case 2:
$$\mathbf{A} = \begin{pmatrix} 0 & 0 \\ 0 & \lambda \end{pmatrix}$$
, $\mathbf{b} = \begin{pmatrix} b_1 \\ b_2 \end{pmatrix}$ with $b_1 \neq 0$.

We can apply a coordinate change of the form $\mathbf{y} = \begin{pmatrix} s & 0 \\ 0 & s \end{pmatrix} \mathbf{z} + \mathbf{v} = s\mathbf{z} + \mathbf{v}$ with $s \neq 0$ (which does not change \mathbf{A}) to move \mathbf{b} into \mathbf{e}_1 . (The explicit transformation is $z_1 = y_1/b_1$, $z_2 = (y_2 + b_2/\lambda)/b_1$.) The new system is equivalent to the scalar equations $y_1' = 1$, $y_2' = \lambda y_2$, which has the general solution

$$\mathbf{y}(t) = \begin{pmatrix} t + c_1 \\ c_2 e^{\lambda t} \end{pmatrix}.$$

The orbits, written as graphs y(x) ($x ext{ } ext$

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Case 3:
$$\mathbf{A} = \begin{pmatrix} 0 & 0 \\ 1 & 0 \end{pmatrix}$$
, $\mathbf{b} = \begin{pmatrix} b_1 \\ b_2 \end{pmatrix}$ with $b_1 \neq 0$.

Again we may assume $\mathbf{b} = (1,0)^T$, and in this case obtain the system $y_1' = 1$, $y_2' = y_1$, which has general solution

$$\mathbf{y}(t) = \begin{pmatrix} t + c_1 \\ t^2/2 + c_1 t + c_2 \end{pmatrix}.$$

From $\mathbf{y}(t-c_1)=\begin{pmatrix}t\\t^2/2+c_1^2/2+c_2\end{pmatrix}$ we see (using a further scaling $\mathbf{z}=\frac{1}{2}\,\mathbf{y}$) that the orbits, written as graphs y(x) ($x\triangleq y_1,\,y\triangleq y_2$) are $y(x)=x^2+c,\,c\in\mathbb{R}$ (integral curves of y'=2x).

Note that families of parabolas, in order to qualify for the orbits of a system $\mathbf{y}' = \mathbf{A}\mathbf{y} + \mathbf{b}$, must partition the plane. Up to a scaling factor this leaves only the possibility of the family which arises from a fixed parabola by shifting it along its axis.

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In the remaining cases $\mathbf{y}' = \mathbf{A}\mathbf{y} + \mathbf{b}$ has at least one critical point. After a translation, one of these may be taken as the origin (0,0), implying that the transformed system is homogeneous.

We consider the cases with non-invertible A first.

Case 4:
$$\mathbf{A} = \begin{pmatrix} 0 & 0 \\ 0 & 0 \end{pmatrix}$$
, $\mathbf{b} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}$.

The general solution is $\mathbf{y}(t) \equiv \mathbf{c}$. All points of \mathbb{R}^2 are critical.

Case 5:
$$\mathbf{A} = \begin{pmatrix} 0 & 0 \\ 0 & \lambda \end{pmatrix}$$
, $\mathbf{b} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}$.

The system is equivalent to $y_1' = 0$, $y_2' = \lambda y_2$ and has general solution

$$\mathbf{y}(t) = \begin{pmatrix} c_1 \\ c_2 e^{\lambda t} \end{pmatrix}.$$

The orbits are the points with $c_2=0$ (i.e. the points on the *x*-axis, which forms the critical line in this case), and the vertical rays $(c_1,0)\pm\mathbb{R}^+(0,1)$. The direction of traverse of the rays depends on the sign of λ .

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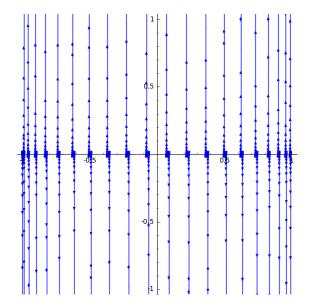


Figure: Phase portrait of
$$\mathbf{y}' = \begin{pmatrix} 0 & 0 \\ 0 & 1 \end{pmatrix} \mathbf{y}$$

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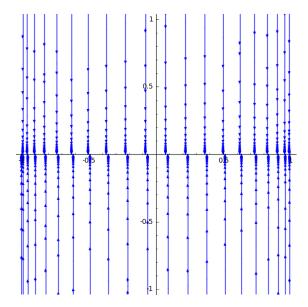


Figure: Phase portrait of
$$\mathbf{y}' = \begin{pmatrix} 0 & 0 \\ 0 & -1 \end{pmatrix} \mathbf{y}$$

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Case 6:
$$\mathbf{A} = \begin{pmatrix} 0 & 0 \\ 1 & 0 \end{pmatrix}, \mathbf{b} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}.$$

The system is equivalent to $y'_1 = 0$, $y'_2 = y_1$ and has general solution

$$\mathbf{y}(t) = \begin{pmatrix} c_1 \\ c_1 t + c_2 \end{pmatrix} = \begin{pmatrix} c_1 \\ c_2 \end{pmatrix} + t \begin{pmatrix} 0 \\ c_1 \end{pmatrix}.$$

The orbits are the points with $c_1=0$ (i.e. the points on the *y*-axis, which forms the critical line in this case), and the vertical lines $(c_1,c_2)+\mathbb{R}(0,c_1)=(c_1,0)+\mathbb{R}(0,1)$. The direction of traverse of the lines is determined by the sign of c_1 . It is N (northward) in the right half plane x>0 and S (southward) in the left half plane x<0.

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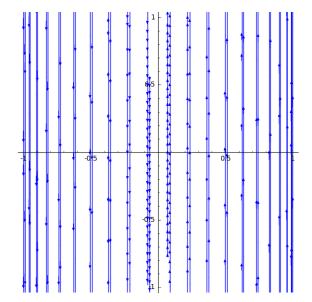


Figure: Phase portrait of
$$\mathbf{y}' = \begin{pmatrix} 0 & 0 \\ 1 & 0 \end{pmatrix} \mathbf{y}$$

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invertible A. These have exactly one critical point, which can be taken as the origin (0,0), making the system homogeneous. If **A** has two distinct eigenvalues λ_1, λ_2 then **A** is diagonalizable

It remains to consider representatives of the systems with

and can be taken as the diagonal matrix $\begin{pmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{pmatrix}$. If $\lambda_1 \in \mathbb{C} \setminus \mathbb{R}$ then necessarily $\lambda_2 = \overline{\lambda}_1$.

If **A** has only one eigenvalue λ of multiplicity 2 then necessarily $\lambda \in \mathbb{R}$, and either **A** is diagonalizable and equal to $\begin{pmatrix} \lambda & 0 \\ 0 & \lambda \end{pmatrix} = \lambda \mathbf{I}_2$ or **A** is not diagonalizable and similar to $\begin{pmatrix} \lambda & 0 \\ 1 & \lambda \end{pmatrix}$.

These cases can be easily distinguished: If $\mathbf{A} = \begin{pmatrix} a & b \\ c & d \end{pmatrix}$ then $\chi_{\mathbf{A}}(X) = X^2 - (a+d)X + ad - bc$

$$\lambda_{1/2} = rac{1}{2} \left(a + d \pm \sqrt{(a+d)^2 - 4(ad-bc)}
ight)$$

$$= rac{1}{2} \left(a + d \pm \sqrt{(a-d)^2 + 4bc}
ight).$$

For example, A has purely imaginary eigenvalues iff the trace is zero (i.e., d = -a) and $a^2 + bc < 0$; in this case $\lambda_{1/2} = \pm i\sqrt{-a^2 - bc}$.

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Case 7: Two distinct nonzero real eigenvalues

If the eigenvalues are λ_1,λ_2 with corresponding eigenvectors $\mathbf{v_1},\mathbf{v_2}$ then the general real solution is

$$\mathbf{y}(t) = c_1 e^{\lambda_1 t} \mathbf{v}_1 + c_2 e^{\lambda_2 t} \mathbf{v}_2, \quad c_1, c_2 \in \mathbb{R}.$$

The four rays $\mathbb{R}^+(\pm \mathbf{v}_1)$, $\mathbb{R}^+(\pm \mathbf{v}_2)$ form orbits (arising from solutions with $c_1=0$ or $c_2=0$).

- 1 $\lambda_1 > \lambda_2 > 0$: Non-stationary solutions $\mathbf{y}(t)$ are unbounded for $t \to \infty$ and satisfy $\lim_{t \to -\infty} \mathbf{y}(t) = \mathbf{0}$. In this case the critical point $\mathbf{0}$ is called a *nodal source*.
- 2 $\lambda_1 < \lambda_2 < 0$: Compared with (1), the roles of $\pm \infty$ are reversed. In particular we have $\lim_{t\to\infty} \mathbf{y}(t) = \mathbf{0}$ for every non-constant solution. Here $\mathbf{0}$ is called a *nodal sink*.
- (3) $\lambda_1 > 0 > \lambda_2$: Here we have $\lim_{t \to -\infty} e^{\lambda_1 t} (\pm \mathbf{v}_1) = \lim_{t \to +\infty} e^{\lambda_2 t} (\pm \mathbf{v}_2) = \mathbf{0}$, i.e., the arrows point outwards (inwards) on the two rays contained in $\mathbb{R}\mathbf{v}_1$ (resp., in $\mathbb{R}\mathbf{v}_2$). For $t \to \infty$ all non-constant solutions approach a ray solution containd in $\mathbb{R}\mathbf{v}_1$ (resp., for $t \to -\infty$ emerge from a ray solution containd in $\mathbb{R}\mathbf{v}_2$). In this case $\mathbf{0}$ is called a *saddle point*.

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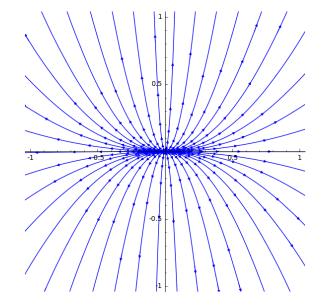


Figure: Phase portrait of $\mathbf{y}' = \begin{pmatrix} 1 & 0 \\ 0 & 2 \end{pmatrix} \mathbf{y}$ The origin is a nodal source.

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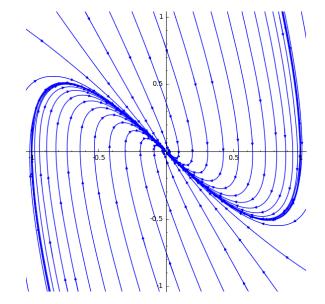


Figure: Phase portrait of $\mathbf{y}'=\begin{pmatrix} 0 & 1 \\ -2 & -3 \end{pmatrix}\mathbf{y}$ The origin is a nodal sink.

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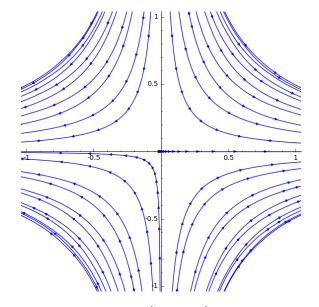


Figure: Phase portrait of $\mathbf{y}' = \begin{pmatrix} 1 & 0 \\ 0 & -1 \end{pmatrix} \mathbf{y}$ The origin is a saddle point.

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Exercise

- a) Suppose that **A** has two distinct real eigenvalues λ_1, λ_2 with corresponding eigenvectors $\mathbf{v}_1, \mathbf{v}_2$. Show that for $t \to \pm \infty$ the tangent unit vector $\frac{\mathbf{y}'(t)}{|\mathbf{y}'(t)|}$ of any non-constant solution $\mathbf{y}(t)$ approaches the direction of one of the four rays $\mathbb{R}^+(\pm \mathbf{v}_1), \mathbb{R}^+(\pm \mathbf{v}_2)$ (i.e., $\pm \frac{\mathbf{v}_1}{|\mathbf{v}_1|}, \pm \frac{\mathbf{v}_2}{|\mathbf{v}_2|}$).
- b) Work out the four possible cases (including the explicit determination of the rays) for the system

$$\mathbf{y}' = \left(\begin{array}{cc} 0 & 1 \\ -2 & -3 \end{array} \right) \mathbf{y}.$$

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Case 8: Two equal (real) eigenvalues, diagonalisable In this case $\mathbf{A} = \lambda \mathbf{I}_2$ and the general solution is

$$\mathbf{y}(t) = \begin{pmatrix} c_1 e^{\lambda t} \\ c_2 e^{\lambda t} \end{pmatrix} = e^{\lambda t} \begin{pmatrix} c_1 \\ c_2 \end{pmatrix}.$$

 \Longrightarrow **y**(t) moves on the ray $\mathbb{R}^+(c_1,c_2)$, provided that $(c_1,c_2) \neq (0,0)$. The direction of traverse is determined by the sign of λ .

One sees that the orbits of non-constant solutions are precisely the rays $\mathbb{R}^+\mathbf{c}$, $\mathbf{c} \in \mathbb{R}^2 \setminus \{\mathbf{0}\}$. Accordingly, the orrigin is called a *star point* in this case.

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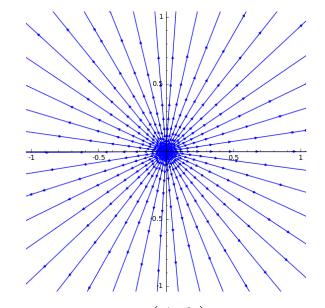


Figure: Phase portrait of $\mathbf{y}' = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \mathbf{y}$ The origin is a star point.

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Exercise Suppose $\mathbf{A} = \begin{pmatrix} \lambda_1 \\ \lambda_2 \end{pmatrix}$ with $\lambda_1 \lambda_2 \neq 0$. (This is essentially Case 7 with $\mathbf{v}_1 = \mathbf{e}_1$, $\mathbf{v}_2 = \mathbf{e}_2$, with the possibility $\lambda_1 = \lambda_2$ included; cf. Case 8.)

a) Which one-parameter family of functions y(x) gives rise to the orbits of $\mathbf{y}' = \mathbf{A}\mathbf{y}$? From which scalar ODE does this family arise?

Hint: Eliminate *t*.

- b) Under which conditions on λ_1 , λ_2 do the orbits form straight lines, respectively, hyperbolas?
- c) What can you conclude from a), b) about the form of the orbits in Case 7 and Case 8 in general?

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Case 9: Two equal (real) eigenvalues, not diagonalisable

In this case the general solution is

$$\mathbf{y}(t) = c_1 \left(e^{\lambda t} \mathbf{v} + t e^{\lambda t} (\mathbf{A} - \lambda \mathbf{I}) \mathbf{v} \right) + c_2 e^{\lambda t} (\mathbf{A} - \lambda \mathbf{I}) \mathbf{v}$$
$$= c_1 e^{\lambda t} \mathbf{v} + (c_1 t + c_2) e^{\lambda t} (\mathbf{A} - \lambda \mathbf{I}) \mathbf{v},$$

where λ denotes the eigenvalue of **A** and **v** is any nonzero vector in \mathbb{R}^2 that is not an eigenvector of **A** (**v** can be taken as \mathbf{e}_1 or \mathbf{e}_2).

There are only two ray orbits, viz. $\pm \mathbb{R}^+(\mathbf{A} - \lambda \mathbf{I})\mathbf{v}$ (contained in the line through the origin spanned by the eigenvector).

The tangent direction of every non-constant solution approaches one of the two ray directions for $t \to \pm \infty$, as can be seen from

$$\mathbf{y}'(t) = c_1 \lambda e^{\lambda t} \mathbf{v} + c_2 \lambda e^{\lambda t} (\mathbf{A} - \lambda \mathbf{I}) \mathbf{v} + c_1 (1 + \lambda t) e^{\lambda t} (\mathbf{A} - \lambda \mathbf{I}) \mathbf{v}$$

$$= t e^{\lambda t} \left[c_1 \lambda (\mathbf{A} - \lambda \mathbf{I}) \mathbf{v} + \frac{c_1 + c_2 \lambda}{t} (\mathbf{A} - \lambda \mathbf{I}) \mathbf{v} + \frac{c_1 \lambda}{t} \mathbf{v} \right].$$

Accordingly, **0** is called an *improper node* in this case.

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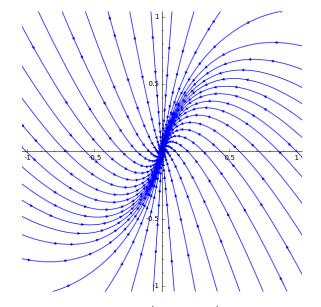


Figure: Phase portrait of $\mathbf{y}' = \begin{pmatrix} -1 & 0 \\ 1 & -1 \end{pmatrix} \mathbf{y}$ The origin is an improper node.

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Case 10: A pair of conjugate complex eigenvalues

If the eigenvalues are $\lambda_1=\mu+\mathrm{i}\,\alpha,\,\lambda_2=\mu-\mathrm{i}\,\alpha$ and $\mathbf{v}_1,\mathbf{v}_2$ are corresponding eigenvectors satisfying $\overline{\mathbf{v}}_1=\mathbf{v}_2,\,$ a complex fundamental system of solutions is $\mathbf{y}_1(t)=\mathrm{e}^{(\mu+\mathrm{i}\,\alpha)t}\mathbf{v}_1,\,$ $\mathbf{y}_2(t)=\overline{\mathbf{y}_1(t)}=\mathrm{e}^{(\mu-\mathrm{i}\,\alpha)t}\overline{\mathbf{v}}_1.$

A real fundamental system of solutions is obtained by extracting real and imaginary part of one complex fundamental solution, say $\mathbf{y}_1(t)$, and is given by

$$\begin{split} t &\mapsto \mathrm{e}^{\mu t} \left[\cos(\alpha t) \operatorname{Re} \mathbf{v}_1 - \sin(\alpha t) \operatorname{Im} \mathbf{v}_1 \right], \\ t &\mapsto \mathrm{e}^{\mu t} \left[\cos(\alpha t) \operatorname{Im} \mathbf{v}_1 + \sin(\alpha t) \operatorname{Re} \mathbf{v}_1 \right]. \end{split}$$

- 1 $\mu > 0$: In this case non-constant solutions are unbounded for $t \to \infty$ and spiral towards 0 for $t \to -\infty$. The critical point 0 is called a *spiral source*.
- 2 μ < 0: The roles of $\pm\infty$ are reversed and solutions spiral into **0** for $t \to +\infty$. The critical point **0** is called a *spiral sink*.
- 3 $\mu=0$: Orbits of non-constant solutions are closed curves (in fact ellipses), and are traversed periodically (with period of revolution $2\pi/\alpha$). The critical point **0** is called a *center*.

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 $\begin{array}{c} \text{Classification} \\ \text{of} \\ \text{Autonomous} \\ \text{Linear 2} \times \text{2} \\ \text{Systems} \end{array}$

Stability of Autonomou Linear Systems

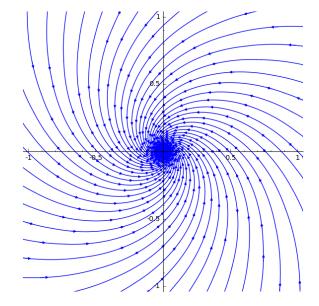


Figure: Phase portrait of $\mathbf{y}' = \begin{pmatrix} -1 & -1 \\ 1 & -1 \end{pmatrix} \mathbf{y}$ The origin is a spiral sink.

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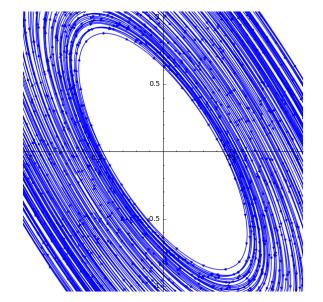


Figure: Phase portrait of $\mathbf{y}' = \begin{pmatrix} 1 & 1 \\ -2 & -1 \end{pmatrix} \mathbf{y}$ The origin is a center.

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Systems $\mathbf{y}' = \mathbf{A}\mathbf{y} + \mathbf{b}$

Recall that a steady-state solution (equilibrium solution, constant solution) $y(t) \equiv y_0$ of a scalar autonomous ODE y' = f(y) was called *asymptotically stable* if there exists $\delta > 0$ such that any solution y(t) satisfying $|y(0) - y_0| < \delta$ exists for all t > 0 and satisfies $\lim_{t \to \infty} y(t) = y_0$ (and "unstable" otherwise).

Definition

Suppose \mathbf{y}_0 is a critical point of the autonomous linear system $\mathbf{y}' = \mathbf{A}\mathbf{y} + \mathbf{b}$ (i.e., $\mathbf{A}\mathbf{y}_0 + \mathbf{b} = \mathbf{0}$ and $\mathbf{y}(t) \equiv \mathbf{y}_0$ is a solution).

1 \mathbf{y}_0 is said to be *stable* if for every $\epsilon > 0$ there exists $\delta > 0$ such that every solution $\mathbf{y}(t)$ of $\mathbf{y}' = \mathbf{A}\mathbf{y} + \mathbf{b}$ with $|\mathbf{y}(0) - \mathbf{y}_0| < \delta$ satisfies

$$|\mathbf{y}(t) - \mathbf{y}_0| < \epsilon$$
 for all $t \ge 0$;

- 2 \mathbf{y}_0 is said to be *asymptotically*) stable if there exists $\delta > 0$ such that every solution $\mathbf{y}(t)$ of $\mathbf{y}' = \mathbf{A}\mathbf{y} + \mathbf{b}$ with $|\mathbf{y}(0) \mathbf{y}_0| < \delta$ satisfies $\lim_{t \to +\infty} \mathbf{y}(t) = \mathbf{y}_0$;
- 3 \mathbf{v}_0 is said to *unstable* otherwise.

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Notes

- 1 The definitions are stated in a manner that makes sense for not necessarily linear autonomous systems $\mathbf{y}' = f(\mathbf{y})$. For linear autonomous systems (1) simplifies to "every solution is bounded on $[0,\infty)$ " and (2) to "every solution satisfies $\lim_{t\to +\infty} \mathbf{y}(t) = \mathbf{y}_0$ ".
- 2 A critical point \mathbf{y}_0 of $\mathbf{y}' = \mathbf{A}\mathbf{y} + \mathbf{b}$ is stable/asymptotically stable/unstable iff the critical point $\mathbf{0}$ of $\mathbf{y}' = \mathbf{A}\mathbf{y}$ has this property. (This follows from the fact that $\mathbf{y}(t)$ solves $\mathbf{y}' = \mathbf{A}\mathbf{y} + \mathbf{b}$ iff $\mathbf{y}(t) \mathbf{y}_0$ solves $\mathbf{y}' = \mathbf{A}\mathbf{y}$.) Hence (1)–(3) are actually properties of the matrix \mathbf{A} . Accordingly we also say that \mathbf{A} is stable/asymptotically stable/unstable in the respective cases.
- 3 A system with more than one critical point cannot be asymptotically stable. For this note that the critical points form an affine subspace C of \mathbb{R}^n . If the dimension of C is ≥ 1 then there are constant solutions arbitrarily close to but different from a given constant solution $\mathbf{y}(t) \equiv \mathbf{y}_0$, and these don't converge to \mathbf{y}_0 .

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Notes (cont'd)

4 The definition can be extended to non-constant solutions $\mathbf{y}_0(t)$ in the obvious way. For linear systems this doesn't yield anything substantially new, however, because for any further solution $\mathbf{y}(t)$ the difference is a solution of the associated homogeneous system.

Using the reduction to the homogeneous case $\mathbf{v}' = \mathbf{A}\mathbf{v}$ in Note 2, we now show the simplifications announced in Note 1: (1) If **0** is a stable point of $\mathbf{y}' = \mathbf{A}\mathbf{y}$, there exists $\delta > 0$ such that $|\mathbf{y}(0)| < \delta$ implies $|\mathbf{y}(t)| < 1$ for $t \ge 0$. If $\mathbf{y}(t)$ is an arbitrary nonzero solution, there exists $\lambda > 0$ such that $|\lambda y(0)| < \delta$ (take $\lambda = \frac{\delta}{2\mathbf{v}(0)}$). Since $\lambda \mathbf{y}(t)$ is a solution as well, this implies $|\lambda \mathbf{y}(t)| < 1$ and hence $|\mathbf{y}(t)| < 1/\lambda$ for all t > 0. Conversely, suppose every solution of $\mathbf{y}' = \mathbf{A}\mathbf{y}$ is bounded on $[0,\infty)$ and let $\mathbf{y}_1(t),\ldots,\mathbf{y}_n(t)$ be a fundamental system of solutions of $\mathbf{y}' = \mathbf{A}\mathbf{y}$. Then there exist M, m > 0 such that $|\mathbf{y}_i(t)| \leq M$ for $t \geq 0$ and $1 \leq i \leq n$ (boundedness assumption) and $|c_1\mathbf{y}_1(0) + \cdots + c_n\mathbf{y}_n(0)| \geq m$ for all $\mathbf{c} = (c_1, \dots, c_n) \in \mathbb{R}^n$ with $|\mathbf{c}| = 1$ (compactness of the unit sphere $S^{n-1} = S_1(\mathbf{0})$).

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Notes (cont'd)

Now we claim that in the definition of stability of ${\bf 0}$ we can choose $\delta = \frac{\epsilon m}{\sqrt{n} M}$. Indeed, assume ${\bf y}(t) = c_1 {\bf y}_1(t) + \cdots + c_n {\bf y}_n(t)$ is a nonzero solution of ${\bf y}' = {\bf A}{\bf y}$ satisfying $|c_1 {\bf y}_1(0) + \cdots + c_n {\bf y}_n(0)| < \frac{\epsilon m}{\sqrt{n} M}$. Then we must have $|{\bf c}| < \frac{\epsilon}{\sqrt{n} M}$ (since ${\bf c} = |{\bf c}| {\bf s}$ with $|{\bf s}| = 1$), and hence

$$|\mathbf{y}(t)| \le |c_1| |\mathbf{y}_1(t)| + \dots + |c_n| |\mathbf{y}_n(t)|$$

 $\le M(|c_1| + \dots + |c_n|) \le M\sqrt{n} |\mathbf{c}| < \epsilon \quad \text{for } t \ge 0.$

(2) Suppose **0** is an asymptotically stable point of $\mathbf{y}' = \mathbf{A}\mathbf{y}$ and $\delta > 0$ is such that $|\mathbf{y}(0)| < \delta$ implies $\lim_{t \to +\infty} \mathbf{y}(t) = \mathbf{0}$. For an arbitary nonzero solution $\mathbf{y}(t)$ of $\mathbf{y}' = \mathbf{A}\mathbf{y}$ there exists $\lambda > 0$ such that $|\lambda \mathbf{y}(0)| < \delta$ (cf. earlier argument) and hence $\lim_{t \to +\infty} \lambda \mathbf{y}(t) = \mathbf{0}$. But then clearly $\lim_{t \to +\infty} \mathbf{y}(t) = \mathbf{0}$ as well.

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Theorem

Suppose \mathbf{y}_0 is a critical point of $\mathbf{y}' = \mathbf{A}\mathbf{y} + \mathbf{b}$.

- **1)** \mathbf{y}_0 is asymptotically stable iff all eigenvalues of \mathbf{A} have real part < 0.
- 2 y_0 is stable iff (i) all eigenvalues of A have real part ≤ 0 and (ii) the geometric multiplicity of each purely imaginary eigenvalue (including zero) equals the algebraic multiplicity.

Consequently, \mathbf{y}_0 is unstable iff \mathbf{A} has at least one eigenvalue with positive real part or a purely imaginary eigenvalue with geom.mult < alg.mult.

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Proof.

We may assume that $\mathbf{b} = \mathbf{0}$.

(1) Suppose **A** has distinct eigenvalues $\lambda_1, \ldots, \lambda_r$ with algebraic multiplicities m_1, \ldots, m_r .

We use the fact that the entries of $e^{\mathbf{A}t}$, and likewise of any solution $\mathbf{y}(t) = e^{\mathbf{A}t}\mathbf{y}(0)$, are linear combinations of functions of the form $t^k e^{\lambda_i t}$ with $0 \le k < m_i$. This can be worked out directly for matrices in JCF and then follows for general \mathbf{A} from the equation $e^{\mathbf{A}t} = \mathbf{S}e^{\mathbf{J}t}\mathbf{S}^{-1}$; or use the "new method" to compute $e^{\mathbf{A}t}$.

$$|t^k e^{\lambda t}| = t^k e^{(\operatorname{Re} \lambda + i \operatorname{Im} \lambda)t} = t^k e^{(\operatorname{Re} \lambda)t} \to 0 \quad \text{for } t \to +\infty$$

holds iff Re λ < 0. From this the if-part is immediate.

For the converse, assume Re $\lambda_1 \geq 0$ and let \mathbf{v}_1 be a corresponding eigenvector.

 \implies $\mathbf{y}(t) = e^{\lambda_1 t} \mathbf{v}_1$ is a solution of $\mathbf{y}' = \mathbf{A}\mathbf{y}$.

Since $e^{\lambda_1 t} \not\to 0$ for $t \to \infty$, the same holds for at least one coordinate function of $\mathbf{y}(t)$ (in fact for each coordinate in which \mathbf{v}_1 has a nonzero entry). Thus there exists a solution $\mathbf{y}(t)$ with $\mathbf{y}(t) \not\to \mathbf{0}$ for $t \to \infty$. As noted previously, this implies that the system cannot be asymptotically stable.

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Proof cont'd.

(2) If the stated conditions are satisfied, eigenspaces corresponding to purely imaginary eigenvalues $\lambda=\mathrm{i}\alpha$ have a basis consisting of eigenvectors and account only for fundamental solutions of the form $\mathbf{y}(t)=\mathrm{e}^{\mathrm{i}\alpha t}\mathbf{v}$ with $\mathbf{v}\in\mathbb{C}^n$. Since such solutions are bounded, and all other eigenvalues have negative real part (accounting for fundamental solutions with limit $\lim_{t\to\infty}\mathbf{y}(t)=\mathbf{0}$), all solutions are bounded on $[0,\infty)$. As noted previosuly, this is equivalent to stability of the system.

Conversely, suppose that the stated conditions are not satisfied. Clearly an eigenvalue λ with $\text{Re}(\lambda)>0$ yields a solution that is unbounded on $[0,\infty)$. A purely imaginary eigenvalue $\lambda=\mathrm{i}\alpha$ with geom.mult < alg.mult has an associated generalized eigenvector \mathbf{w} with $(\mathbf{A}-\lambda\mathbf{I})\mathbf{w}\neq\mathbf{0}$, $(\mathbf{A}-\lambda\mathbf{I})^2\mathbf{w}=\mathbf{0}$, and hence yields a solution of the form

$$\mathbf{y}(t) = \mathrm{e}^{\mathrm{i} \alpha t} \mathbf{w} + t \, \mathrm{e}^{\mathrm{i} \alpha t} \underbrace{(\mathbf{A} - \mathrm{i} \alpha \, \mathbf{I}) \mathbf{w}}_{\neq \mathbf{0}}.$$

Since such solutions are unbounded on $[0, \infty)$ (because of the factor t), the system cannot be stable in either case.

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The case n=2

A nonzero real (!) matrix $\mathbf{A} = \begin{pmatrix} a & b \\ c & d \end{pmatrix} \in \mathbb{R}^{2 \times 2}$ is asymptotically stable iff $\operatorname{tr}(\mathbf{A}) = a + d < 0 \wedge \det(\mathbf{A}) = ad - bc > 0$, and stable but not asymptotically stable iff $\operatorname{tr}(\mathbf{A}) = 0 \wedge \det(\mathbf{A}) \geq 0$.

This follows from $a + d = \lambda_1 + \lambda_2$, $ad - bc = \lambda_1 \lambda_2$ and

$$\lambda_{1,2} = \frac{1}{2} \left(a + d \pm \sqrt{(a+d)^2 - 4(ad-bc)} \right) = \frac{1}{2} \left(a + d \pm \sqrt{(a-d)^2 + 4bc} \right)$$

by inspection. (Consider the two possible cases (i) $\lambda_1, \lambda_2 \in \mathbb{R}$ and (ii) $\lambda_1 = \overline{\lambda}_2 \in \mathbb{C} \setminus \mathbb{R}$.)

Thus nodal and spiral sinks are asymptotically stable; nodal and spiral sources and saddle points are unstable; centers are stable but not asymptotically stable; and star points and improper nodes can be either asymptotically stable or unstable, depending on the sign of the (real) eigenvalue λ .

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Solving y' = Ay by a Change-of-Variables

Recall that the general solution of an autonomous (= time-independent) homogeneous linear system $\mathbf{y}' = \mathbf{A}\mathbf{y}$ is $\mathbf{y}(t) = \mathbf{e}^{\mathbf{A}t}\mathbf{y}(0)$, where $\mathbf{y}(0) \in \mathbb{C}^n$ can be arbitrarily chosen.

Change of Variables

Suppose $\mathbf{y}(t)$ solves $\mathbf{y}' = \mathbf{A}\mathbf{y}$ and $\mathbf{z}(t) = \mathbf{T}\mathbf{y}(t)$ for some $\mathbf{T} \in \mathbb{C}^{n \times n}$.

$$\mathbf{z}'(t) = \mathbf{T}\mathbf{y}'(t) = \mathbf{T}\mathbf{A}\mathbf{y}(t) = \mathbf{T}\mathbf{A}\mathbf{T}^{-1}\mathbf{z}(t)$$

In terms of the inverse $\mathbf{S} = \mathbf{T}^{-1}$ this says that the change of variables $\mathbf{y}(t) = \mathbf{S}\mathbf{z}(t)$ transforms $\mathbf{y}' = \mathbf{A}\mathbf{y}$ into $\mathbf{z}' = \mathbf{S}^{-1}\mathbf{A}\mathbf{S}\mathbf{z}$. The initial values transform as $\mathbf{y}(0) = \mathbf{S}\mathbf{z}(0)$, $\mathbf{z}(0) = \mathbf{T}\mathbf{y}(0)$.

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Example

We solve the initial value problem

$$\mathbf{y}' = \mathbf{A}\mathbf{y} = \begin{pmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ -8 & -12 & -6 \end{pmatrix} \mathbf{y}, \quad \mathbf{y}(0) = \begin{pmatrix} 1 \\ 0 \\ -2 \end{pmatrix}.$$

This system arises from the scalar 3rd-order equation y''' = -6y'' - 12y' - 8y by order reduction, i.e., the substitution $(y_1, y_2, y_3) = (y, y', y'')$. The initial value $\mathbf{y}(0) = (1, 0, -2)^T$ corresponds to y(0) = 1, y'(0) = 0, y''(0) = -2.

From previous considerations we know that $\chi_{\mathbf{A}}(X)=(X+2)^3$ and $\mathbf{N}=\mathbf{A}+2\mathbf{I}_3=\left(\begin{smallmatrix}2&1&0\\0&2&1\\-8&-12&-4\end{smallmatrix}\right)$ satisfies $\mathbf{N}^3=\mathbf{0},\,\mathbf{N}^2\neq\mathbf{0}.$

One finds that $\mathbf{N}^2\mathbf{e}_1 = (4, -8, 16)^T \neq \mathbf{0}$.

 \implies The matrix **J** of $f_{\mathbf{A}}$ with respect to the basis $\{\mathbf{e}_1, \mathbf{N}\mathbf{e}_1, \mathbf{N}^2\mathbf{e}_1\}$ is in JCF, i.e.,

$$\begin{pmatrix} 1 & 2 & 4 \\ 0 & 0 & -8 \\ 0 & -8 & 16 \end{pmatrix}^{-1} \begin{pmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ -8 & -12 & -6 \end{pmatrix} \begin{pmatrix} 1 & 2 & 4 \\ 0 & 0 & -8 \\ 0 & -8 & 16 \end{pmatrix} = \begin{pmatrix} -2 & 0 & 0 \\ 1 & -2 & 0 \\ 0 & 1 & -2 \end{pmatrix}.$$

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Example (cont'd)

The system $\mathbf{z}' = \mathbf{J}\mathbf{z}$, i.e., $z_1' = -2z_1$, $z_2' = z_1 - 2z_2$, $z_3' = z_2 - 2z_3$, is solved by

$$\mathbf{z}(t) = e^{-2t} \exp \left[\begin{pmatrix} 0 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{pmatrix} t \right] \mathbf{z}(0) = e^{-2t} \begin{pmatrix} 1 & 0 & 0 \\ t & 1 & 0 \\ \frac{1}{2}t^2 & t & 1 \end{pmatrix} \mathbf{z}(0).$$

z(0) is determined from

$$\left(\begin{array}{c} 1 \\ 0 \\ -2 \end{array} \right) = \textbf{y}(0) = \textbf{Sz}(0) = \left(\begin{array}{ccc} 1 & 2 & 4 \\ 0 & 0 & -8 \\ 0 & -8 & 16 \end{array} \right) \textbf{z}(0),$$

i.e., $\mathbf{z}(0) = (\frac{1}{2}, \frac{1}{4}, 0)^{\mathsf{T}}$.

$$\Rightarrow \mathbf{y}(t) = \mathbf{Sz}(t) = e^{-2t} \begin{pmatrix} 1 & 2 & 4 \\ 0 & 0 & -8 \\ 0 & -8 & 16 \end{pmatrix} \begin{pmatrix} 1 & 0 & 0 \\ t & 1 & 0 \\ \frac{1}{2}t^2 & t & 1 \end{pmatrix} \begin{pmatrix} \frac{1}{2} \\ \frac{1}{4} \\ 0 \end{pmatrix}$$
$$= e^{-2t} \begin{pmatrix} 1 & 2 & 4 \\ 0 & 0 & -8 \\ 0 & -8 & 16 \end{pmatrix} \begin{pmatrix} \frac{1}{2} \\ \frac{t}{2} + \frac{1}{4} \\ \frac{t^2}{4} + \frac{t}{4} \end{pmatrix} = e^{-2t} \begin{pmatrix} t^2 + 2t + 1 \\ -2t^2 - 2t \\ 4t^2 - 2 \end{pmatrix}$$