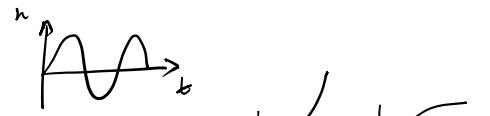
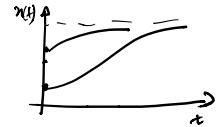


\* The study of dynamical systems is the study of how things change over time

- Mass on a spring  $m \frac{d^2x}{dt^2} = -kx$  
- population growth  $\frac{dn}{dt} = rn$   $\frac{dn}{dr} = rn(1-n/r_{max})$  
- fraction of population with a particular allele  $\frac{dn}{dt} = sn(1-n)$  
- Radioactive decay   $\frac{dn}{dt} = -kn$

\* It is the study of deterministic change, which means there is exact repeatability for the same exact conditions for the dynamics, including the initial conditions



\* It is the study of continuous change, where quantities can change infinitesimally over infinitesimal time.

- Sometimes this will be an approximation of the true discrete quantity that is changing
- e.g. population growth :

$$N_{t+1} = 2N_t \Rightarrow N_t = 2^t N_0$$

$$\Rightarrow \frac{dN}{dt} = rN \quad N(t) = e^{rt} N_0 \quad r = \ln 2$$

→ When  $N$  is large the 2 descriptions are identical.

In general, dynamical equations are expressed in terms of time-derivatives:

$$c_1 \frac{d}{dt}(\text{something}) + c_2 \frac{d^2}{dt^2}(\text{something}) + c_3 \frac{d^3}{dt^3}(\text{something}) + \dots = f(\text{something})$$

where  $c_i$ 's are constants.

\* We will focus on 1<sup>st</sup> order systems where the equations are

$$\frac{d}{dt}(\text{something}) = f(\text{something})$$

\* Although linear systems are included, the subject is mainly concerned with how to study non-linear systems, where  $f$  is a non-linear function with terms  $(\text{something})^n$  where  $n > 1$ , or  $\exp(\text{something})$  which are typically not solvable exactly:

Example Allele frequency dynamics in a diploid population

$$\frac{dn}{dt} = s [h + (1-2h)n] n(1-n) \quad \text{does not have a closed-form solution} \\ (\text{i.e. not expressible in terms of standard functions})$$

→ In this case this ODE can be integrated to give  $t(n)$ , but not inverted to give  $n(t)$ .

\* We will also look at 2D systems of 1<sup>st</sup> order differential eqns.

$$\frac{d}{dt}(\text{something}_1) = f(\text{something}_1, \text{something}_2)$$

$$\frac{d}{dt}(\text{something}_2) = g(\text{something}_1, \text{something}_2)$$

\* However, we will focus on understanding linear systems, as a basis of understanding  
non-linear systems

\* How do we construct a dynamical system?

→ When we look at our system we need to ask what are the elements of our model which cause the (something) we are interested to change?

E.g. population growth of bacteria

- 1) They divide at a given rate doubling number on division
- 2) They die at a given rate.

Rate :

Mechanism 1

Mechanism 2

$$\frac{d}{dt} (\text{something}) = (\text{change in number})_1 + (\text{change in number})_2 \\ [\text{per unit time}] \qquad \qquad \qquad [\text{per unit time}]$$

$$\frac{dN}{dt} = \left( \frac{dN}{dt} \right)_1 + \left( \frac{dN}{dt} \right)_2$$

1) Doubling : rate  $v$  : if each member of population adds exactly  $v\delta t$  then  $N$  members will add  $\delta N_1 = Nv\delta t$ .

2) Death : rate  $k$  : if each member loses exactly  $k\delta t$  then  $N$  members loose  $\delta N_2 = Nk\delta t$ .

$$\begin{aligned}\Rightarrow \delta N &= \delta N_1 + \delta N_2 \\ &= Nv\delta t - Nk\delta t \\ &= N\delta t(v-k)\end{aligned}$$

$$\Rightarrow \frac{\delta N}{\delta t} = N(v-k)$$

$$\Rightarrow \text{In continuous limit, } \lim_{\delta t \rightarrow 0} \left\{ \frac{\delta N}{\delta t} \right\} = \frac{dN}{dt} = N(v-k)$$

\* Note units of  $r$  &  $k$ : rate per second per individual  $\Rightarrow$  to get population level rate need to multiply by  $N$

$\rightarrow$  Let's add 3<sup>rd</sup> mechanism: spontaneous growth.

3) Out of thin air  $\alpha$  members of the population are added to the population per unit time  $\Rightarrow$  in time  $\Delta t$ ,  $\alpha \Delta t$  are added.

$$\begin{aligned}\Rightarrow \frac{dN}{dt} &= \left(\frac{dN}{dt}\right)_1 + \left(\frac{dN}{dt}\right)_2 + \left(\frac{dN}{dt}\right)_3 \\ &= rN - kN + \alpha\end{aligned}$$

[\* Mechanism 3 does not exist! \* this is just used as an illustration.]

\*  $\alpha$  is slightly different: it's units are number of individuals added per unit time, so is not multiplied by  $N$ .

\* Rates might not be constant, but depend on changing quantity we are modelling

Ex: Logistic growth. i) growth depends on how much food/resources are available

ii) this depends inversely on the current size of the population; smaller populations have more resources to share than larger populations.

→ It's typical to characterise this limit or resources in terms of the number of individuals that can be supported  $N_{\max}$ .

$$\Rightarrow r(N) = r\left(1 - \frac{N}{N_{\max}}\right) \begin{cases} r & \text{for } N=0 \\ 0 & \text{for } N=N_{\max} \end{cases}$$

→ this is a rate of individuals added per individual per unit time.

$$\Rightarrow \delta N_1 = r(N)N = r(1 - N/N_{\max})N$$

$$\begin{aligned} \Rightarrow \frac{dN}{dt} &= \left(\frac{dN}{dt}\right)_1 + \left(\frac{dN}{dt}\right)_2 \\ &= rN(1 - N/N_{\max}) - kN \end{aligned}$$

\*NB. we can mix & match between these different mechanisms of change 1), 2) & 3) & different types of each contribution (e.g. exponential vs logistic growth) to construct our dynamical system or ODE

$$\text{e.g. Exp. growth + spontaneous (no death)} : \frac{dN}{dt} = rN + \alpha$$

$$\text{Logistic growth (w/ death)} : \frac{dN}{dt} = rN(1 - N/N_{\max})$$

$$\text{Only spontaneous} : \frac{dN}{dt} = \alpha$$

- \* These ways of continuing the differential equation are based on the idea of "mass action kinetics" from chemistry
- \* There are other ways of generating ODEs for example from mechanics physical laws, e.g Newton's Law

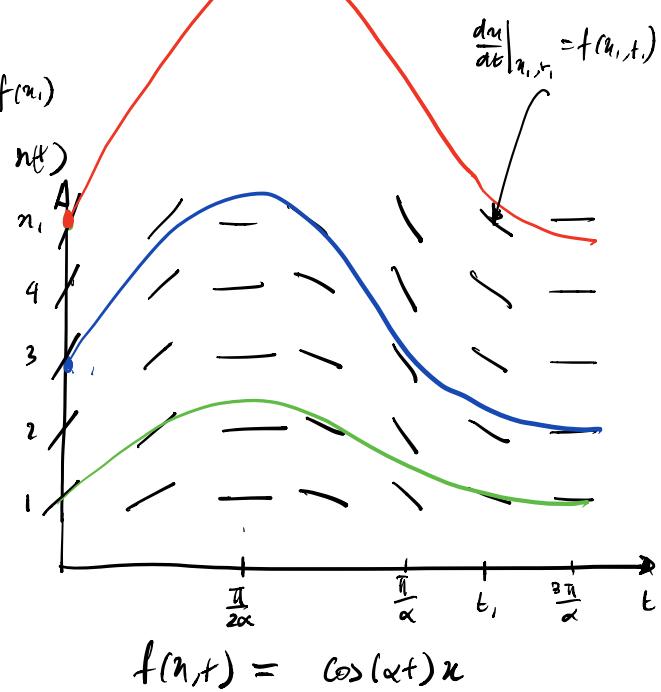
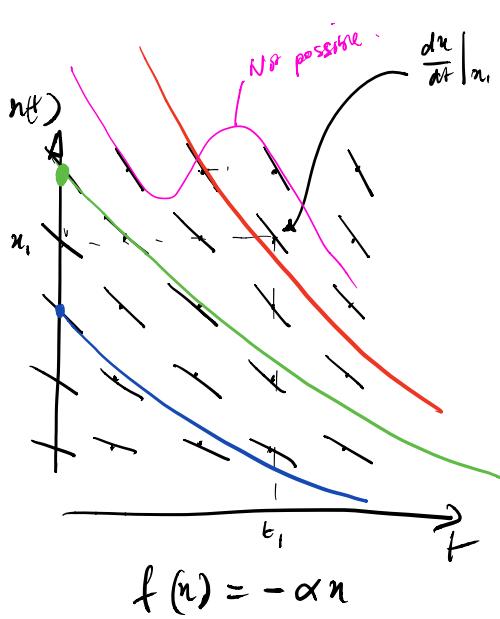
$$(\text{Net force}) = \text{mass} \times \text{accel}'$$

$$F = m \frac{d^2r}{dt^2}$$

1st order differential eqns.

$$\frac{dn}{dt} = f(n) \quad \text{or} \quad \frac{dx}{dt} = f(t, n)$$

- \* We want to solve these eqns of  $n(t)$ , subject to initial condition  $x(0)=x_0$
- but what do they mean?



- \* Plotting  $\frac{dn}{dt} = f(n)$  (or  $\frac{dx}{dt} = f(t, n)$ ) for different values of  $n$  &  $t$  allows us to visualise the effective flow-field or vector-field  
→ like water flowing in pipe or over obstacles. (But point has no momentum!)

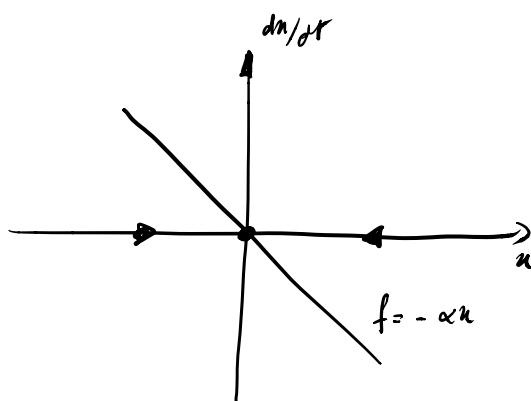
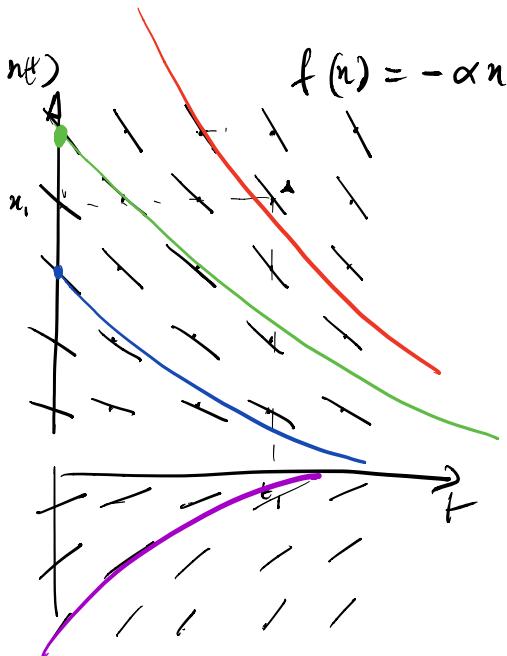
(field is just something that varies continuously in coordinate space )

## Autonomous 1<sup>st</sup> order differential eqns.

$$\frac{dx}{dt} = f(x)$$

\* As flow-field  $f(x)$  does not depend on time the time axis in above plots become redundant;

Example  $f(x) = -\alpha x \quad \Rightarrow \quad \frac{dx}{dt} = -\alpha x$



\*  $\frac{dx}{dt} < 0$  for  $x > 0$

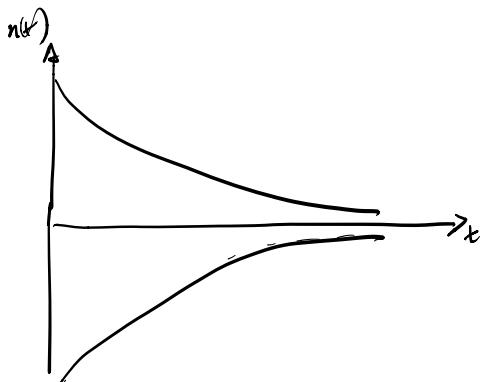
⇒ flows cause  $x$  to decrease → indicated by arrows on  $x$ -axis. ←

\*  $\frac{dx}{dt} > 0$  for  $x < 0$  →

\* Once it reaches  $x=0$   $\frac{dx}{dt}=0$

nothing changes → this is a "fixed point". •

\* Qualitative solution curves



\*  $n > 0$  :  $n$  decreases &  $\frac{dn}{dt}$  becomes

less & less negative

$\left[ \frac{dn}{dt} \text{ is increasing} \Rightarrow \frac{d^2n}{dt^2} > 0 \Rightarrow \text{curves are concave up} \right]$

\*  $n < 0$  :  $n$  increases &  $\frac{dn}{dt}$  decreases

$\left[ \frac{dn}{dt} \text{ is decreasing} \Rightarrow \frac{d^2n}{dt^2} < 0 \Rightarrow \text{curves are concave down} \right]$

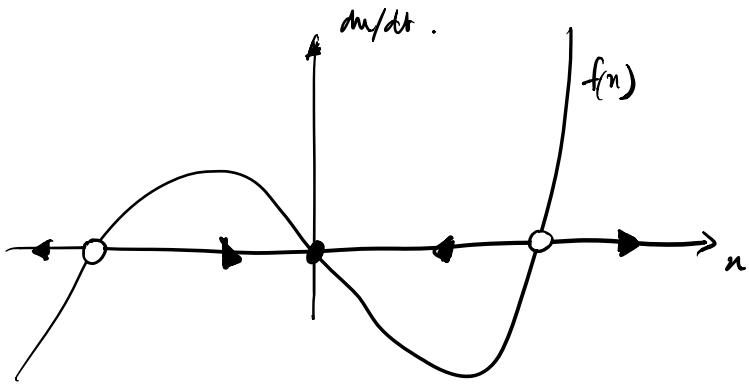
N.B. We know solution is  $n(t) = n_0 e^{-\alpha t} \rightarrow$  Qualitatively, we have drawn curves that are correct.

\* However with exact equation we can ask, for example, time  $t^*$  to decay to half initial condition?

$$n(t) = \frac{n_0}{2} \Rightarrow n_0 e^{-\alpha t} = \frac{n_0}{2}$$

$$\Rightarrow t^* = -\frac{1}{\alpha} \ln \frac{1}{2} = \frac{1}{\alpha} \ln 2$$

\* 1D (1<sup>st</sup> order autonomous) phase portraits.

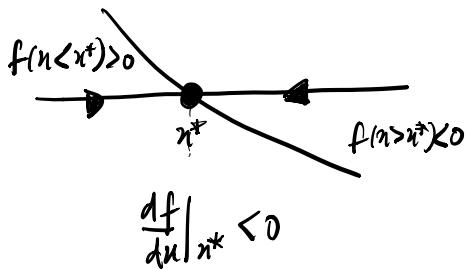


\* Fixed points are determined by where  $f(n^*) = 0$  or where  $f(n)$  crosses the  $n$ -axis

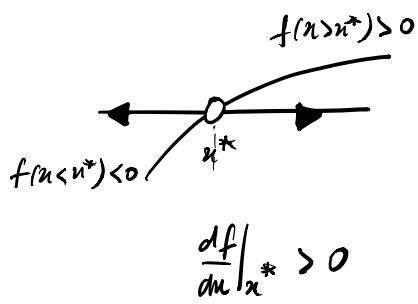
\* In general, many fixed points  $n_1^*, n_2^*, n_3^*, \dots$  depending on how complicated  $f(n)$ .

\* Stability : how do we determine stability

• stable fixed point

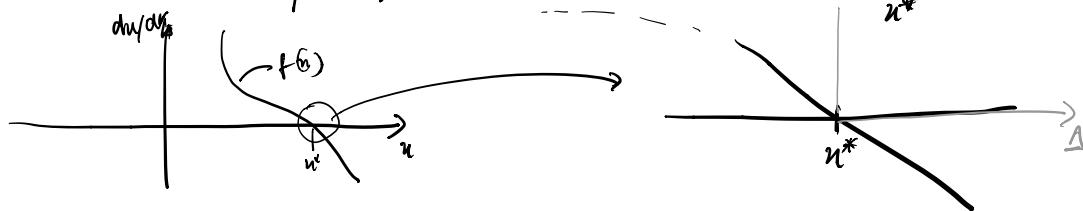


○ unstable fixed point.



Proof: (when  $\frac{df}{dx}|_{x^*} \neq 0$ )

if  $x^*$  is our fixed point, let  $\Delta = x - x^*$  & assume  $\frac{\Delta}{x^*} \ll 1$



$$\frac{d\Delta}{dt} = \frac{d}{dt}(x - x^*) = \frac{dx}{dt} = f(x) = f(\Delta + x^*)$$

$$\Rightarrow \frac{d\Delta}{dt} = f(x^* + \Delta)$$

$$\approx f(x^*) + \Delta \frac{df}{dx} + \frac{1}{2} \Delta^2 \frac{d^2f}{dx^2} + \dots$$

$$1) f(x^*) = 0$$

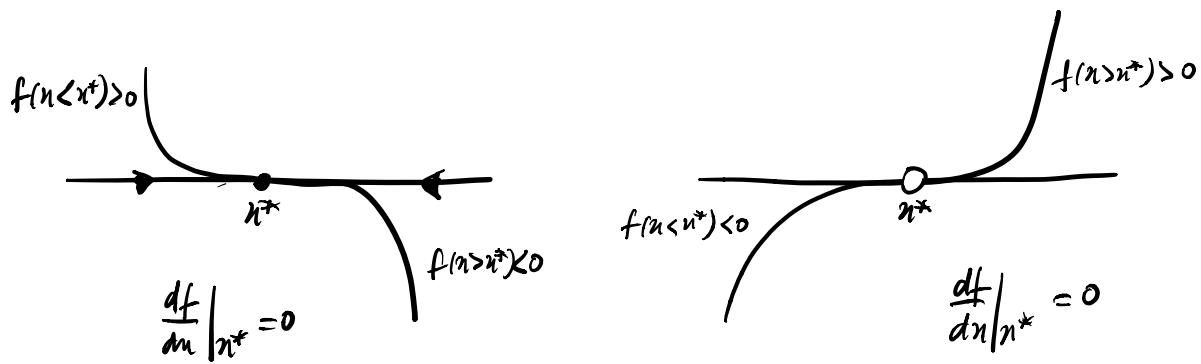
$$2) \Delta^2 \ll \Delta$$

$$\Rightarrow \frac{d\Delta}{dt} \approx \frac{df}{dx} \Delta$$

$\Rightarrow$  if  $\frac{df}{dx} > 0$   $\Delta$  grows from fixed point  $\Rightarrow$  UNSTABLE.

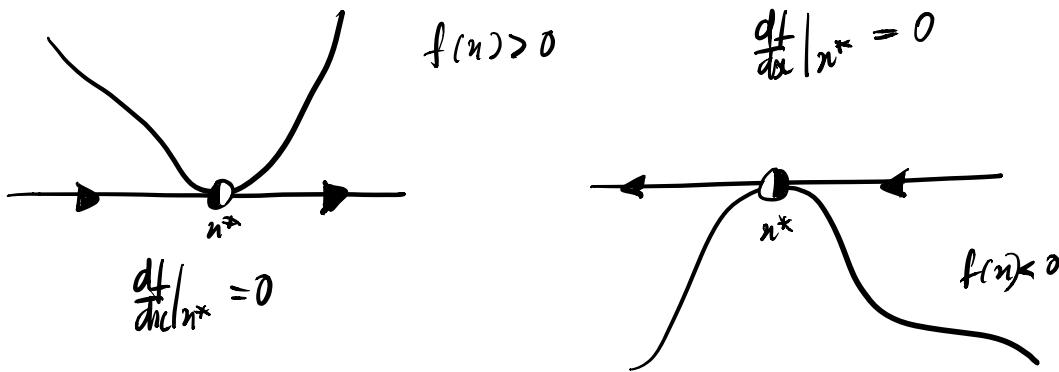
if  $\frac{df}{dx} < 0$   $\Delta$  shrinks towards fixed point  $\Rightarrow$  STABLE.

Q: What happens if  $\frac{df}{dx}|_{x^*} = 0$ ?



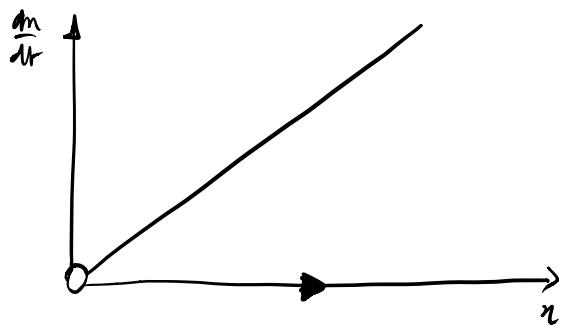
$$\text{e.g. } \frac{d\Delta}{dt} = \Delta \cancel{\frac{df}{d\Delta}} + \frac{1}{2} \Delta^2 \cancel{\frac{d^2f}{d\Delta^2}} + \frac{1}{3!} \Delta^3 \frac{d^3f}{d\Delta^3} + \dots$$

• half-stable fixed point.



$$\text{e.g. } \frac{d\Delta}{dt} \approx \Delta \cancel{\frac{df}{d\Delta}} + \frac{1}{2} \Delta^2 \frac{d^2f}{d\Delta^2} + \dots$$

\* Exponential growth  $\frac{dn}{dt} = rn$  ( $r > 0$ )  $\left( \frac{dN}{dt} = rN \right)$ .



1) Fixed points  $\frac{dn}{dt} = 0 \Rightarrow n = 0 \Rightarrow n^* = 0$

2) Stability  $\frac{dn}{dt}|_{n=n^*} = r > 0 \Rightarrow \text{unstable}$

$\Rightarrow n$  increases forever for any  $n(0) = n_0 > 0$  & monotonically

\* Without exact solution difficult to be quantitative;

e.g. Does population  $n$  reach infinity in a finite time?

Twice  $t^*$  to double initial population?

$\Rightarrow$  We know that  $n$  increases monotonically  $\Rightarrow$  from phase portrait  $\frac{dn}{dt}$  increases  $\Rightarrow \frac{d^2n}{dt^2} > 0$

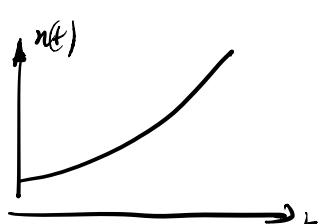
$\Rightarrow n(t)$  must be convex (concave up)

\* We know solution is  $n(t) = n_0 e^{rt}$

$\Rightarrow$  doubling time  $t^*$ :

$$n(t) = 2n_0 \Rightarrow n_0 e^{rt^*} = 2n_0$$

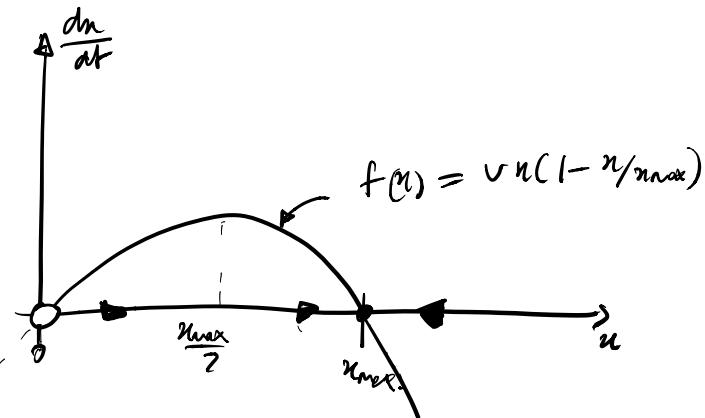
$$t^* = \frac{1}{r} \ln(2)$$



\* Logistic growth.

$$\frac{dn}{dt} = v n \left(1 - \frac{n}{n_{\max}}\right)$$

1) Fixed points :  $n_1^* = 0$  &  $n_2^* = n_{\max}$ .



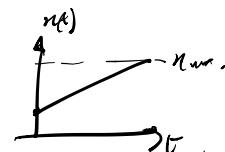
2) Stability (By inspection or : )

$$\frac{df}{dn}\Big|_{n_1^*} = v \left(1 - \frac{2n}{n_{\max}}\right)\Big|_{n_1^*} = v > 0 \quad \text{UNSTABLE}$$

$$\frac{df}{dn}\Big|_{n_2^*} = v \left(1 - \frac{2n}{n_{\max}}\right)\Big|_{n_2^*} = -v < 0 \quad \text{STABLE}$$

→ For all initial conditions (except  $n_0=0$ ) we have a single equilibrium solution

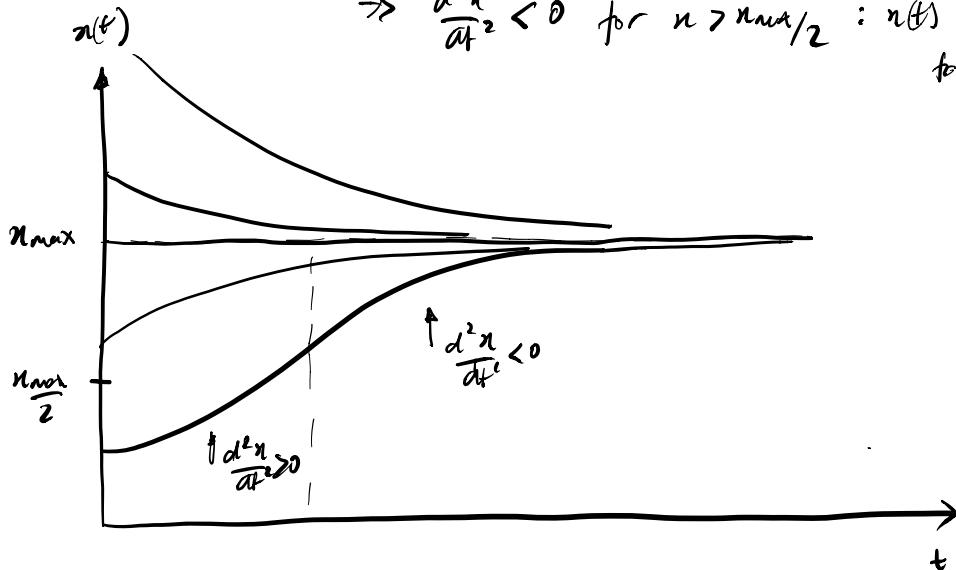
Q: What does it mean biologically if  $n_0=0$  ?



\* Can we sketch the solutions? Are the solutions straight lines?

1) for  $0 < n_0 < \frac{n_{\max}}{2}$   $\rightarrow \frac{dn}{dt}$  is increasing for  $n < \frac{n_{\max}}{2}$   $\cup$   
 $\rightarrow \frac{d^2n}{dt^2} > 0$  for  $n < \frac{n_{\max}}{2}$ :  $n(t)$  should be convex  
 for  $n < \frac{n_{\max}}{2}$

$\rightarrow$  once  $n > \frac{n_{\max}}{2}$   $\frac{dn}{dt}$  is decreasing  $\cap$   
 $\rightarrow \frac{d^2n}{dt^2} < 0$  for  $n > \frac{n_{\max}}{2}$ :  $n(t)$  should be concave  
 for  $n > \frac{n_{\max}}{2}$



2) for  $\frac{n_{\max}}{2} < n_0 < n_{\max}$ : as above  $\frac{d^2n}{dt^2} < 0 \Rightarrow n(t)$  is concave.

3) for  $n_0 > n_{\max}$ : As we move towards the fixed point  $n^* = n_{\max}$   
 from above  $\frac{dn}{dt}$  is increasing ( $|\frac{dx}{dt}|$  is decreasing)

$\rightarrow \frac{d^2n}{dt^2} > 0 \Rightarrow n(t)$  is convex  $\cup$

\* Both exponential & logistic growth have exact analytical solutions, which we discuss below

$\rightarrow$  In general, many 1D dynamical systems do not have exact solutions  
 $\rightarrow$  This approach is the only way to get qualitative behaviour

\* Exact solution of logistic differential eqn.

- Using partial fractions can show solution to

$$\frac{dn}{dt} = v n (1 - n/n_{\max})$$

is  $n(t) = \frac{e^{vt} n_0 n_{\max}}{n_{\max} - n_0 + n_0 e^{vt}}$  (Tutorial Question)

\* Limits :

$\rightarrow$  limit at  $t \rightarrow \infty$  as  $t \rightarrow \infty$

- for  $t$  large  $n_0 e^{vt} \gg n_{\max} - n_0$

$$\rightarrow n(t) \rightarrow \frac{e^{vt} n_0 n_{\max}}{n_0 e^{vt}} = n_{\max}.$$

$\rightarrow$  limit at  $n(t)$  for short times :

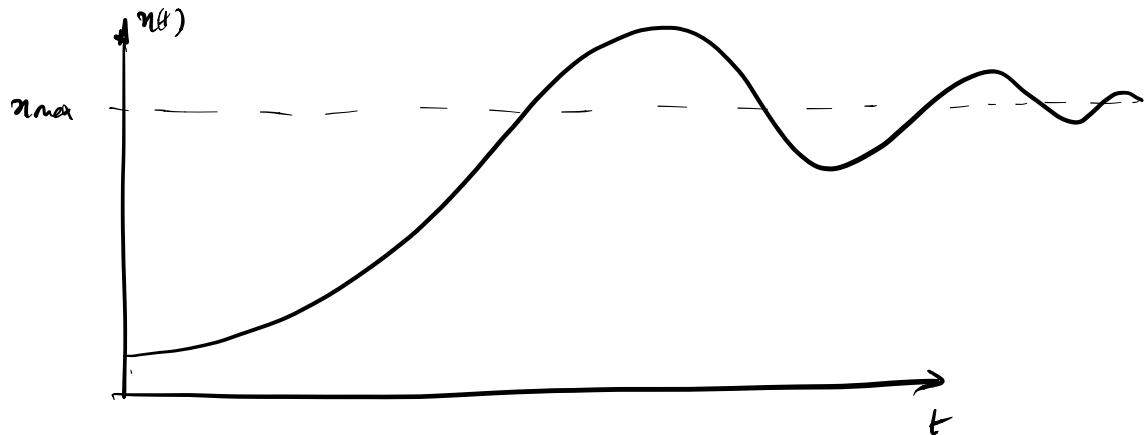
- if  $n_0 e^{vt} \ll n_{\max} - n_0$

$$\rightarrow n(t) \approx \frac{n_0 n_{\max}}{n_{\max} - n_0} e^{vt} \rightarrow \text{simple exponential growth.}$$

$\rightarrow$  if  $n_0 > n_{\max}/2$ , then  $n_0 > n_{\max} - n_0 \Rightarrow n_0 e^{vt} \ll n_{\max} - n_0$   
cannot be satisfied!

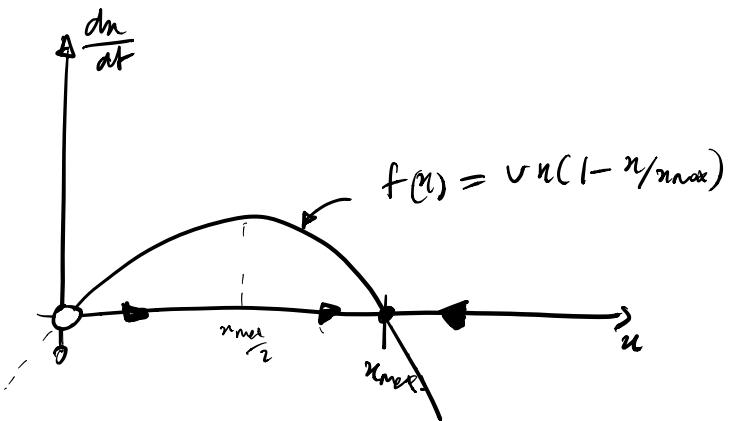
\* Impossibility of oscillations in 1D systems (1<sup>st</sup> order autonomous system)

Q: In the logistic growth model, why doesn't the population size overshoot & then oscillate around the fixed point?



→ Maybe the population doesn't "realize" its impending limit and temporarily grows beyond the carrying capacity??

→ Phase-portrait



\* For autonomous 1<sup>st</sup> order systems the flow-field is completely specified  $f(n)$ ; in order for there to be oscillations we need flow-field to change direction under different conditions. → we need another degree of freedom  
→ oscillations are impossible in 1D autonomous systems

\* 2<sup>nd</sup> order systems

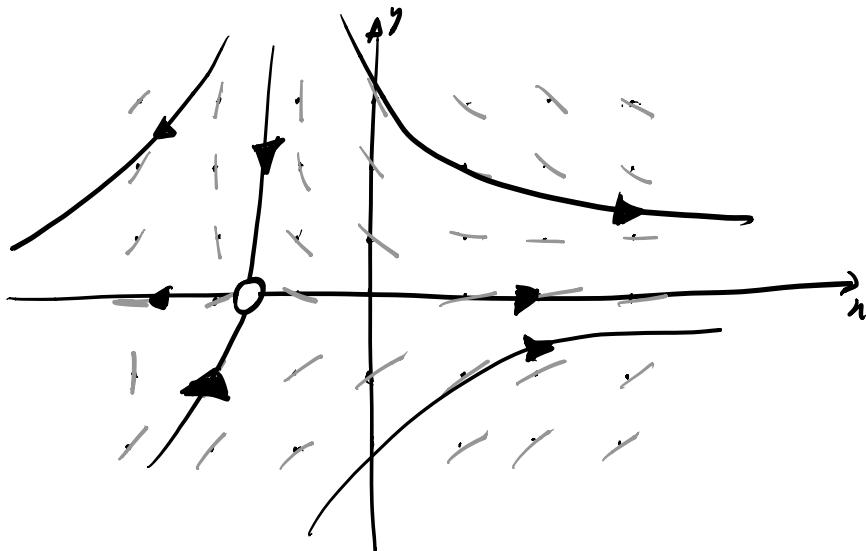
$$\frac{dx}{dt} = \dot{x} = f(x, y)$$

$$\frac{dy}{dt} = \dot{y} = g(x, y)$$

\* Again in general it is unlikely that we can find a closed-form analytical solution.

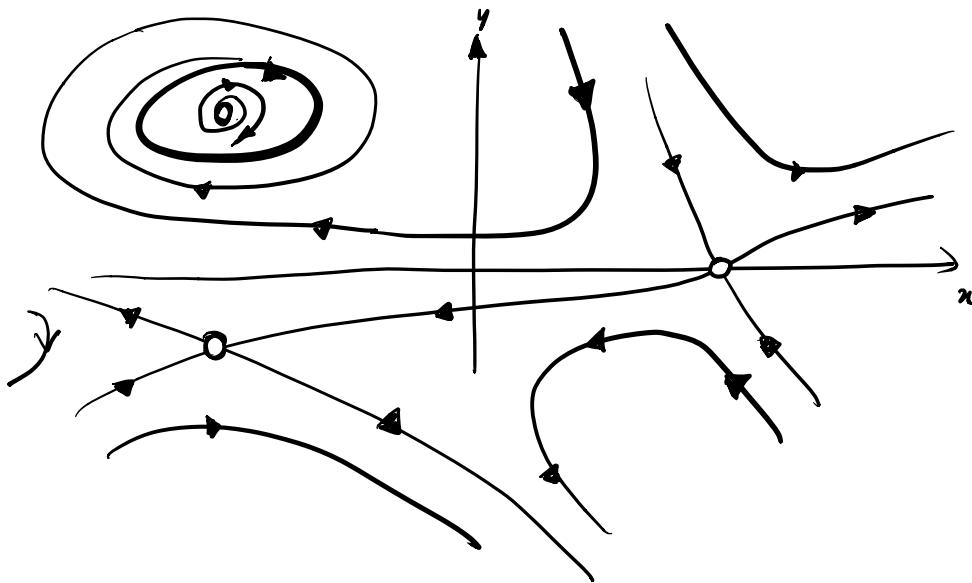
→ We use phase-portraits to gain qualitative understanding of dynamics.

→ we plot the vector  $(\dot{x}, \dot{y})$  at a number of points on a  $x-y$  axis to indicate the flow field.



→ Each of the black trajectories must follow the local slope in grey.

⇒ The phase portrait can in principle be very complicated

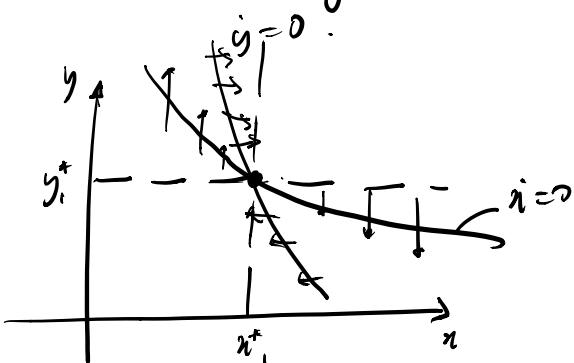


- \* We have 1) fixed points which can be stable • or unstable ○
  - 2) Closed orbits (only ① or above)
    - where solution is periodic in it  $x(t) = x(t+T)$   
 $y(t) = y(t+T)$
- As trajectories from within & outside closed orbit converge on it, it is stable.
- \* The general strategy to understanding such dynamical systems is to analyse the behavior near the fixed points, where behaviour becomes approximately linear.

## \*Phase Plane analysis of non-linear 2D systems

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

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



1) Find nullclines :

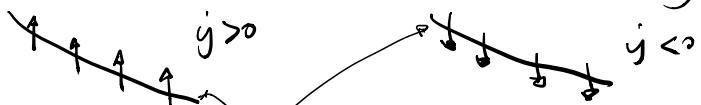
→ these are defined to be the curves for which  $\dot{x}=0$

→ separately  $\dot{y}=0$ .

→ On each nullcline the vector field is either all vertical for  $\dot{x}=0$   
or all horizontal for  $\dot{y}=0$ .

→ this gives additional information on the qualitative dynamics of  
the system

2) i) on  $\dot{x}=0$  nullcline examine how  $\dot{y}$  is changing ( $\dot{y}>0$  or  $\dot{y}<0$ )



$\dot{x}=0$  produces a curve  $y = F_x(x)$  → plug into eqn for  $\dot{y}$

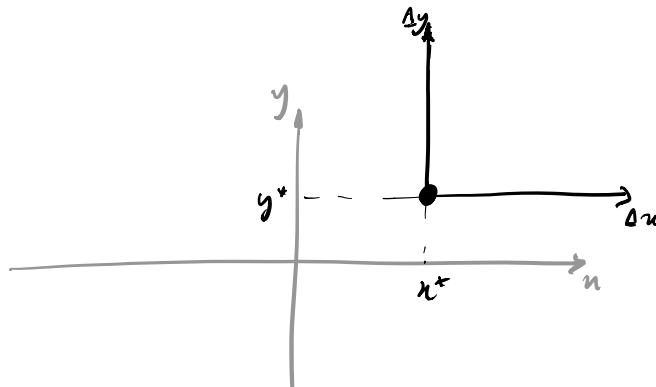
ii) on  $\dot{y}=0$  nullcline examine how  $\dot{x}$  is changing ( $\dot{x}>0$  or  $\dot{x}<0$ )



$\dot{y}=0$  produces a curve  $y = F_y(x)$  → plug into eqn for  $\dot{x}$

3) For each fixed point calculate effective linearised dynamics near it.

→ This requires expanding the nonlinear function  $f(x,y)$  &  $g(x,y)$  to linear order about the fixed point  $x^*, y^*$



$$(10) \quad f(u) = f(u^*) + \frac{df}{du} \Big|_{u=u^*} (u - u^*) + \frac{1}{2!} \frac{d^2f}{du^2} \Big|_{u=u^*} (u - u^*)^2 + \dots$$

$$u = u^* + \Delta u \quad \Rightarrow \Delta u = (u - u^*)$$

$$f(u^* + \Delta u) = f(u^*) + \frac{df}{du} \Big|_{u=u^*} \Delta u + \dots$$

$$u = u^* + \Delta u \quad \Delta y = y^* + \Delta y$$

$$\Rightarrow x = x^* + \Delta x = \Delta u \quad \& \quad y = y^* + \Delta y = \Delta y$$

$$\begin{aligned} \Rightarrow \Delta u &= f(u^* + \Delta u, y^* + \Delta y) = \underbrace{f(u^*, y^*)}_{=0} + \left( \frac{\partial f}{\partial u} \Big|_{u=u^*, y=y^*} \right) \Delta u + \left( \frac{\partial f}{\partial y} \Big|_{u=u^*, y=y^*} \right) \Delta y + \dots \\ &= \frac{\partial f}{\partial u} \Big|_{u^*, y^*} \Delta x + \frac{\partial f}{\partial y} \Big|_{u^*, y^*} \Delta y + \dots \end{aligned}$$

$$\Delta y = g(u^* + \Delta u, y^* + \Delta y) = \frac{\partial g}{\partial u} \Big|_{u^*, y^*} \Delta u + \frac{\partial g}{\partial y} \Big|_{u^*, y^*} \Delta y + \dots$$

$$\Rightarrow \Delta x = f(x^* + \Delta x, y^* + \Delta y) \approx \frac{\partial f}{\partial x} \Big|_{x^*, y^*} \Delta x + \frac{\partial f}{\partial y} \Big|_{x^*, y^*} \Delta y$$

$$\Delta y = g(x^* + \Delta x, y^* + \Delta y) \approx \frac{\partial g}{\partial x} \Big|_{x^*, y^*} \Delta x + \frac{\partial g}{\partial y} \Big|_{x^*, y^*} \Delta y$$

$\Rightarrow$  Linear system as long as we don't let  $\Delta x$  &  $\Delta y$  become too large.

\* Matrix form

$$\begin{pmatrix} \Delta x \\ \Delta y \end{pmatrix} = \begin{pmatrix} \frac{\partial f}{\partial x} \Big|_+ & \frac{\partial f}{\partial y} \Big|_+ \\ \frac{\partial g}{\partial x} \Big|_+ & \frac{\partial g}{\partial y} \Big|_+ \end{pmatrix} \begin{pmatrix} \Delta x \\ \Delta y \end{pmatrix}$$

N.B. these entries  
are constants near  
any fixed point.

$\rightarrow$  this matrix  $\underline{\underline{J}}$  is conventionally called the "Jacobian matrix"  
& also arises when doing a change of variable in differential eqns  
or evaluating double integrals.

$\rightarrow$  We can use linear analysis of previous section (eigenvectors & eigenvalues)  
to determine behaviour near each fixed point.

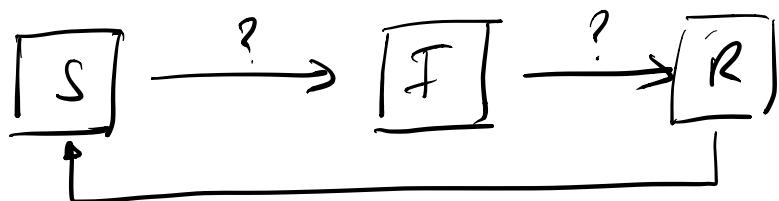
$\rightarrow$  Each of these fixed points will fall into one of the categories  
discussed depending on the eigenvalues & the Jacobian matrix  $\underline{\underline{J}}$ .

SIRS epidemic eqns. - model of many  
infectious.

S - Susceptible to infection

I - Infected

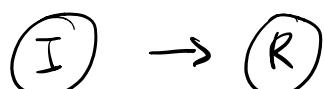
R - Recovered & immune to infection



1) Infection event



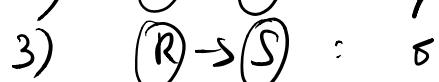
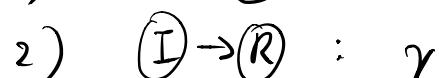
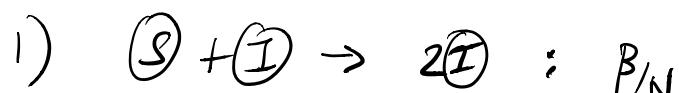
2) Recovery event



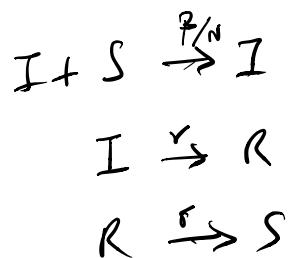
3) Lossing immunity.



→ Need to assign rates to how quickly these events happen.



→ Way we write this  
is as a chemical  
reaction



For each event what is change in number.

Event .	Change in S	Change in I	Change in R
$S + I \xrightarrow{\beta/N} 2I$	-1	+1	0
$I \xrightarrow{\gamma} R$	0	-1	+1
$R \xrightarrow{\sigma} S$	+1	0	-1

$$\Rightarrow \frac{dS}{dt} = -\frac{\beta}{N} SI + \sigma R$$

$$\frac{dI}{dt} = +\frac{\beta}{N} SI - \gamma I$$

$$\frac{dR}{dt} = \gamma I - \sigma R$$

3 × 3 system!!!

But  $S + I + R = N \Rightarrow$  We can eliminate 1 variable.

$$\Rightarrow \text{Let } R = N - (S + I)$$

$$\Rightarrow \frac{dS}{dt} = -\frac{\beta}{N} SI + \sigma(N - S - I)$$

$$\frac{dI}{dt} = +\frac{\beta}{N} SI - \gamma I$$

$R_0$  defined by when epidemic grows

$$\frac{dT}{dt} > 0$$

$$\Rightarrow \frac{dT}{dt} = \frac{\beta}{N} SI - \gamma I \\ = \left( \frac{\beta}{N} S - \gamma \right) I > 0.$$

→ Infection level does not change this criterion

$$\Rightarrow \frac{\beta}{N} S - \gamma > 0$$

$$\gamma \left( \frac{\beta S}{\gamma N} - 1 \right) > 0.$$

$$\Rightarrow R_0 = \frac{\beta S}{\gamma N} > 0 \quad \text{epidemic grows}$$

If whole population is susceptible (say at  $t=0$ ) then  $S=N$  &  $R_0 = \frac{\beta}{\gamma} = R_0$

(more generally  $R_0 = R_0 \left( \frac{S}{N} \right)$ )

Nullchines

$$\frac{dS}{dt} = 0 \Rightarrow -\frac{\beta}{N} SI + r(N-S-I) = 0$$

$$-\frac{\beta S}{N} I - \sigma I + r(N-S) = 0.$$

$$\Rightarrow -\left(\frac{\beta S}{N} + \sigma\right)I + r(N-S) = 0$$

$$\Rightarrow I = \frac{r(N-S)}{\sigma + \frac{\beta S}{N}}$$

$$\frac{dI}{dt} = 0 \Rightarrow \frac{\beta}{N} SI - \gamma I = 0.$$

$$\frac{\beta S}{N} - \gamma = 0$$

$$\Rightarrow \frac{\beta S}{\gamma N} = 1 \Rightarrow S = \frac{N\gamma}{\beta}$$

$\frac{\beta S}{\gamma N} = R_e$  the effective R-number.

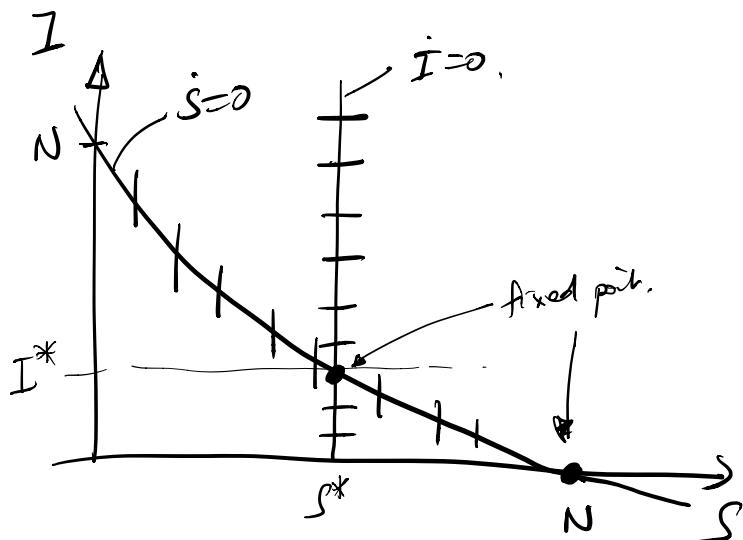
$\times \frac{\beta}{\gamma} = R_0$  the R-number when everyone is susceptible.

$\rightarrow$

$$\dot{S} = 0 \text{ nullcline : } I = \frac{\sigma(N-S)}{\sigma + \beta S/N}$$

$$= \frac{\sigma(N-S)}{\sigma + \gamma R_0 S/N}$$

$$\dot{I} = 0 \text{ nullcline : } S = \frac{N\gamma}{\beta} = N/R_0$$



\* Need to figure out directions of phase flow on the nullclines

1<sup>st</sup> find fixed point  $S^* \times I^*$

1)  $\dot{I}=0$  says:  $\boxed{S^* = \frac{Nr}{\beta}}$   $\rightarrow$  Plug into  $S=0$  condition.

$$\begin{aligned} S=0 : I^* &= \frac{\sigma(N-S^*)}{\sigma + \beta S^*/N} \\ &= \frac{\sigma(N - \frac{Nr}{\beta})}{\sigma + \frac{\beta}{N} \times \frac{Nr}{\beta}} \\ &= \frac{\sigma N(1 - r/\beta)}{\sigma + r} \quad R_0 = \beta/\gamma \end{aligned}$$

$$\boxed{I^* = \frac{\sigma N(1 - 1/R_0)}{\sigma + r}}$$

N.B. for  $R_0 > 1$   $1/R_0 < 1 \Rightarrow I^* > 0$

$\rightarrow$  with waning immunity &  $R_0 > 1$  the epidemic is endemic

for  $R_0 \leq 1$   $I^* = 0 \rightarrow$  the epidemic goes extinct.  
even with waning immunity.

On  $\dot{S}=0$ , how is  $I$  changing?

$\dot{S}=0$  nullcline defined by

$$I = \frac{\sigma(N)S}{\sigma + \beta S/N}$$



$$\frac{dI}{dt} = \left( \frac{\beta S}{N} - \gamma \right) I$$

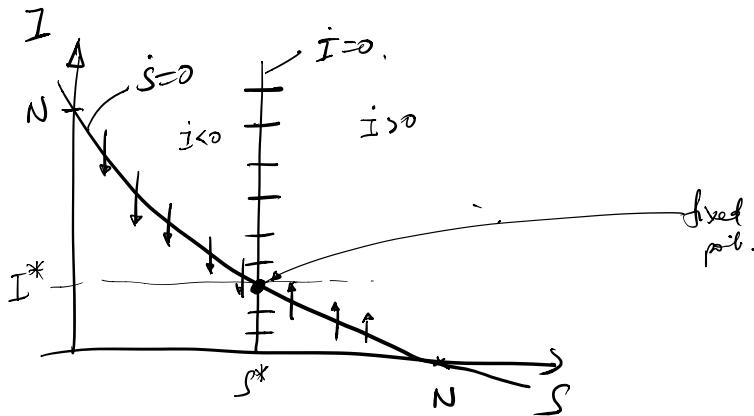
But  $I$  is always +ve ( $I > 0$ )  $\Rightarrow$  cannot determine sign  $\Rightarrow$  only determined by  $S$ .

$\Rightarrow$  if  $\frac{\beta S}{N} - \gamma > 0 \quad \dot{I} > 0$

if  $\frac{\beta S}{N} - \gamma < 0 \quad \dot{I} < 0$

If  $S > S^*$  ( $R_e > 1$ ) then  $\dot{I} > 0$

If  $S < S^*$  ( $R_e < 1$ ) then  $\dot{I} < 0$



On  $\dot{I}=0$  what is  $S$  doing?

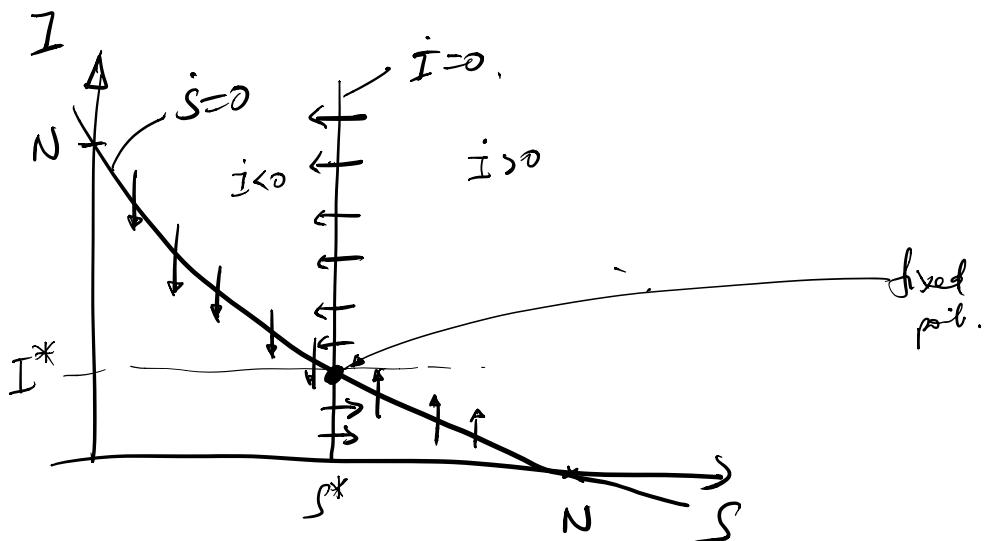
$$\dot{I}=0$$

defined by a line  $I = F(S)$ . Here  $S = \frac{N_I}{B} = S^*$

$$\begin{aligned}\frac{dS}{dt} &= -\frac{\beta S I}{N} + \sigma(N - I - S^*) \\ &= -\left(\frac{\beta S}{N} + \tau\right) I + \sigma(N - S^*)\end{aligned}$$

We know if we plug in  $I = I^*$   $\frac{dS}{dt} = 0$

$\Rightarrow$  we can see  $I > I^* \frac{dS}{dt} < 0$  &  $I < I^* \frac{dS}{dt} > 0$



$\Rightarrow$  We expect rotational motion around the fixed point.

→ To examine stability need to analyse dynamics close to fixed point  $S^*$  &  $I^*$

→ Calculate matrix of partial derivatives (Jacobian) at the fixed point:

$$\frac{dS}{dt} = -\left(\frac{\beta S}{N} + \sigma\right)I + \sigma(N-S) = f(S, I)$$

$$\frac{dI}{dt} = \left(\frac{\beta S}{N} - \gamma\right)I = g(S, I)$$

$$J = \begin{pmatrix} \frac{\partial f}{\partial S} & \frac{\partial f}{\partial I} \\ \frac{\partial g}{\partial S} & \frac{\partial g}{\partial I} \end{pmatrix}$$

$$\begin{aligned} \frac{\partial f}{\partial S} &= \frac{\partial}{\partial S} \left( -\left(\frac{\beta S}{N} + \sigma\right)I + \sigma(N-S) \right) \\ &= -\left(\gamma + \frac{\beta I}{N}\right) \end{aligned} \quad \begin{aligned} \frac{\partial f}{\partial I} &= \frac{\partial}{\partial I} \left( -\left(\frac{\beta S}{N} + \sigma\right)I + \sigma(N-S) \right) \\ &= -\left(\frac{\beta S}{N} + \sigma\right) \end{aligned}$$

$$\begin{aligned} \frac{\partial g}{\partial S} &= \frac{\partial}{\partial S} \left(\frac{\beta S}{N} - \gamma\right)I \\ &= \frac{\beta I}{N} \end{aligned} \quad \begin{aligned} \frac{\partial g}{\partial I} &= \frac{\partial}{\partial I} \left(\frac{\beta S}{N} - \gamma\right)I \\ &= \frac{\beta S}{N} - \gamma \end{aligned}$$

$$\Rightarrow J = \begin{pmatrix} \frac{\partial f}{\partial S} & \frac{\partial f}{\partial I} \\ \frac{\partial g}{\partial S} & \frac{\partial g}{\partial I} \end{pmatrix} = \begin{pmatrix} -(\sigma + \frac{\beta I}{N}) & -(\frac{\beta S}{N} + \gamma) \\ \frac{\beta I}{N} & \frac{\beta S}{N} - \gamma \end{pmatrix}$$

$\rightarrow$  Evaluate Jacobian matrix at the fixed point.

$$\begin{aligned} J|_{S=S^*, I=I^*} &= \begin{pmatrix} -(\sigma + \frac{\beta I^*}{N}) & -(\frac{\beta S^*}{N} + \gamma) \\ \frac{\beta I^*}{N} & \frac{\beta S^*}{N} - \gamma \end{pmatrix} \\ &= \begin{pmatrix} -\left(\sigma + \frac{\beta \sigma N(1-\gamma/\beta)}{\sigma+\gamma}\right) & -(\gamma+\sigma) \\ \frac{\beta \sigma N(1-\gamma/\beta)}{\sigma+\gamma} & \gamma-\gamma \end{pmatrix} \\ &= \begin{pmatrix} -\sigma\left(1 + \frac{\beta-\gamma}{\sigma+\gamma}\right) & -(\gamma+\sigma) \\ \frac{\sigma(\beta-\gamma)}{\sigma+\gamma} & 0 \end{pmatrix} \\ &= \begin{pmatrix} -\sigma\left(\frac{\sigma+\gamma+\beta-\gamma}{\sigma+\gamma}\right) & -(\gamma+\sigma) \\ \frac{\sigma(\beta-\gamma)}{\sigma+\gamma} & 0 \end{pmatrix} \end{aligned}$$

$$\boxed{\underline{\underline{J}} \Big|_{S=S^*, I=I^*} = \begin{pmatrix} -\sigma \frac{(\sigma+\beta)}{\sigma+\gamma} & -(\gamma+\delta) \\ \sigma \frac{(\beta-\gamma)}{\sigma+\gamma} & 0 \end{pmatrix}}$$

Things we can say without explicitly calculating eigenvalues.

i)  $\text{Tr}(\underline{\underline{J}}) < 0$  as  $\sigma > 0, \beta > 0 \wedge \gamma > 0$

2) Remember  $\underline{\underline{A}} = \begin{pmatrix} 0 & -1 \\ 1 & 0 \end{pmatrix}$   $\rightarrow$  rotation anti-clockwise

i)  $\Rightarrow$  if  $\beta - \gamma > 0$  we expect a stable spiral

$\rightarrow$  equivalent to  $R_o > 1 \Rightarrow$  stable spiral.

ii) if  $\beta - \gamma < 0$  ( $R_o < 1$ )  $\Rightarrow$  no oscillations

$$\text{Tr}(\underline{\underline{J}}) = -\sigma \frac{(\sigma + \beta)}{\sigma + \gamma} \quad |\underline{\underline{J}}| = 0 - \cancel{(\sigma)} \frac{\sigma(\beta - \gamma)}{\cancel{\sigma + \gamma}} \\ = \sigma(\beta - \gamma)$$

$\rightarrow$  Simplify:  $\sigma \ll \gamma \approx \beta$  immunity is "long" lasting.

$$\rightarrow \text{Tr}(\underline{\underline{J}}) \approx -\sigma \frac{\beta}{\gamma} = -\sigma R_0 \quad \times \quad |\underline{\underline{J}}| = \gamma \sigma (R_0 - 1)$$

$$\Rightarrow \lambda = \frac{1}{2} \left( -\sigma R_0 \pm \sqrt{\sigma^2 R_0^2 - 4 \gamma \sigma (R_0 - 1)} \right) \\ = -\frac{\sigma R_0}{2} \pm \frac{1}{2} \sigma R_0 \sqrt{1 - \frac{4 \gamma \sigma (R_0 - 1)}{\sigma^2 R_0^2}} \\ = -\frac{\sigma R_0}{2} \left( 1 \pm \sqrt{1 - \frac{4 \gamma}{\sigma} \frac{(R_0 - 1)}{R_0^2}} \right)$$

$\Rightarrow$  if  $R_0 < 1$  no imaginary part  $\Rightarrow$  no oscillations

if  $R_0 > 1$  we have criterion for complex eigenvalues

$$\cancel{4\gamma} \frac{R_0 - 1}{R_0^2} > 1$$

$\Rightarrow$  if  $\sigma \ll \gamma \Rightarrow \frac{\gamma}{\sigma} \gg 1 \quad \times R_0 - 1$  is not very small  
 $\Rightarrow \text{Im}(\lambda) \neq 0$

for  $R_0 > 1$

- 1)  $\operatorname{Re}(\lambda) < 0 \rightarrow \text{stable}$
- 2)  $\operatorname{Im}(\lambda) \neq 0 \rightarrow \text{spiral.}$

