

# EE16B

# Designing Information Devices and Systems II

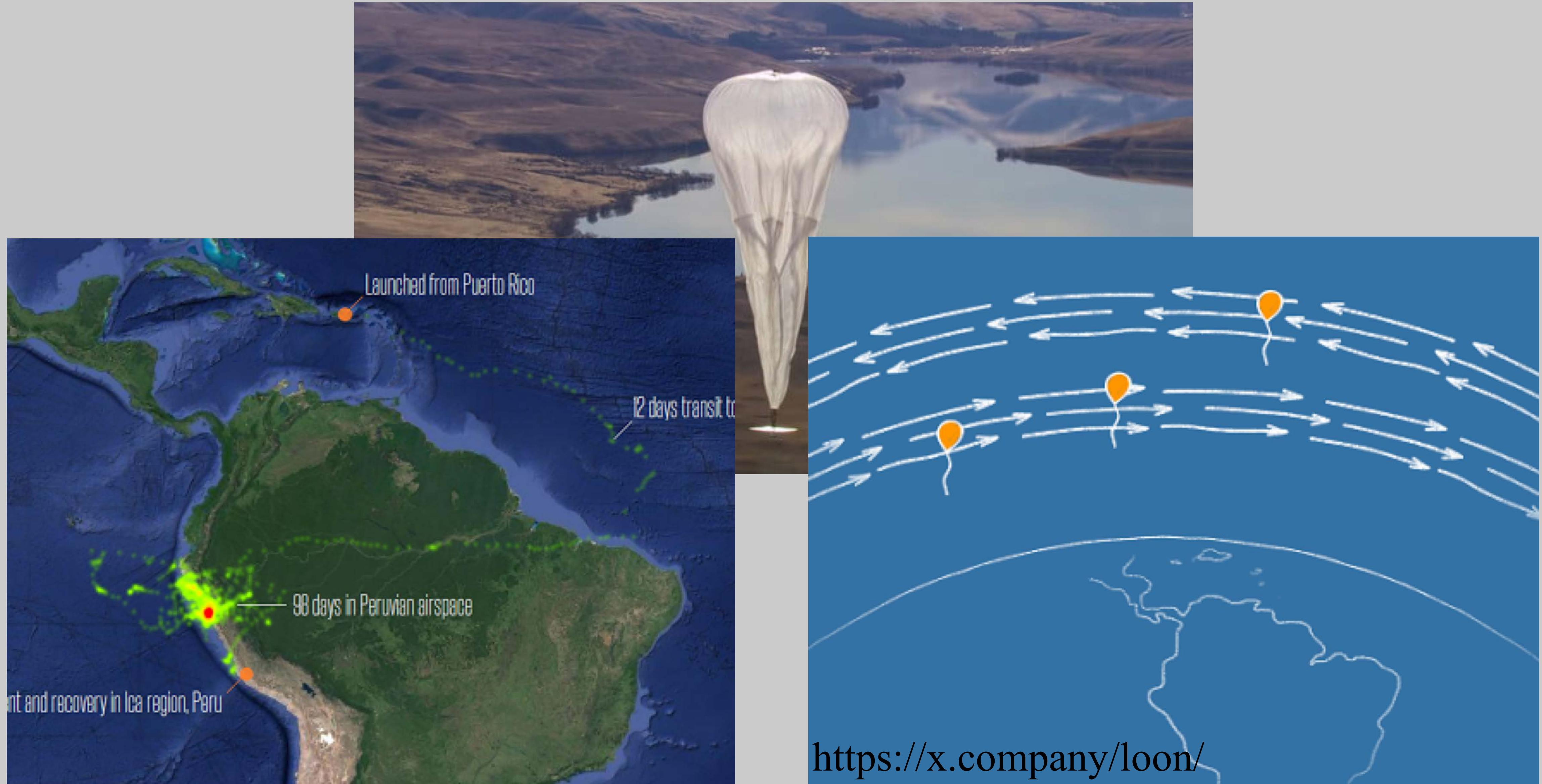
Lecture 8B  
State Feedback Control Cont  
System ID

# Intro

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- Last time
  - State feedback control
  - Eigen value assignment
- Today:
  - Continue state feedback control
  - Example of cooperative, adaptive cruise control
  - System ID

# GOOGLE PROJECT LOON BALLOONS



# Continuous Time

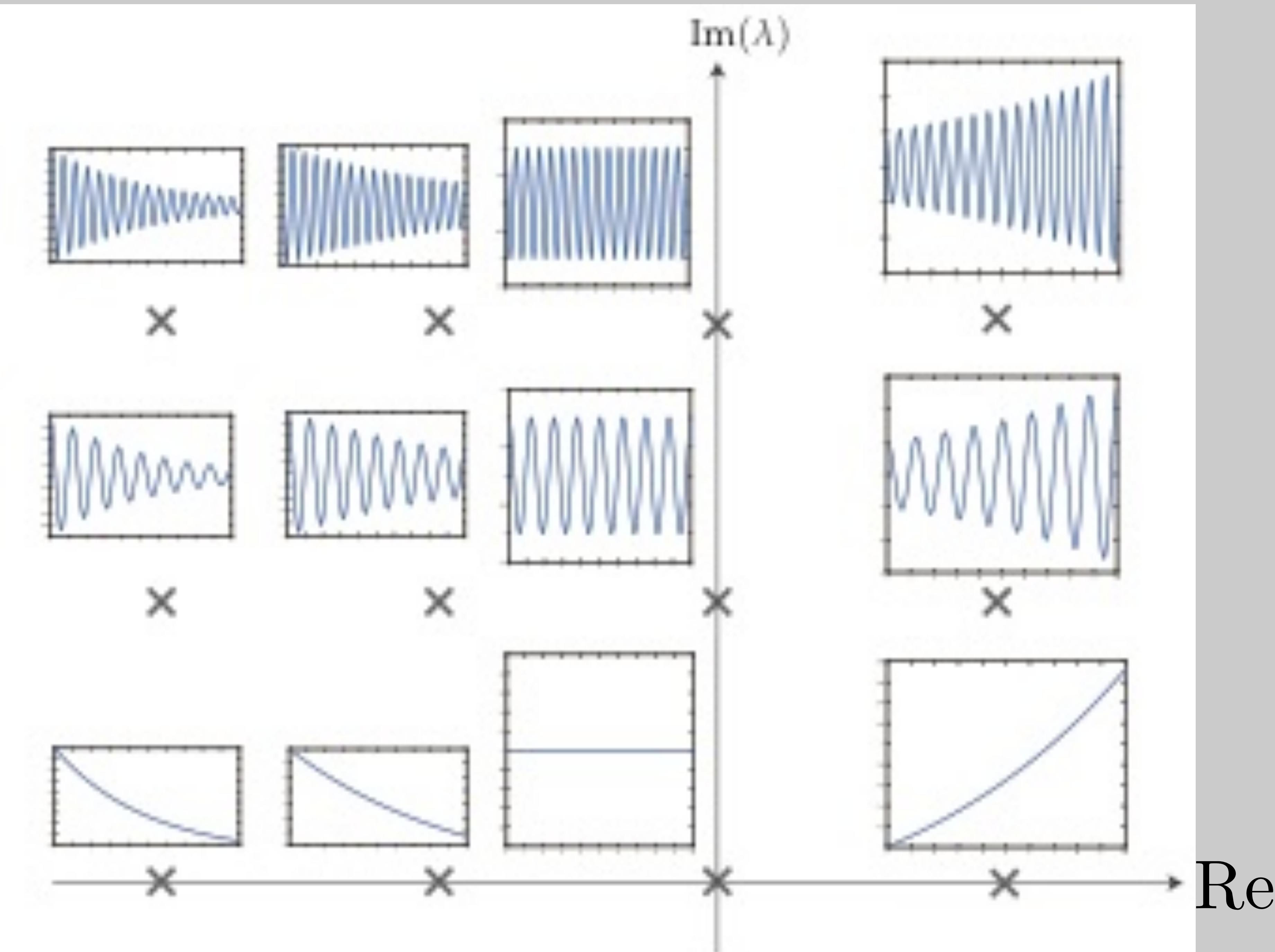
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$$\frac{d}{dt} \vec{x}(t) = A\vec{x}(t) + Bu(t)$$

$$u(t) = K\vec{x}(t)$$

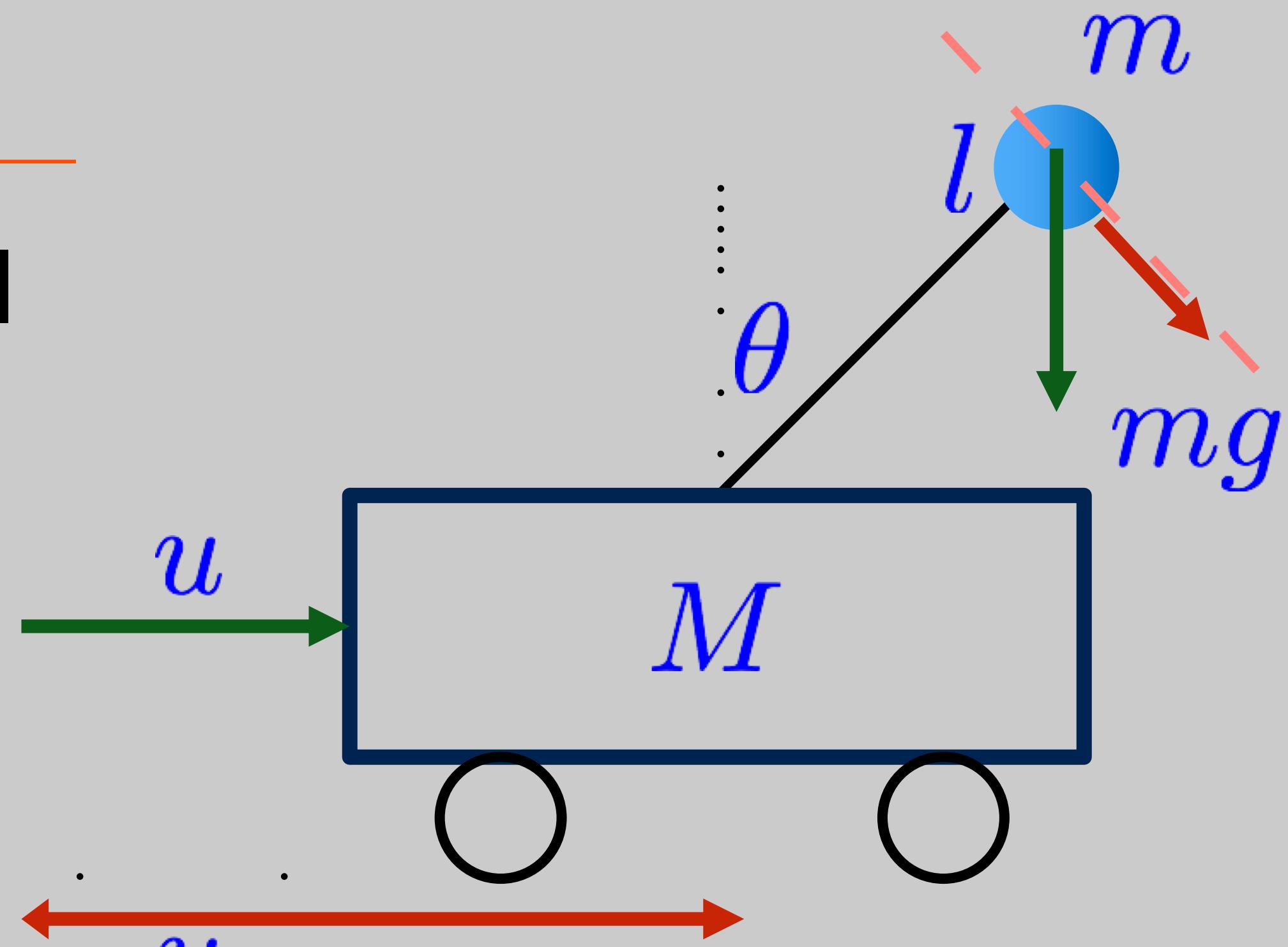
$$\frac{d}{dt} \vec{x}(t) = (A + BK)\vec{x}(t)$$

Choose  $K$  s.t. ,  $\text{Re } \lambda_i(A+BK) < 0$ ,  $i=1,2,3\dots n$



## Example 3: Pole on a Cart

Design state-feedback control



$$\ddot{y} = \frac{1}{\frac{M}{m} + \sin^2 \theta} \left( \frac{u}{m} + \dot{\theta}^2 l \sin \theta - g \sin \theta \cos \theta \right)$$

$$\ddot{\theta} = \frac{1}{l(\frac{M}{m} + \sin^2 \theta)} \left( -\frac{u}{m} \cos \theta - \dot{\theta}^2 l \sin \theta \cos \theta + \frac{M+m}{m} g \sin \theta \right)$$

## Example 3: Pole on a Cart

Linearization about  $\theta = 0 \quad \dot{\theta} = 0$

State space model:

$$\frac{d}{dt} \begin{bmatrix} \theta(t) \\ \dot{\theta}(t) \\ \dot{y}(t) \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 \\ \frac{M+m}{Ml}g & 0 & 0 \\ -\frac{m}{M}g & 0 & 0 \end{bmatrix} \begin{bmatrix} \theta(t) \\ \dot{\theta}(t) \\ \dot{y}(t) \end{bmatrix} + \begin{bmatrix} 0 \\ -\frac{1}{Ml} \\ \frac{1}{M} \end{bmatrix} u(t)$$

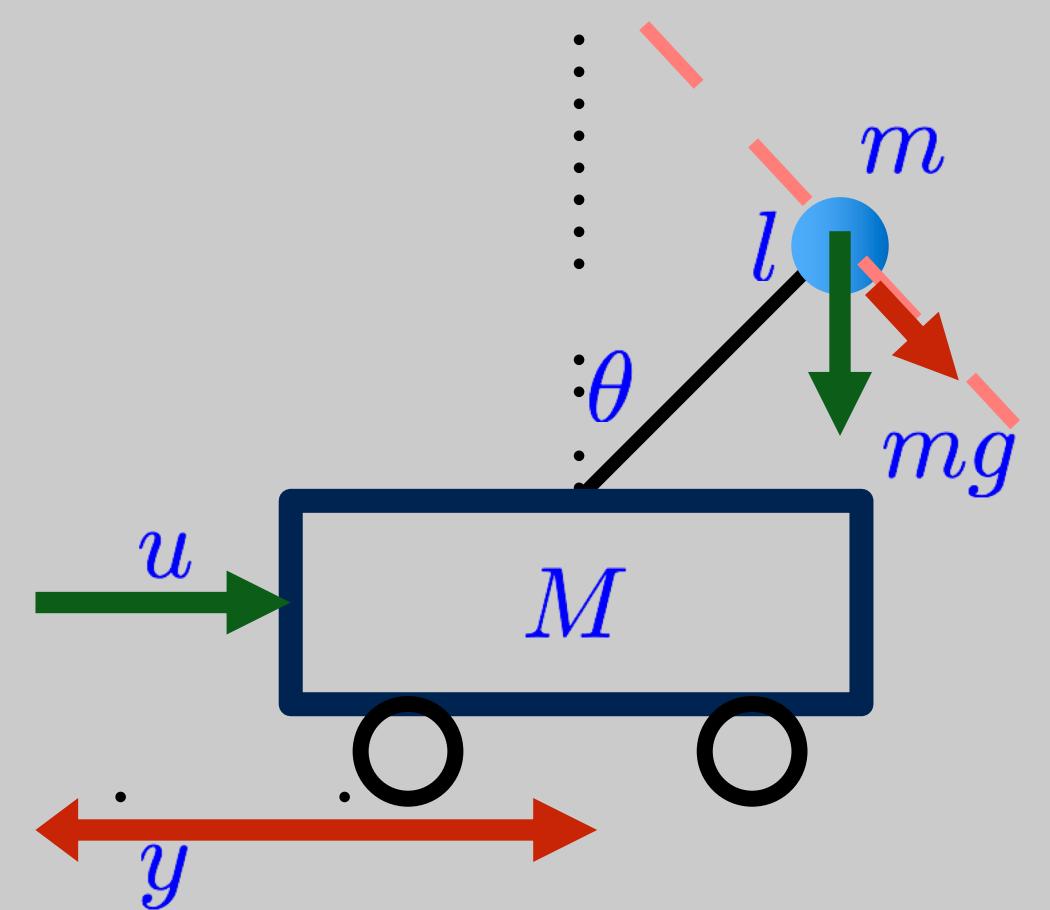
$$M = 1$$

$$m = 0.1$$

$$l = 1$$

$$g = 1$$

$$A = \begin{bmatrix} 0 & 1 & 0 \\ 11 & 0 & 0 \\ -1 & 0 & 0 \end{bmatrix} \quad B = \begin{bmatrix} 0 \\ -1 \\ 1 \end{bmatrix}$$



## Controller

$$M = 1$$

$$m = 0.1$$

$$l = 1$$

$$g = 1$$

$$A = \begin{bmatrix} 0 & 1 & 0 \\ 11 & 0 & 0 \\ -1 & 0 & 0 \end{bmatrix} \quad B = \begin{bmatrix} 0 \\ -1 \\ 1 \end{bmatrix}$$

$$u(t) = k_1\theta(t) + k_2\dot{\theta}(t) + k_3\dot{y}(t)$$

$$A + BK = \begin{bmatrix} 0 & 1 & 0 \\ 11 - k_1 & -k_2 & -k_3 \\ -1 + k_1 & k_2 & k_3 \end{bmatrix}$$

Characteristic polynomial:

$$\text{Desired: } \lambda^3 + (k_2 - k_3)\lambda^2 + (k_1 - 11)\lambda + 10k_3 = 0$$

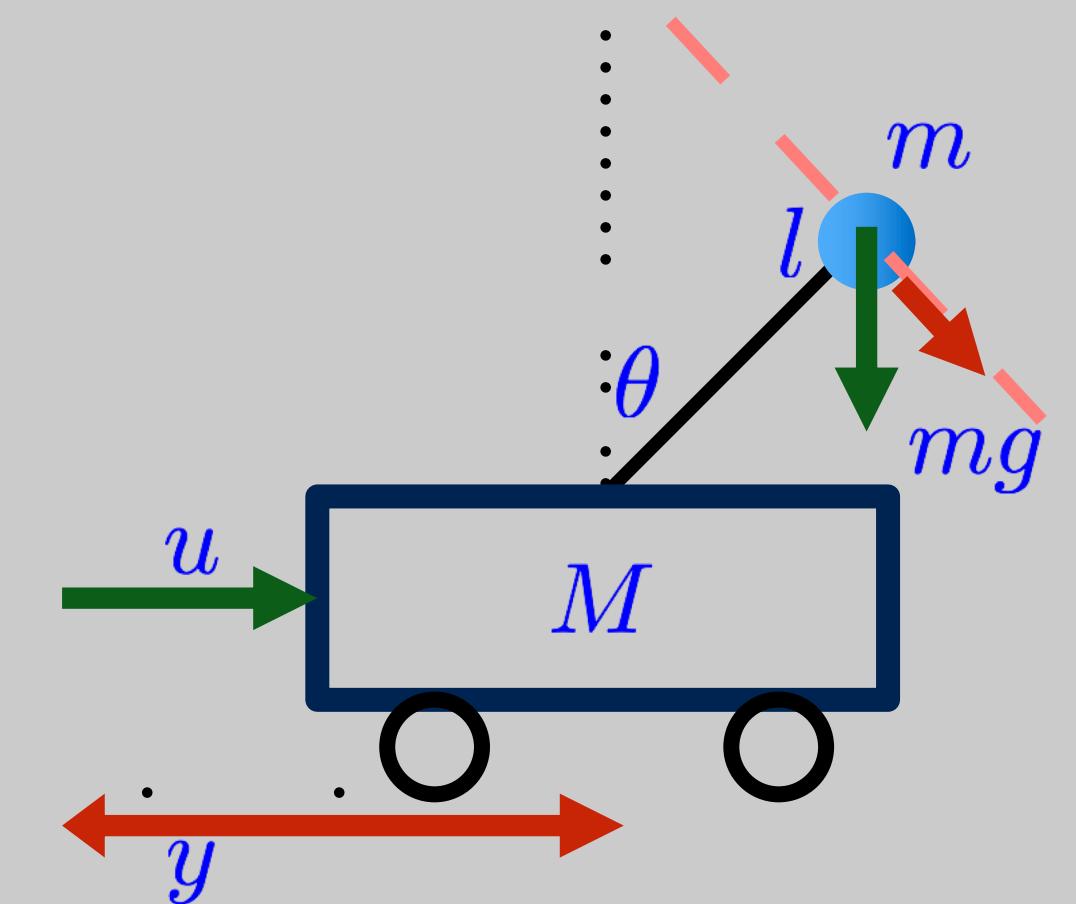
$$(\lambda - \lambda_1)(\lambda - \lambda_2)(\lambda - \lambda_3)$$

Match coeff.

$$A + BK = \begin{bmatrix} 0 & 1 & 0 \\ 11 - k_1 & -k_2 & -k_3 \\ -1 + k_1 & k_2 & k_3 \end{bmatrix}$$

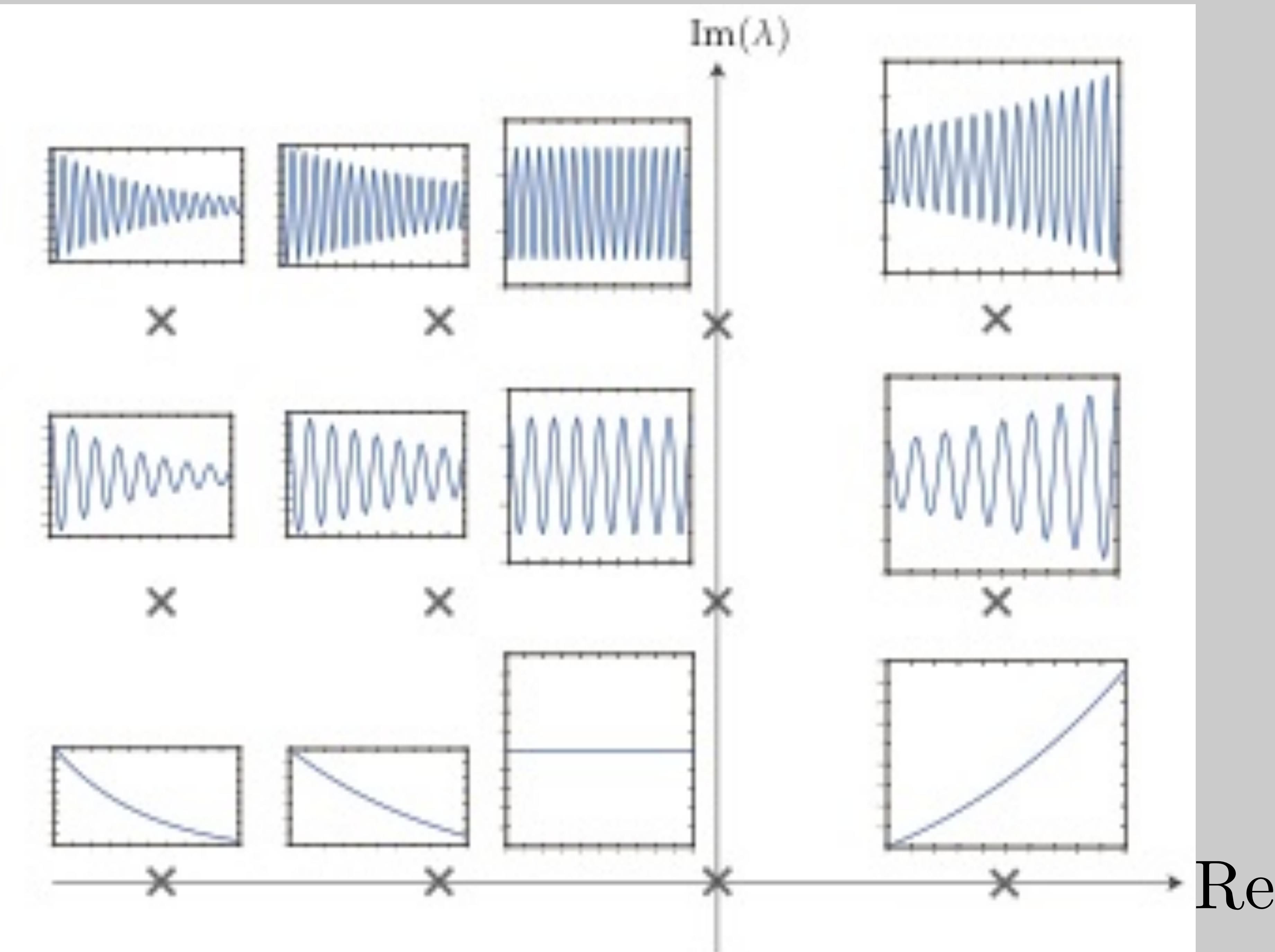
$$\lambda^3 + (k_2 - k_3)\lambda^2 + (k_1 - 11)\lambda + 10k_3 = 0$$

$$\lambda^3 - (\lambda_1 + \lambda_2 + \lambda_3)\lambda^2 - (\lambda_1\lambda_2 + \lambda_1\lambda_3 + \lambda_2\lambda_3)\lambda - \lambda_1\lambda_2\lambda_3 = 0$$



$$\begin{bmatrix} 0 & 1 & -1 \\ 1 & 0 & 0 \\ 0 & 0 & 10 \end{bmatrix} \begin{bmatrix} k_1 \\ k_2 \\ k_3 \end{bmatrix} = \begin{bmatrix} -(\lambda_1 + \lambda_2 + \lambda_3) \\ -(\lambda_1\lambda_2 + \lambda_1\lambda_3 + \lambda_2\lambda_3) + 11 \\ \lambda_1\lambda_2\lambda_3 \end{bmatrix}$$

$$\begin{bmatrix} k_1 \\ k_2 \\ k_3 \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 0.1 \\ 0 & 0 & 0.1 \end{bmatrix}^{-1} \begin{bmatrix} -(\lambda_1 + \lambda_2 + \lambda_3) \\ -(\lambda_1\lambda_2 + \lambda_1\lambda_3 + \lambda_2\lambda_3) + 11 \\ -\lambda_1\lambda_2\lambda_3 \end{bmatrix}$$



# Controller

What is open loop? (no feedback control,  $k_i=0$ ):

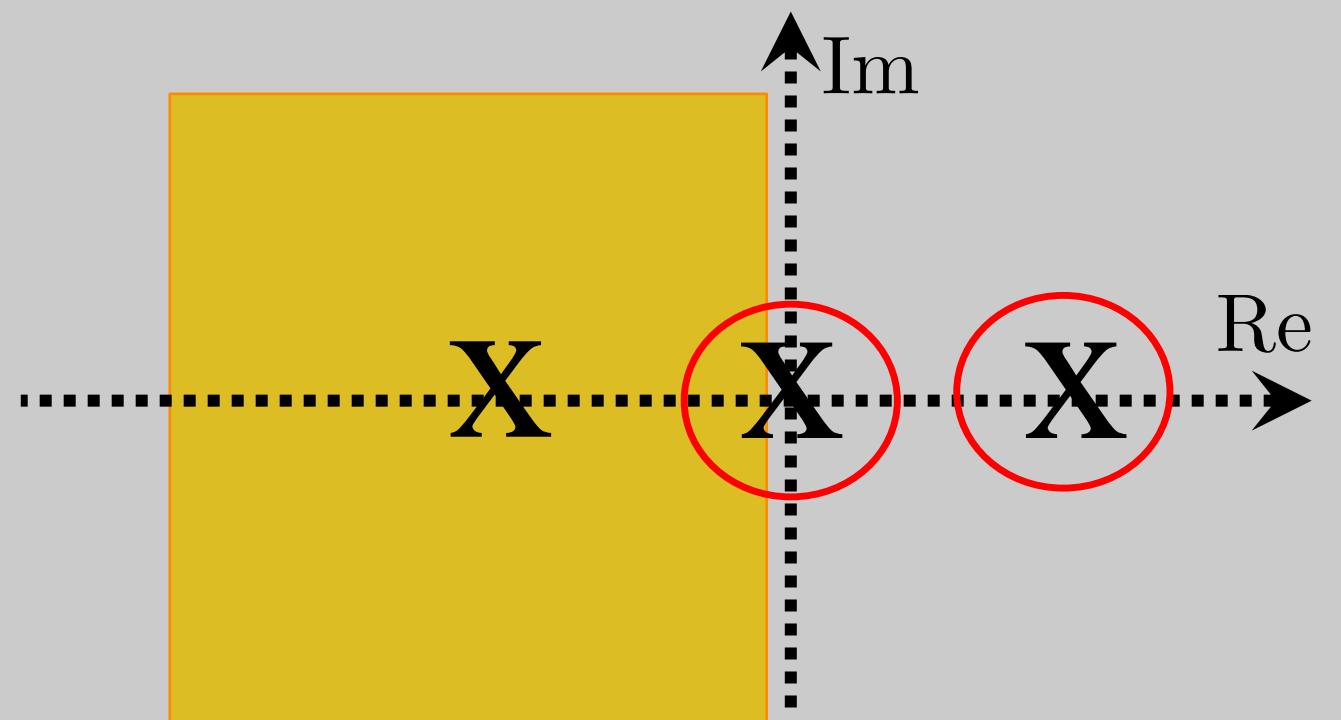
$$\lambda^3 + (k_2 - k_3)\lambda^2 + (k_1 - 11)\lambda + 10k_3 = 0$$

$$\lambda^3 - 11\lambda = 0$$

$$\lambda(\lambda^2 - 11) = 0$$

Ask yourself what if you can control just one, or two state variables?

Controller  
moves bad  
eigen-values  
left!

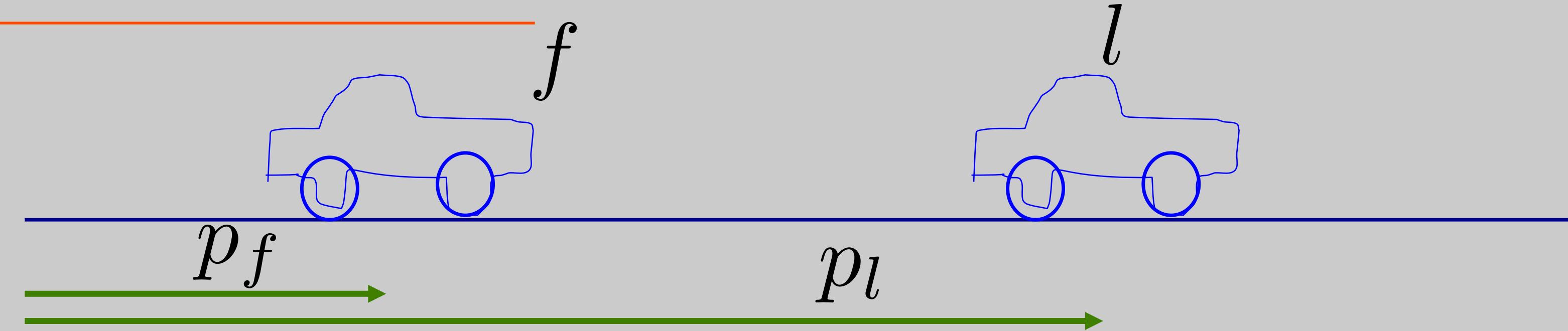


# PLATOONING



# Cooperative Adaptive Cruise control

Example:



$$\frac{d}{dt} p_l(t) = v_l(t)$$

$$\frac{d}{dt} v_l(t) = u_l(t)$$

$$x_1(t) = p_l(t) - p_f(t) - \delta$$

$$x_2(t) = v_l(t) - v_f(t)$$

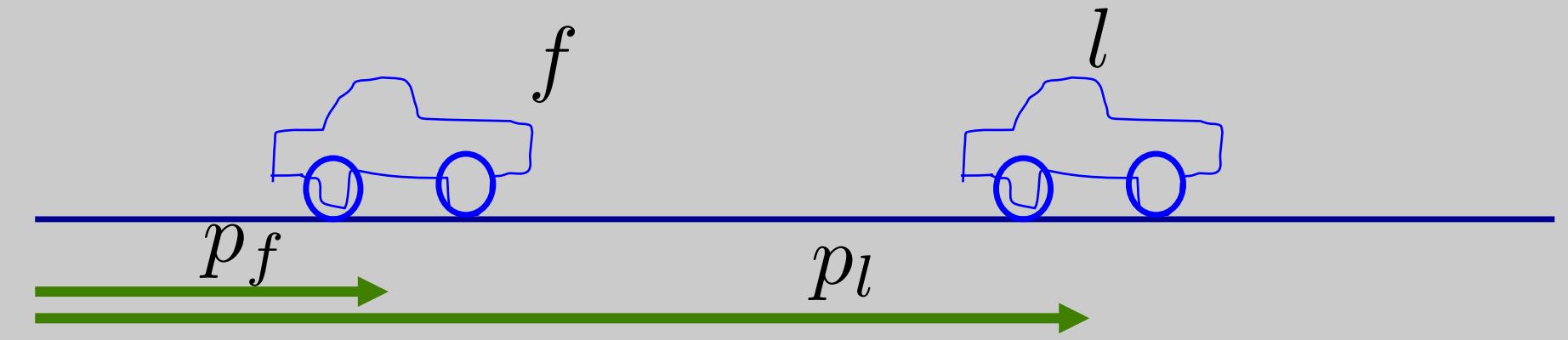
$$\frac{d}{dt} p_f(t) = v_f(t)$$

$$\frac{d}{dt} v_f(t) = u_f(t)$$

$$\frac{d}{dt} x_1(t) = v_l(t) - v_f(t)$$

$$\frac{d}{dt} x_2(t) = u_l(t) - u_f(t) \triangleq u(t)$$

# Cooperative Adaptive Cruise control



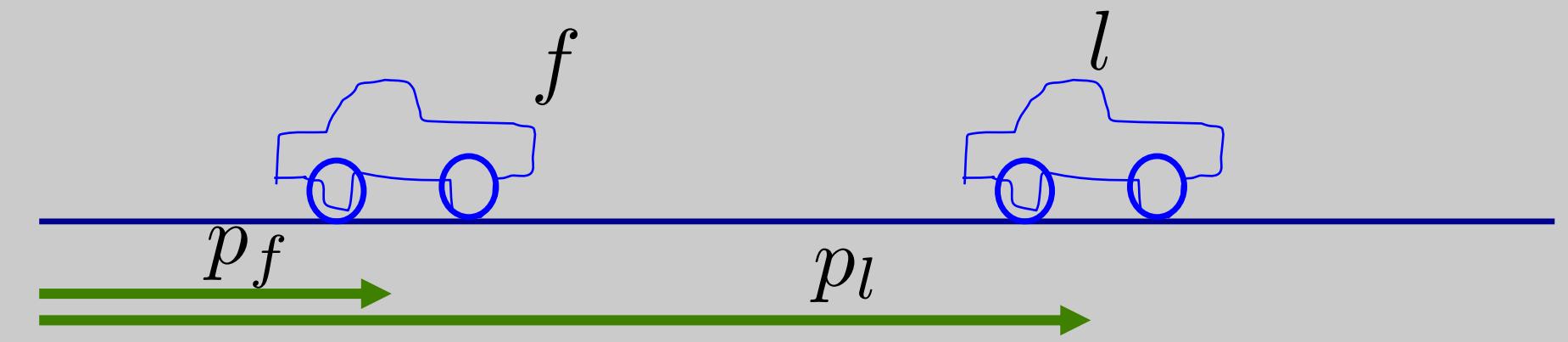
$$\frac{d}{dt}x_1(t) = v_l(t) - v_f(t)$$

$$\frac{d}{dt}x_2(t) = u_l(t) - u_f(t) \triangleq u(t)$$

$$A = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \quad B = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \quad \Rightarrow A + BK = \begin{bmatrix} 0 & 1 \\ k_1 & k_2 \end{bmatrix}$$

Q) What eigen-values will you want here?

Let's look at input more closely...



$$u(t) = k_1 x_1(t) + k_2 x_2(t)$$

$$\Rightarrow u(t) = k_1(p_l(t) - p_f(t) - \delta) + k_2(v_l(t) - v_f(t))$$

But leader chooses his own acceleration  $u_l(t)$

$$u(t) = u_l(t) - u_f(t)$$

$$\begin{aligned} u_f(t) &= u_l(t) - u(t) \\ &= u_l(t) - k_1(p_l(t) - p_f(t) - \delta) - k_2(v_l(t) - v_f(t)) \end{aligned}$$

Q) What does the follower need to know to implement?

A) Cooperative (vehicle2vehicle comm.)  
range sensor (for distance and velocity)

# Outputs

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$$\vec{x}(t+1) = A\vec{x}(t) + Bu(t)$$

Can't always measure state directly or all states...

Define output:

$$\vec{y}(t) = C\vec{x}(t)$$

p x n matrix for p outputs

# Outputs

$$\vec{x}(t+1) = A\vec{x}(t) + Bu(t)$$

Can't always measure state directly or all states...

Define output:

$$\vec{y}(t) = C\vec{x}(t)$$

p x n matrix for p outputs

$$y = x_1 \Rightarrow C = [1 \ 0 \ 0 \ \dots \ 0]$$

$$y = x_1 + x_2 \Rightarrow C = [1 \ 1 \ 0 \ \dots \ 0]$$

$$\vec{y} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \Rightarrow C = \begin{bmatrix} 1 & 0 & 0 & \dots & 0 \\ 0 & 1 & 0 & \dots & 0 \end{bmatrix}$$

$$\vec{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}$$

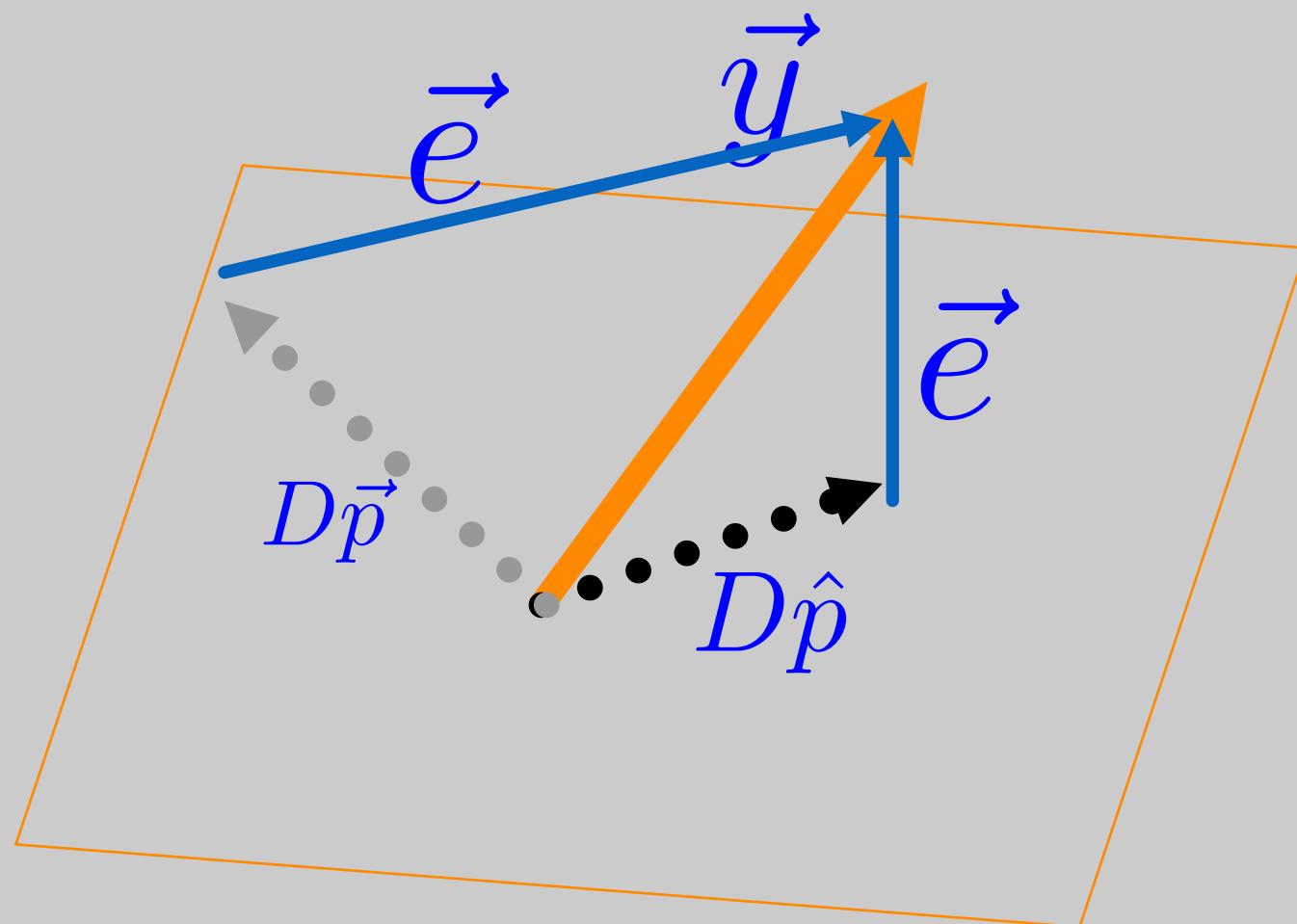
# Least Squares

$$\vec{y} = D\vec{p} + \vec{e}$$

$$p \in \mathcal{R}^k$$

$$y \in \mathcal{R}^l$$

$$\begin{array}{c} \boxed{\phantom{0}} \\ ?= \end{array} \begin{array}{c} \boxed{\phantom{000}} \\ + \end{array} \begin{array}{c} \boxed{\phantom{0}} \\ + \end{array} \begin{array}{c} \boxed{\phantom{0}} \end{array}$$



Least Squares, minimizes  $\|\vec{e}\|$ , which is orthogonal to columns of D

$$D^T \vec{e} = 0 \quad \Rightarrow D^T (\vec{y} - D\hat{p}) = 0 \quad \Rightarrow D^T \vec{y} - D^T D\hat{p} = 0$$

# Least Squares

---

$$\vec{y} = D\vec{p} + \vec{e}$$

$$\Rightarrow D^T \vec{y} - D^T D \hat{p} = 0$$

$$D^T D \hat{p} = D^T \vec{y}$$

If  $D^T D$  is invertible,

$$\hat{p} = (D^T D)^{-1} D^T \vec{y}$$

# Scalar System ID

$$x(t+1) = \lambda x(t) + bu(t) + w(t) \quad y(t) = 1 \cdot x(t)$$

$$x(1) = \lambda x(0) + bu(0) + w(0), \quad y(1) = x(1)$$

$$x(2) = \lambda x(1) + bu(1) + w(1), \quad y(2) = x(2)$$

⋮

$$x(l) = \lambda x(l-1) + bu(l-1) + w(l-1), \quad y(l) = x(l)$$

$$\operatorname{argmin}_{\lambda,b} \|\vec{w}\| \Rightarrow \operatorname{argmin}_{\vec{p}}$$

$$\left[ \begin{array}{c} D \\ \vdots \\ 1 \end{array} \right] \left[ \begin{array}{c} \lambda \\ b \\ \vec{p} \end{array} \right] - \left[ \begin{array}{c} \vec{y} \\ \vdots \\ \vec{w} \end{array} \right]$$

# Scalar System ID

$$\Rightarrow \operatorname{argmin}_{\vec{p}} \left\| \begin{bmatrix} x(0) & u(0) \\ x(1) & (1) \\ \vdots & \\ x(l) & u(l) \end{bmatrix} \begin{bmatrix} \lambda \\ b \end{bmatrix} - \begin{bmatrix} y(1) \\ y(2) \\ \vdots \\ y(l) \end{bmatrix} \right\|$$

Least Squares Estimate:

$$\hat{p} = (D^T D)^{-1} D^T \vec{y}$$

# 2x2 Matrix System ID

$$\vec{x}(t+1) = A\vec{x}(t) + Bu(t) + \vec{w}(t)$$

$$\begin{bmatrix} y_0(t+1) \\ y_1(t+1) \end{bmatrix} \approx \begin{bmatrix} a_{00} & a_{01} \\ a_{10} & a_{11} \end{bmatrix} \begin{bmatrix} x_0(t) \\ x_1(t) \end{bmatrix} + \begin{bmatrix} b_0 u(t) \\ b_1 u(t) \end{bmatrix}$$

$$\begin{bmatrix} & \end{bmatrix} \begin{bmatrix} a_{00} \\ a_{01} \\ b_0 \end{bmatrix} = \begin{bmatrix} & \end{bmatrix} \quad \begin{bmatrix} & \end{bmatrix} \begin{bmatrix} a_{10} \\ a_{11} \\ b_1 \end{bmatrix} = \begin{bmatrix} & \end{bmatrix}$$

# 2x2 Matrix System ID

$$\begin{bmatrix} x_0(0) & x_1(0) & u(0) \\ x_0(1) & x_1(1) & u(1) \\ \vdots & & \\ x_0(l) & x_1(l) & u(l) \end{bmatrix} \begin{bmatrix} a_{00} \\ a_{01} \\ b_0 \end{bmatrix} \approx \begin{bmatrix} y_0(1) \\ y_0(2) \\ \vdots \\ y(l) \end{bmatrix}$$

$\vec{p}_0$

$D$

$$\begin{bmatrix} x_0(0) & x_1(0) & u(0) \\ x_0(1) & x_1(1) & u(1) \\ \vdots & & \\ x_0(l) & x_1(l) & u(l) \end{bmatrix} \begin{bmatrix} a_{10} \\ a_{11} \\ b_1 \end{bmatrix} \approx \begin{bmatrix} y_1(1) \\ y_1(2) \\ \vdots \\ y(l) \end{bmatrix}$$

$\vec{p}_1$

$D$

$$\hat{p}_0 = (D^T D)^{-1} D^T \vec{y}_0$$

$$\hat{p}_1 = (D^T D)^{-1} D^T \vec{y}_1$$

# General Matrix System ID

$$\begin{bmatrix} x_0(0) & x_1(0) & u(0) \\ x_0(1) & x_1(1) & u(1) \\ \vdots & & \\ x_0(l) & x_1(l) & u(l) \end{bmatrix}_D \vec{p}_0 \approx \begin{bmatrix} y_0(1) \\ y_0(2) \\ \vdots \\ y(l) \end{bmatrix}_{\vec{y}_0}$$

$$\begin{bmatrix} x_0(0) & x_1(0) & u(0) \\ x_0(1) & x_1(1) & u(1) \\ \vdots & & \\ x_0(l) & x_1(l) & u(l) \end{bmatrix}_D \vec{p}_1 \approx \begin{bmatrix} y_1(1) \\ y_1(2) \\ \vdots \\ y(l) \end{bmatrix}_{\vec{y}_0}$$

$$\begin{bmatrix} x_0(0) & x_1(0) & u(0) \\ x_0(1) & x_1(1) & u(1) \\ \vdots & & \\ x_0(l) & x_1(l) & u(l) \end{bmatrix} \begin{bmatrix} a_{00} & a_{01} \\ a_{01} & b_0 \end{bmatrix} \approx \begin{bmatrix} y_0(1) \\ y_0(2) \\ \vdots \\ y(l) \end{bmatrix} \begin{bmatrix} a_{10} \\ a_{11} \\ b_1 \end{bmatrix}$$

$$\begin{bmatrix} \vec{x}^T(0) & u(0) \\ \vec{x}^T(1) & u(1) \\ \vdots & \\ \vec{x}^T(l) & u(l) \end{bmatrix}_D \begin{bmatrix} A^T \\ B^T \\ P \end{bmatrix} = \begin{bmatrix} \vec{y}^T(0) \\ \vec{y}^T(1) \\ \vdots \\ \vec{y}^T(l) \end{bmatrix}_Y \Rightarrow \hat{P} = (D^T D)^{-1} D^T \vec{Y}$$

# Control Recap

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- Controllability:

$$\vec{x}(n) - A^n \vec{x}(0) = \begin{bmatrix} A^{n-1}B & A^{n-2}B & \dots & AB & B \end{bmatrix} \begin{bmatrix} u(0) \\ u(1) \\ \vdots \\ u(n-1) \end{bmatrix}$$

If  $R_n$  is full rank then  
we can move to any  
target value

Same rank test for  
continuous time

- Open loop control:

Can use the above equation to design an input sequence – and apply it blindly. Accuracy of result will depend on accuracy of model.

# Control Recap – State Feedback

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$$u(t) = K \vec{x}(t)$$

Closed-loop system:  $\Rightarrow \vec{x}(t+1) = (A + BK)\vec{x}(t)$

Must choose  $K$  s.t.  $A+BK$  has eigenvalues inside the unit circle (or left half-plane for continuous time)

If controllable, can assign eigenvalues for  $A+BK$  arbitrarily

If not, some eigenvalues of  $A$  can not be changed!  
(could be OK, if stable, bad news if not)

# System Identification

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Given a system:

$$\vec{x}(t + 1) = A\vec{x}(t) + Bu(t)$$

Can we learn A, and B by applying inputs and observing resulting states?

# How Does MRI Work? (some today – more later!)

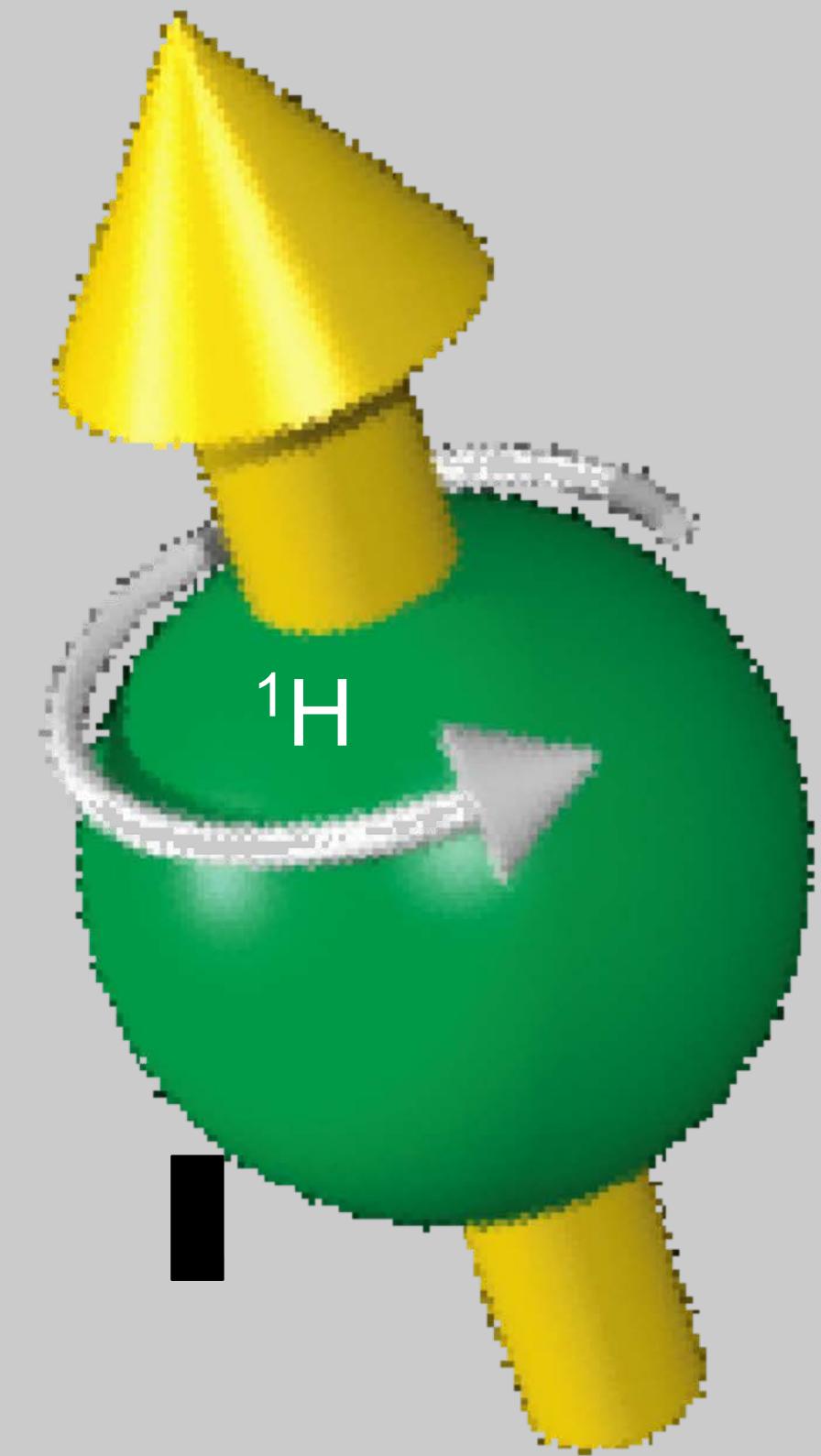
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- Magnetic Polarization
  - Very strong uniform magnet
- Excitation
  - Very powerful RF transmitter
- Acquisition
  - Location is encoded by gradient magnetic fields
  - Very powerful audio amps

# Polarization

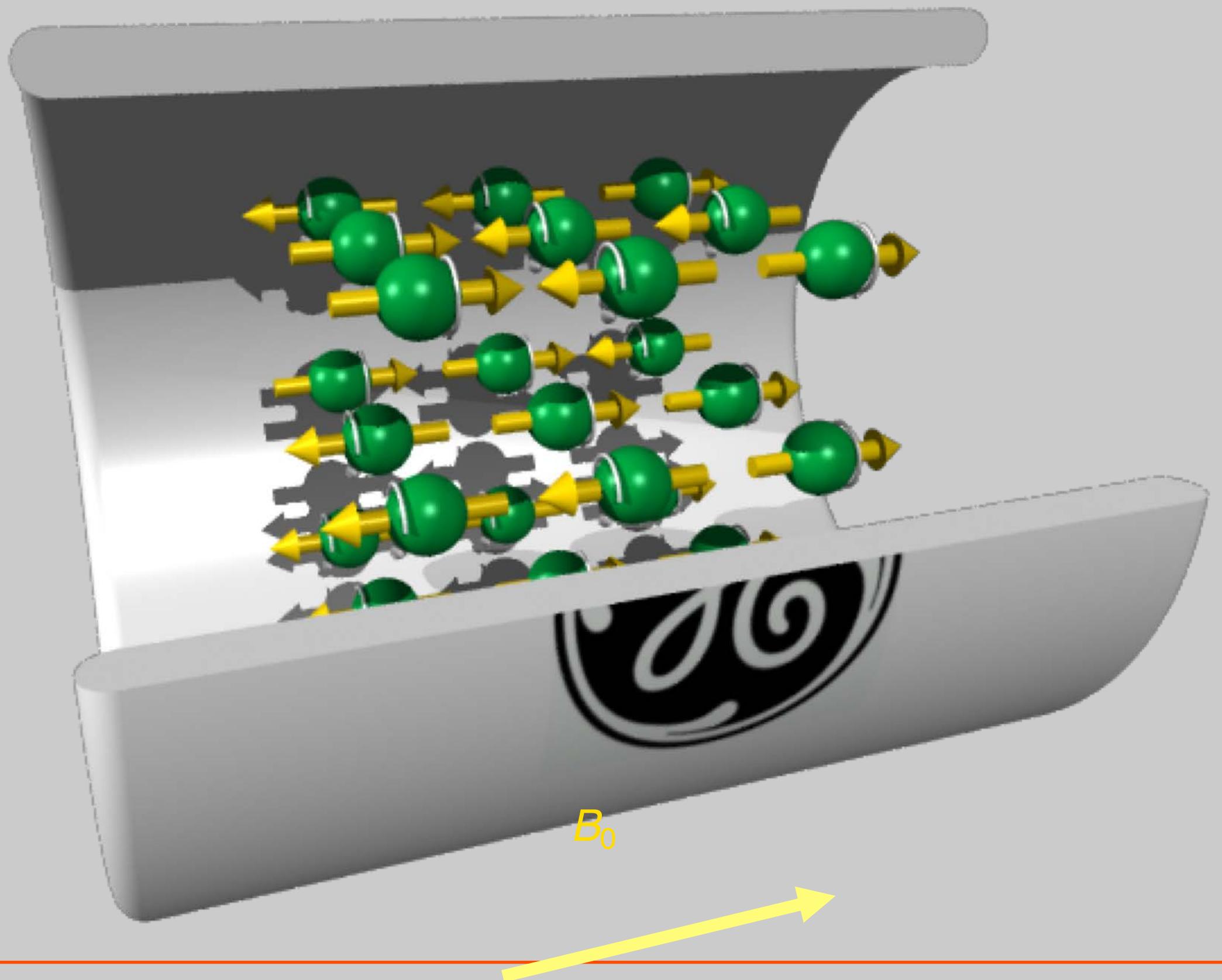
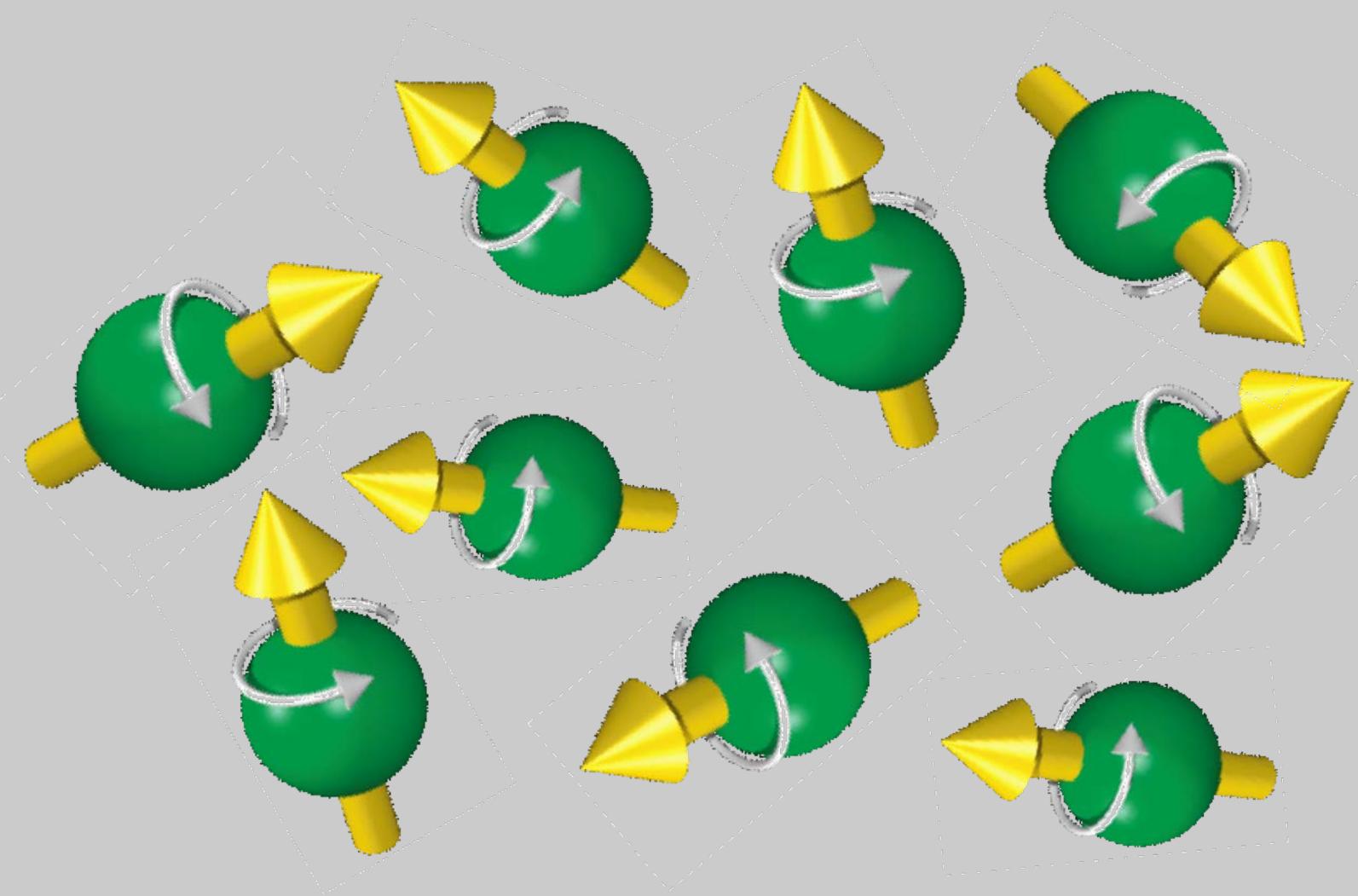
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- Protons have a magnetic moment
- Protons have spins
- Like rotating magnets



# Polarization

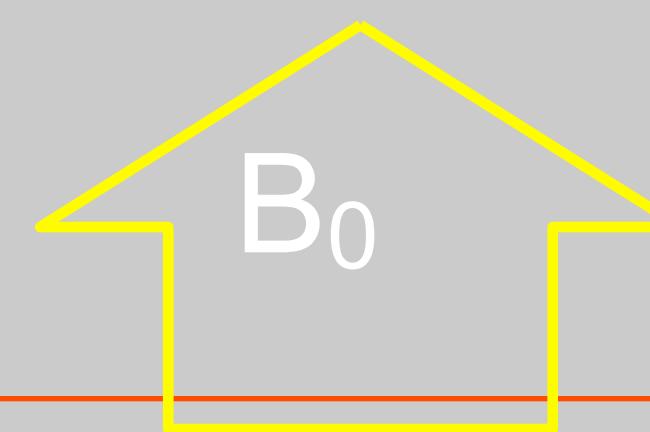
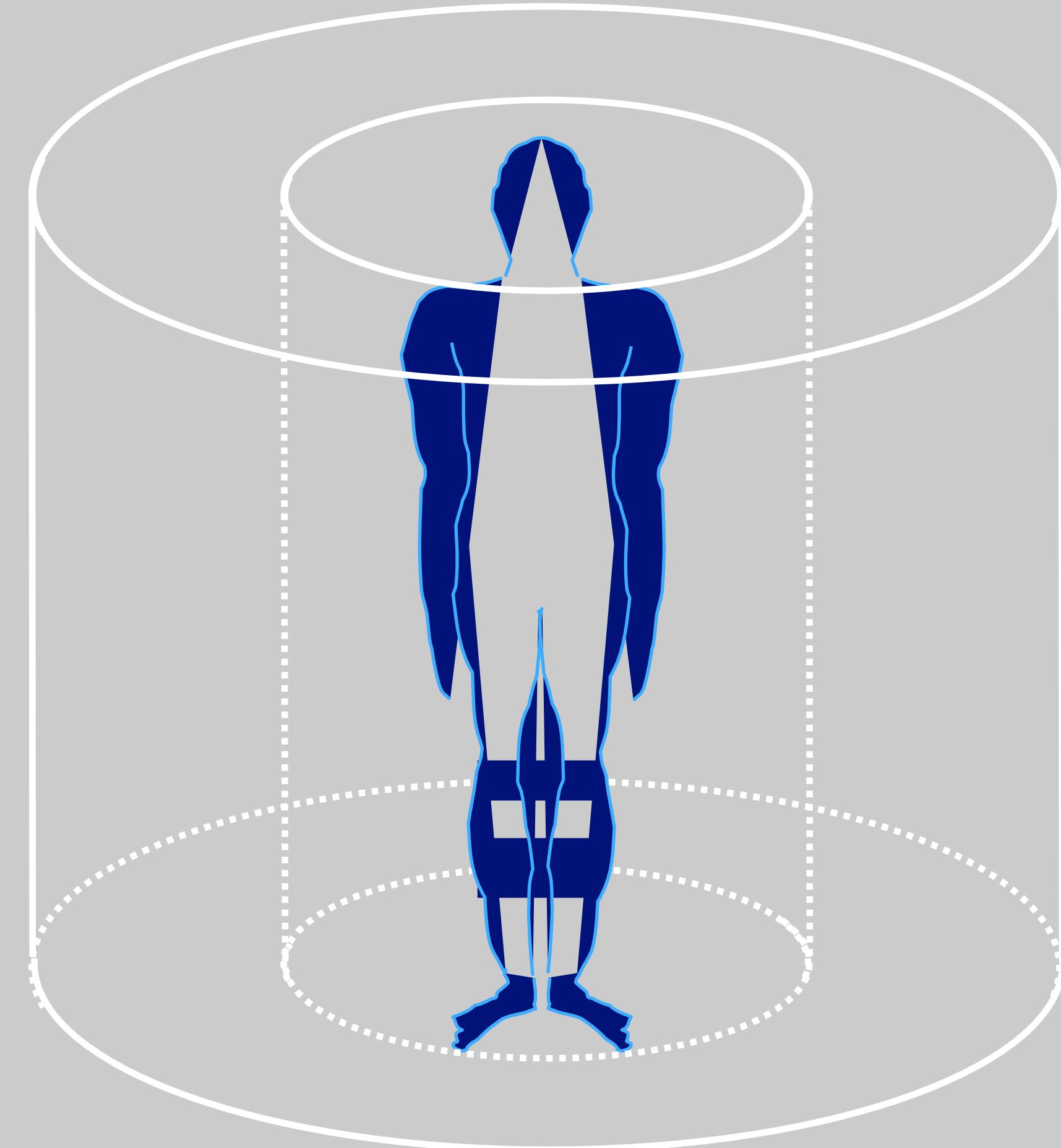
- Body has a lot of protons
- In a strong magnetic field  $B_0$ , spins align with  $B_0$  giving a net magnetization



# Polarizing Magnet

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- 0.1 to 12 Tesla
- 0.5 to 3 T common
- 1 T is 10,000 Gauss
- Earth's field is 0.5G
- Typically a superconducting magnet



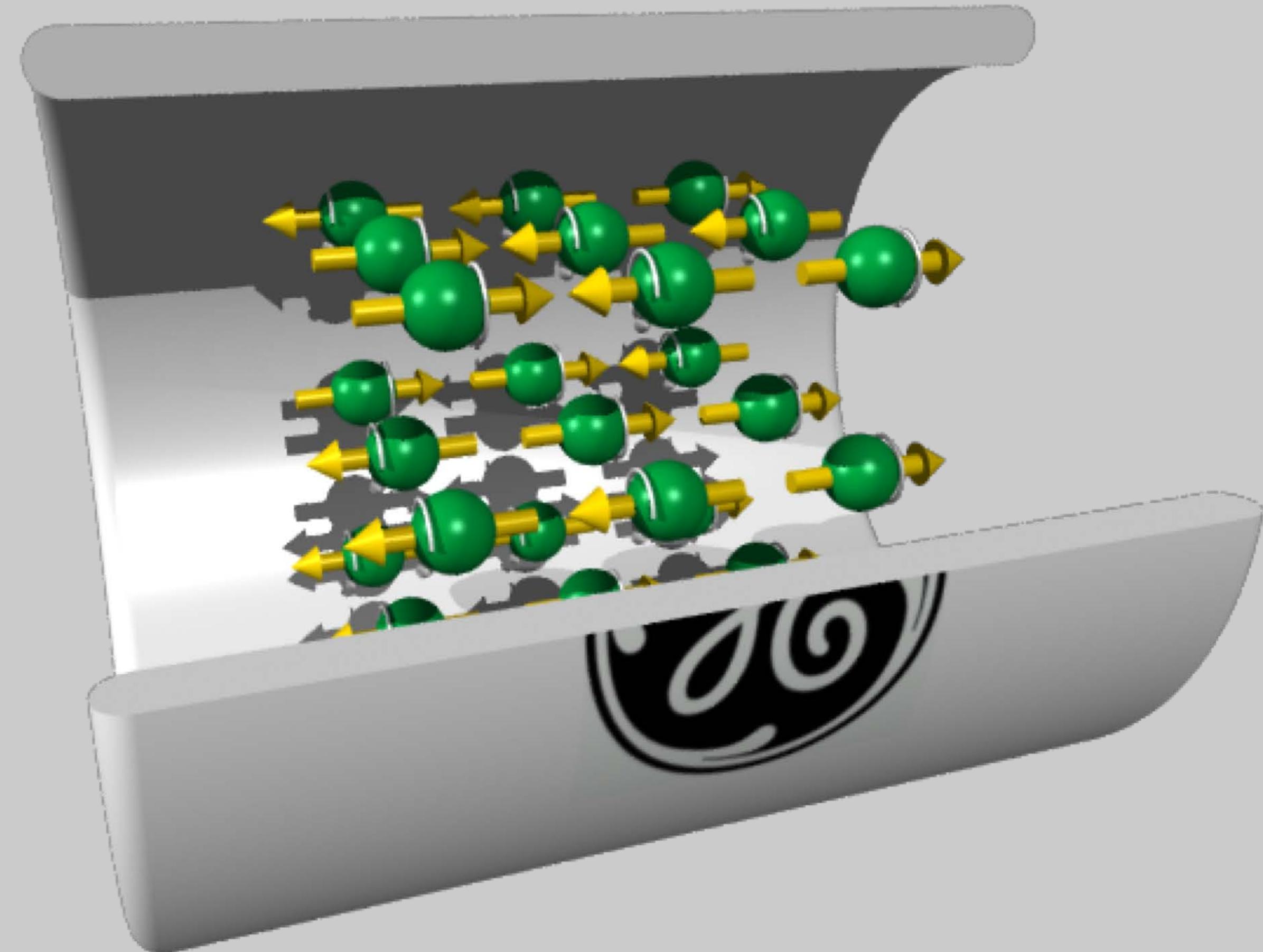
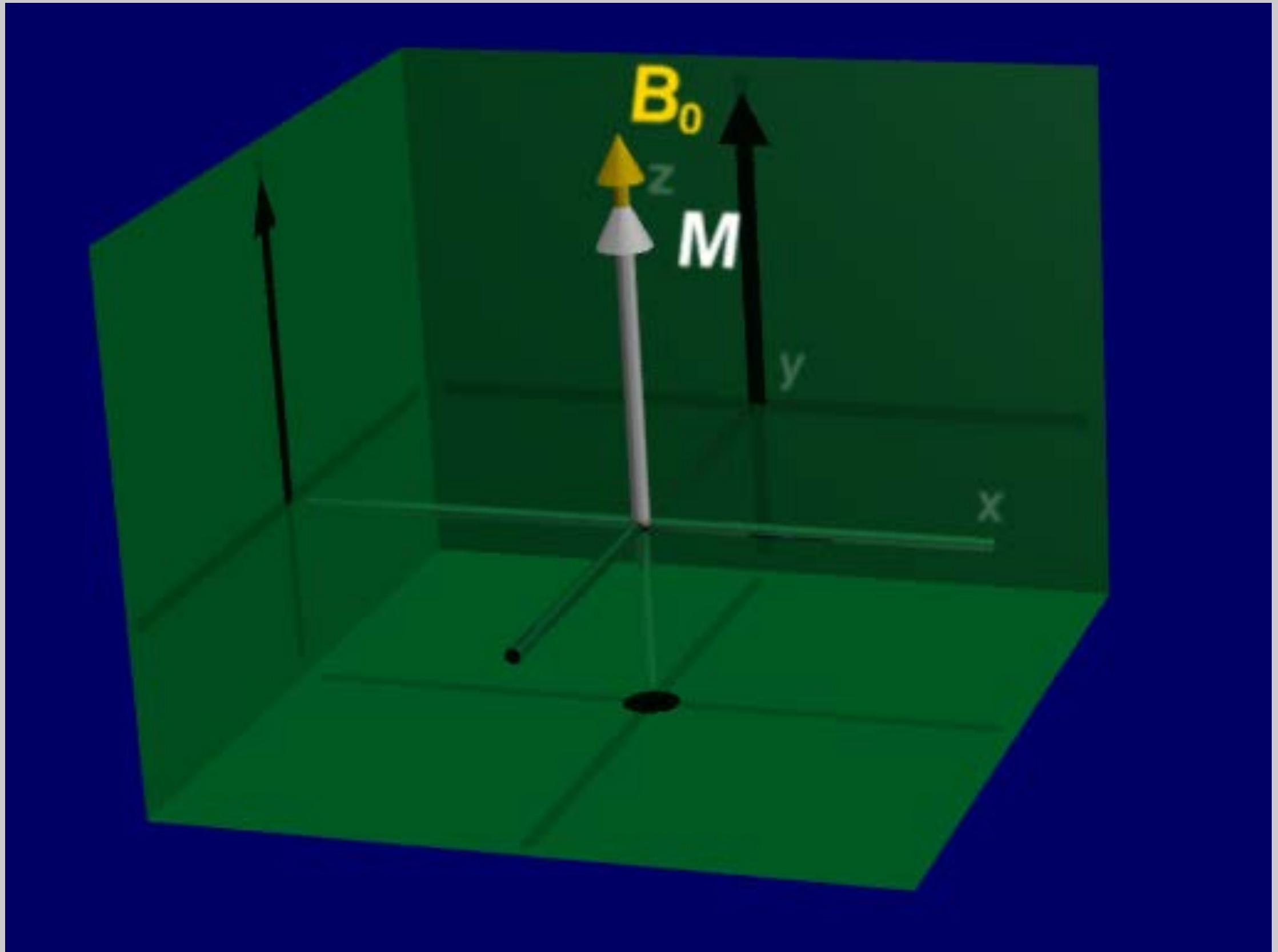
# Typical MRI Scanner





A magnetic  
object

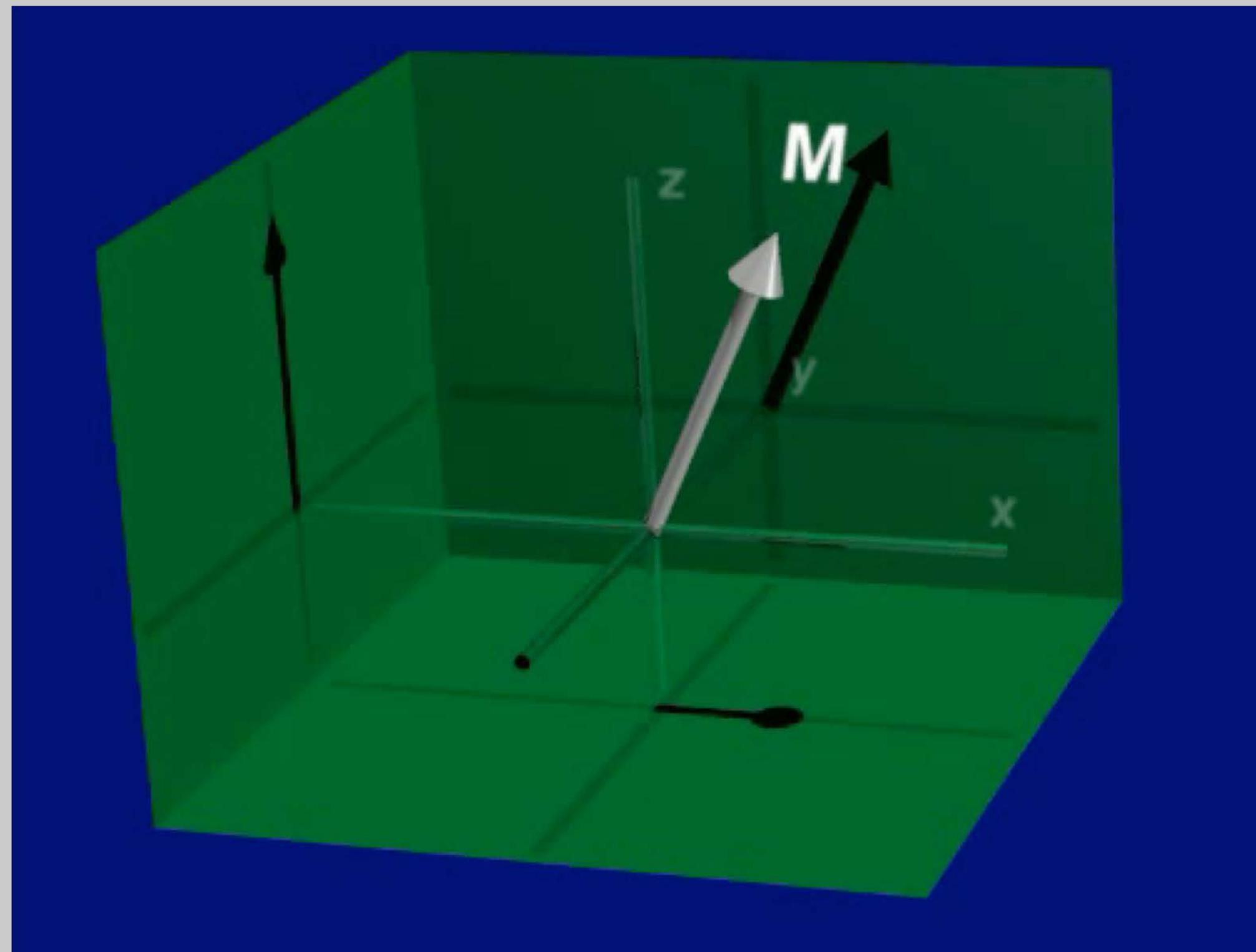
# Polarization



# Free Precession

- Much like a spinning top
- Frequency proportional to the field
- $f = 127\text{MHz} @ 3\text{T}$

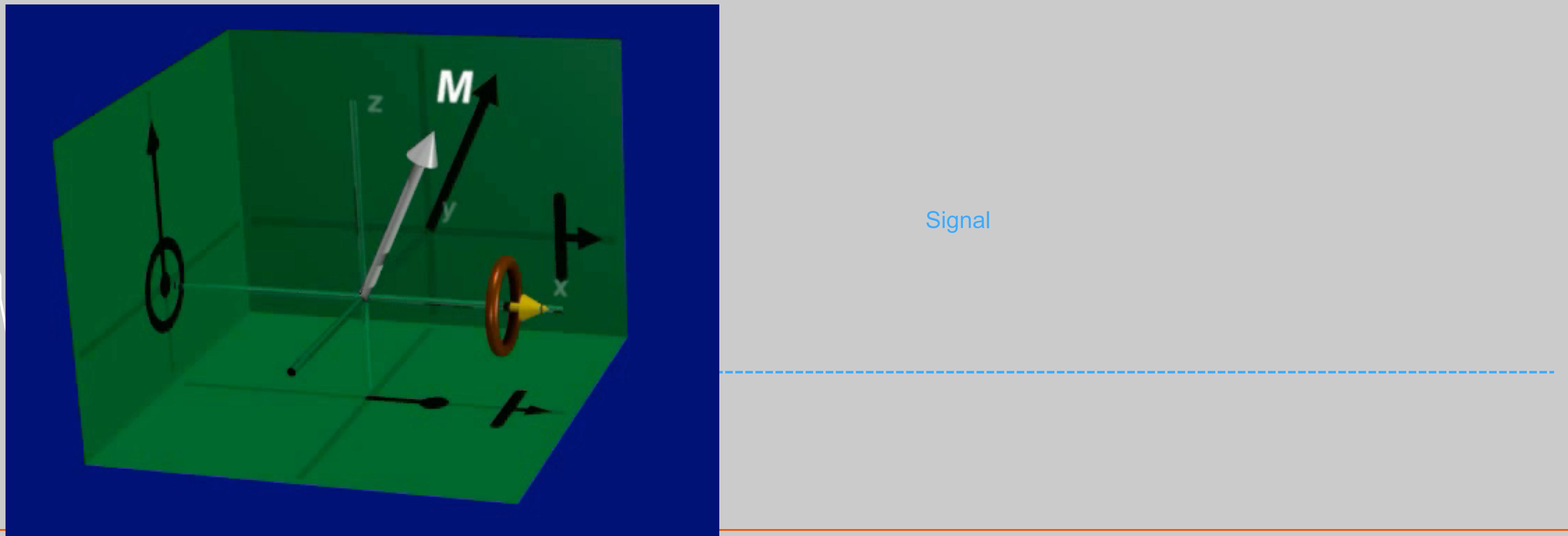
$$\frac{d\vec{M}}{dt} = \vec{M} \times \gamma \vec{B}$$

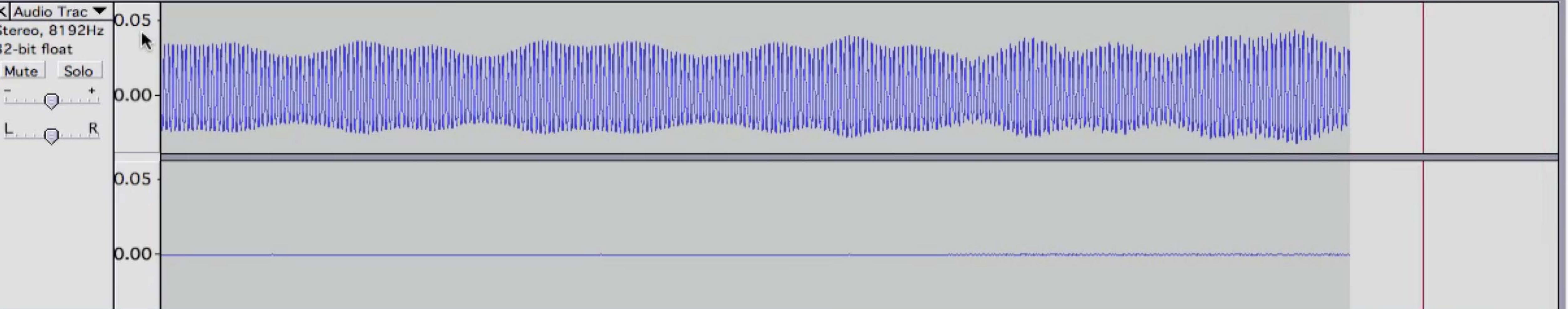
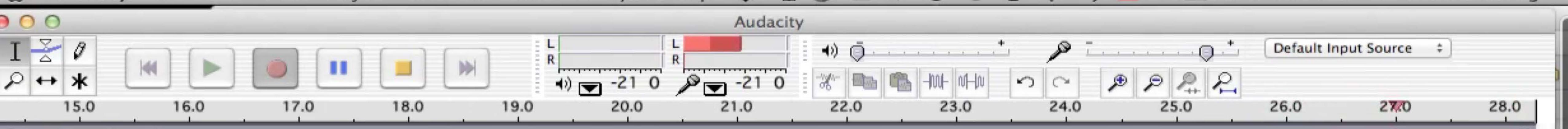


# Free Precession

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- Precession induces magnetic flux
- Flux induces voltage in a coil





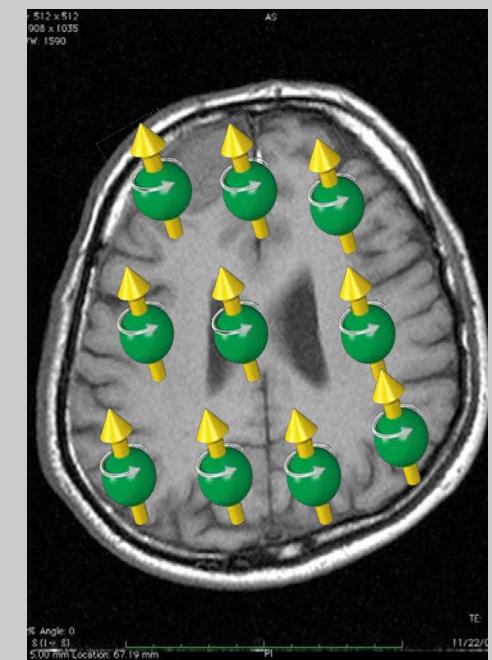
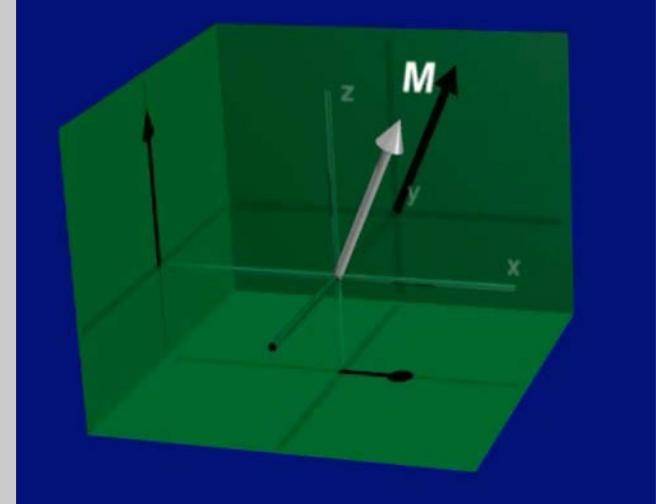
Disk space remains for recording 761 hours and 21 minutes

Project rate: 8192

Cursor: 0:00.000000 min:sec [Snap-To Off]

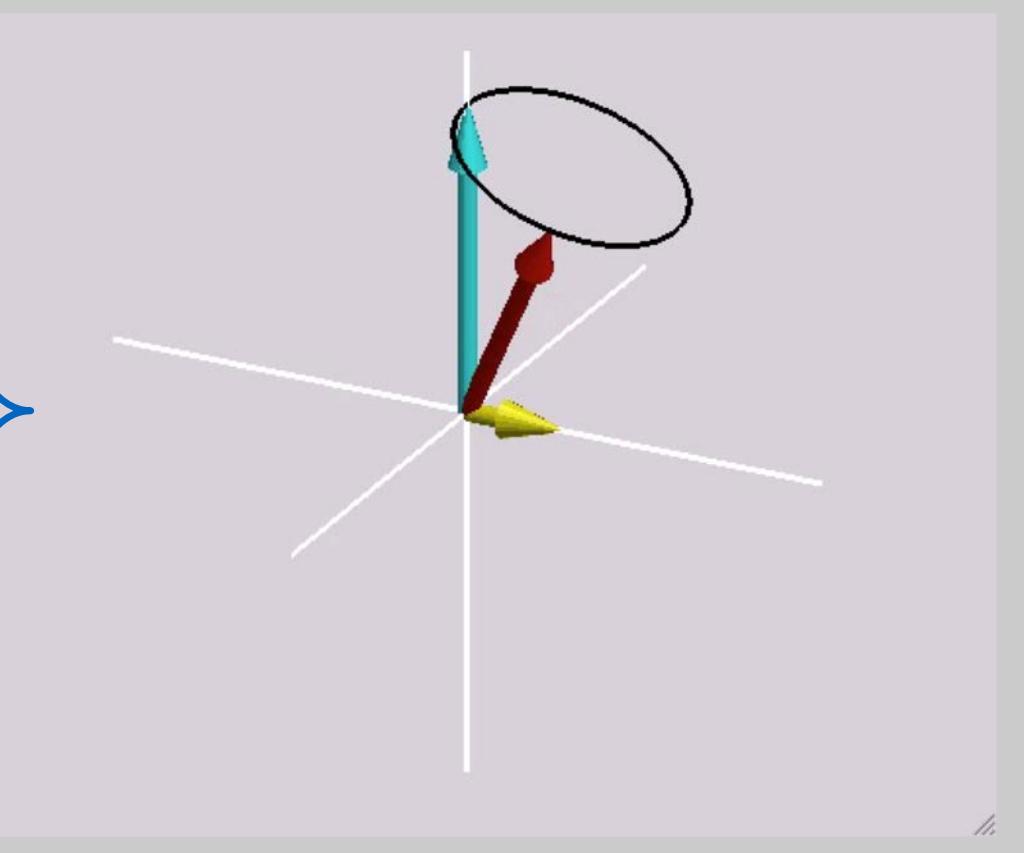
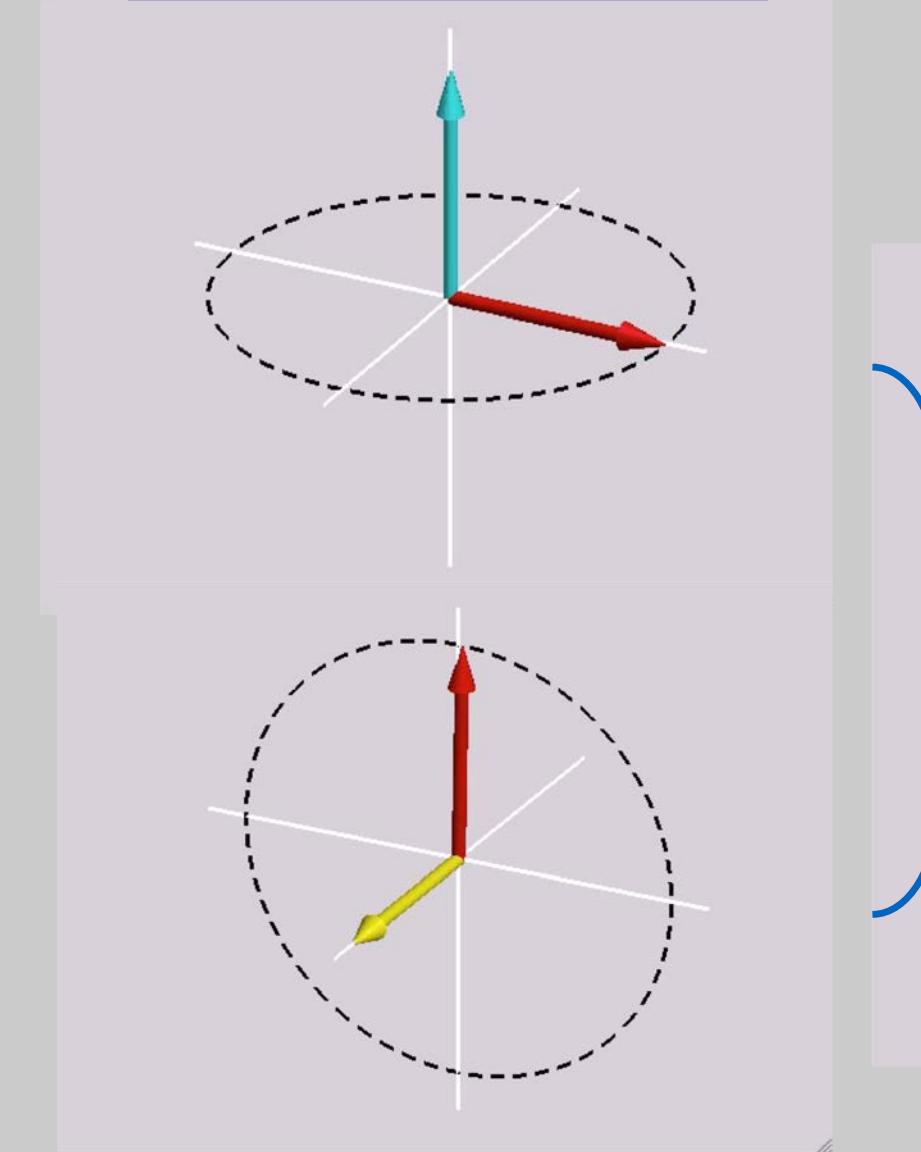
## Free precession

$$\begin{bmatrix} \dot{M}_x(\vec{r}, t) \\ \dot{M}_y(\vec{r}, t) \\ \dot{M}_z(\vec{r}, t) \end{bmatrix} = \begin{bmatrix} 0 & \gamma B_0 & 0 \\ -\gamma B_0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} M_x(\vec{r}, t) \\ M_y(\vec{r}, t) \\ M_z(\vec{r}, t) \end{bmatrix}$$



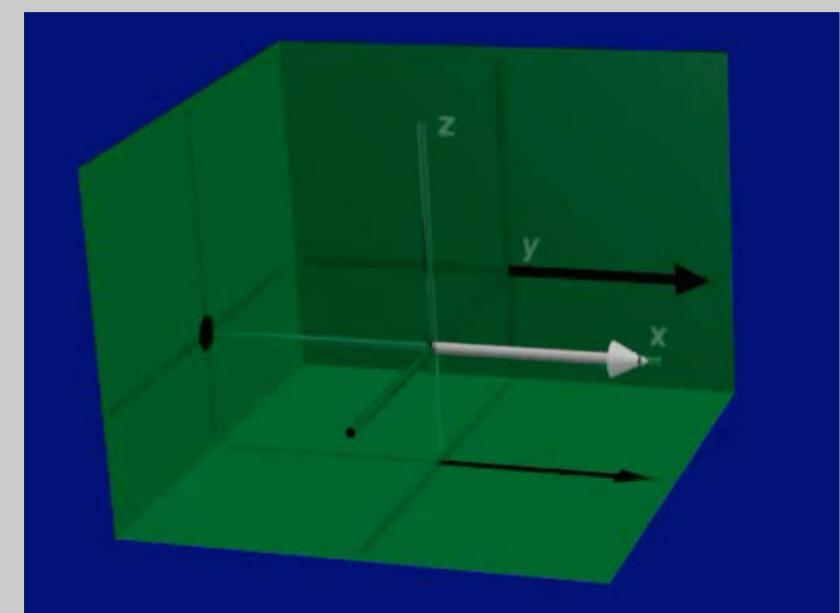
## Gradient encoding

$$\begin{bmatrix} \dot{M}_x(\vec{r}, t) \\ \dot{M}_y(\vec{r}, t) \\ \dot{M}_z(\vec{r}, t) \end{bmatrix} = \begin{bmatrix} 0 & \gamma \vec{G}(t) \cdot \vec{r} & 0 \\ -\gamma \vec{G}(t) \cdot \vec{r} & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} M_x(\vec{r}, t) \\ M_y(\vec{r}, t) \\ M_z(\vec{r}, t) \end{bmatrix}$$



## RF excitation

$$\begin{bmatrix} \dot{M}_x(\vec{r}, t) \\ \dot{M}_y(\vec{r}, t) \\ \dot{M}_z(\vec{r}, t) \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & \gamma B_{1x}(t) \\ 0 & -\gamma B_{1x}(t) & 0 \end{bmatrix} \begin{bmatrix} M_x(\vec{r}, t) \\ M_y(\vec{r}, t) \\ M_z(\vec{r}, t) \end{bmatrix}$$



## Relaxation

$$\begin{bmatrix} \dot{M}_x(\vec{r}, t) \\ \dot{M}_y(\vec{r}, t) \\ \dot{M}_z(\vec{r}, t) \end{bmatrix} = \begin{bmatrix} -\frac{1}{T_2} & 0 & 0 \\ 0 & -\frac{1}{T_2} & 0 \\ 0 & 0 & -\frac{1}{T_1} \end{bmatrix} \begin{bmatrix} M_x(\vec{r}, t) \\ M_y(\vec{r}, t) \\ M_z(\vec{r}, t) \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ \frac{1}{T_1} \end{bmatrix} M_0(\vec{r})$$

# The Bloch Equation

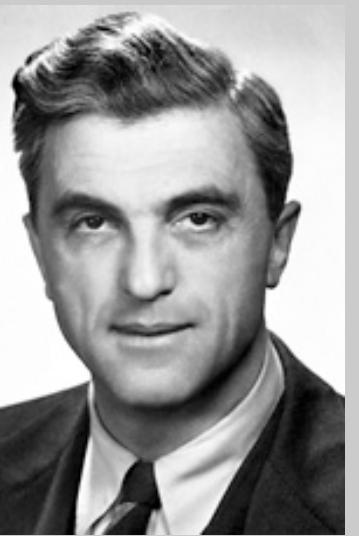
$$\begin{bmatrix} \dot{M}_x(\vec{r}, t) \\ \dot{M}_y(\vec{r}, t) \\ \dot{M}_z(\vec{r}, t) \end{bmatrix} = \begin{bmatrix} -\frac{1}{T_2}(\vec{r}) & \gamma \vec{G}^t \cdot \vec{r} & -\gamma B_{1y}^{(t)} \\ -\gamma \vec{G}^t \cdot \vec{r} & -\frac{1}{T_2}(\vec{r}) & \gamma B_{1x}^{(t)} \\ \gamma B_{1y}^{(t)} & -\gamma B_{1x}^{(t)} & -\frac{1}{T_1}(\vec{r}) \end{bmatrix} \begin{bmatrix} M_x(\vec{r}, t) \\ M_y(\vec{r}, t) \\ M_z(\vec{r}, t) \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ \frac{1}{T_1} \end{bmatrix} M_0(\vec{r})$$

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

Observe:  $\vec{y}(t) = \int_{\vec{R}} CM(\vec{r}, t) d\vec{r}$

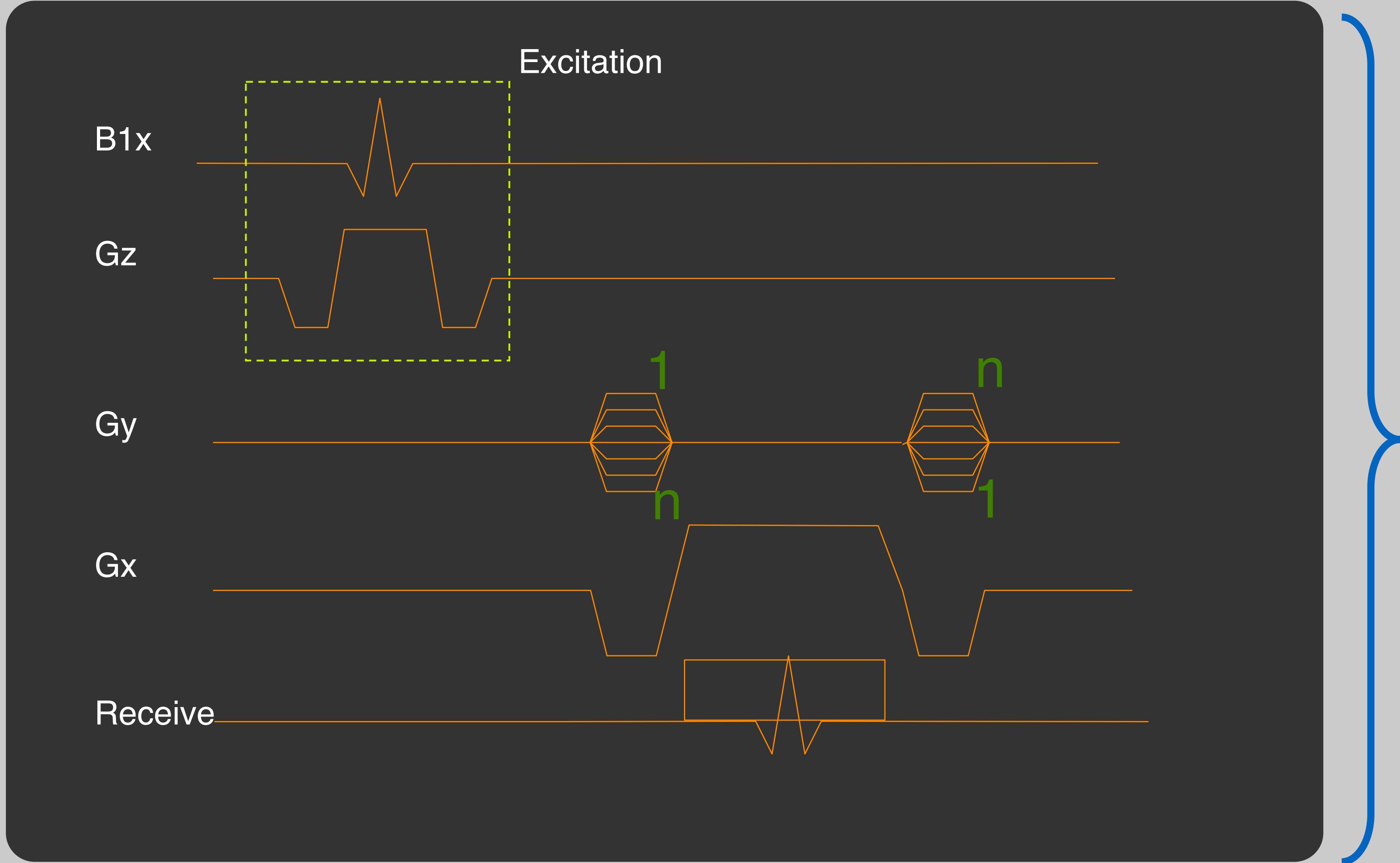
Inputs:  $G_x(t), G_y(t), G_z(t), B_{1x}(t), B_{1y}(t)$

Unknown:  $M_0(\vec{r})$  The image!



# MRI Pulse Sequence

$$\begin{bmatrix} \dot{M}_x(\vec{r}, t) \\ \dot{M}_y(\vec{r}, t) \\ \dot{M}_z(\vec{r}, t) \end{bmatrix} = \begin{bmatrix} -\frac{1}{T_2}(\vec{r}) & \gamma \vec{G}^t \cdot \vec{r} & -\gamma B_{1y}^{(t)} \\ -\gamma \vec{G}^t \cdot \vec{r} & -\frac{1}{T_2}(\vec{r}) & \gamma B_{1x}^{(t)} \\ \gamma B_{1y}^{(t)} & -\gamma B_{1x}^{(t)} & -\frac{1}{T_1}(\vec{r}) \end{bmatrix} \begin{bmatrix} M_x(\vec{r}, t) \\ M_y(\vec{r}, t) \\ M_z(\vec{r}, t) \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ \frac{1}{T_1} \end{bmatrix} M_0(\vec{r})$$



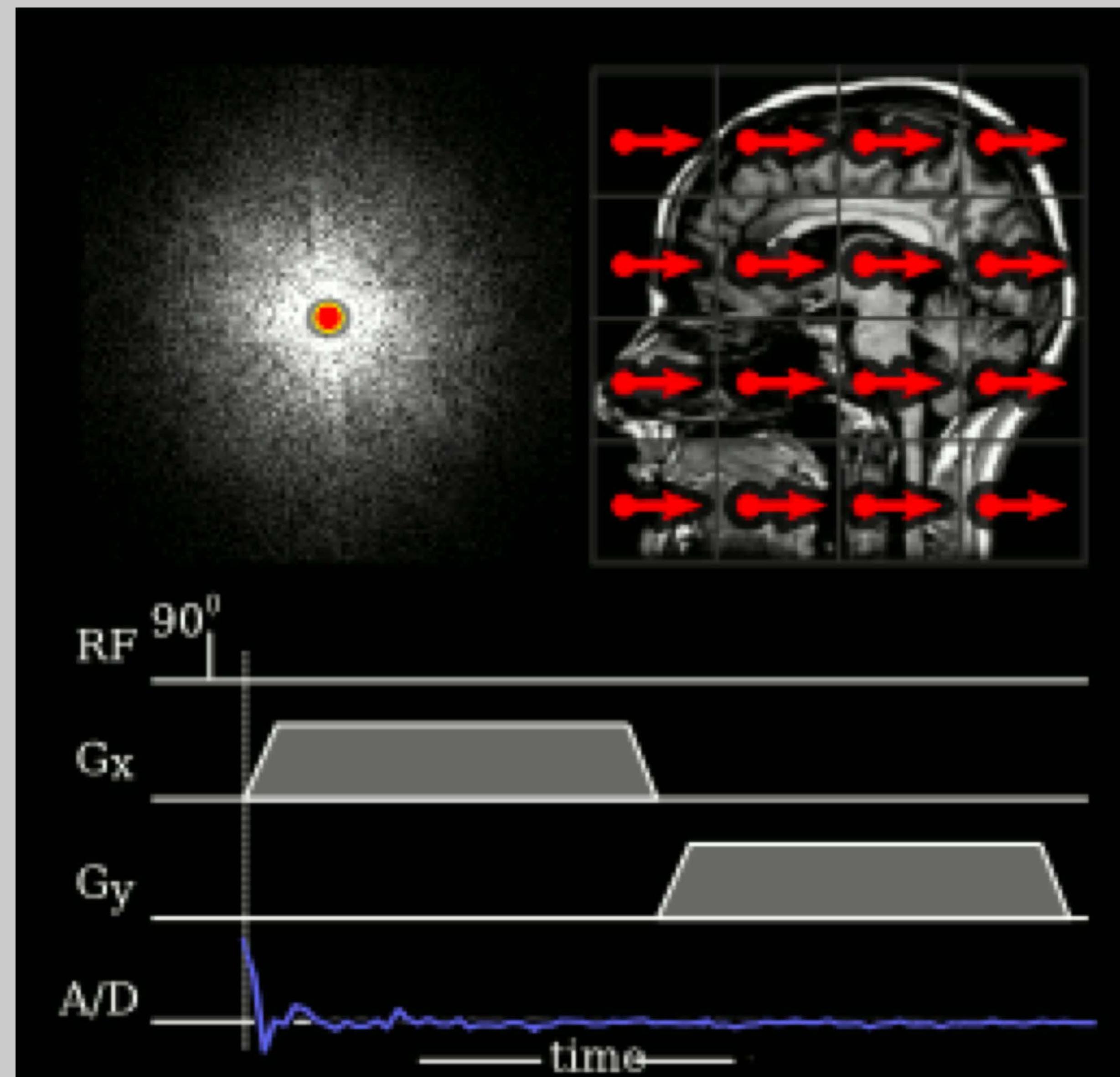
Repeat *n* times  
rate = TR seconds

# Acquisition

Observe:

$$\vec{y}(t) = \int_{\vec{R}} CM(\vec{r}, t) d\vec{r}$$

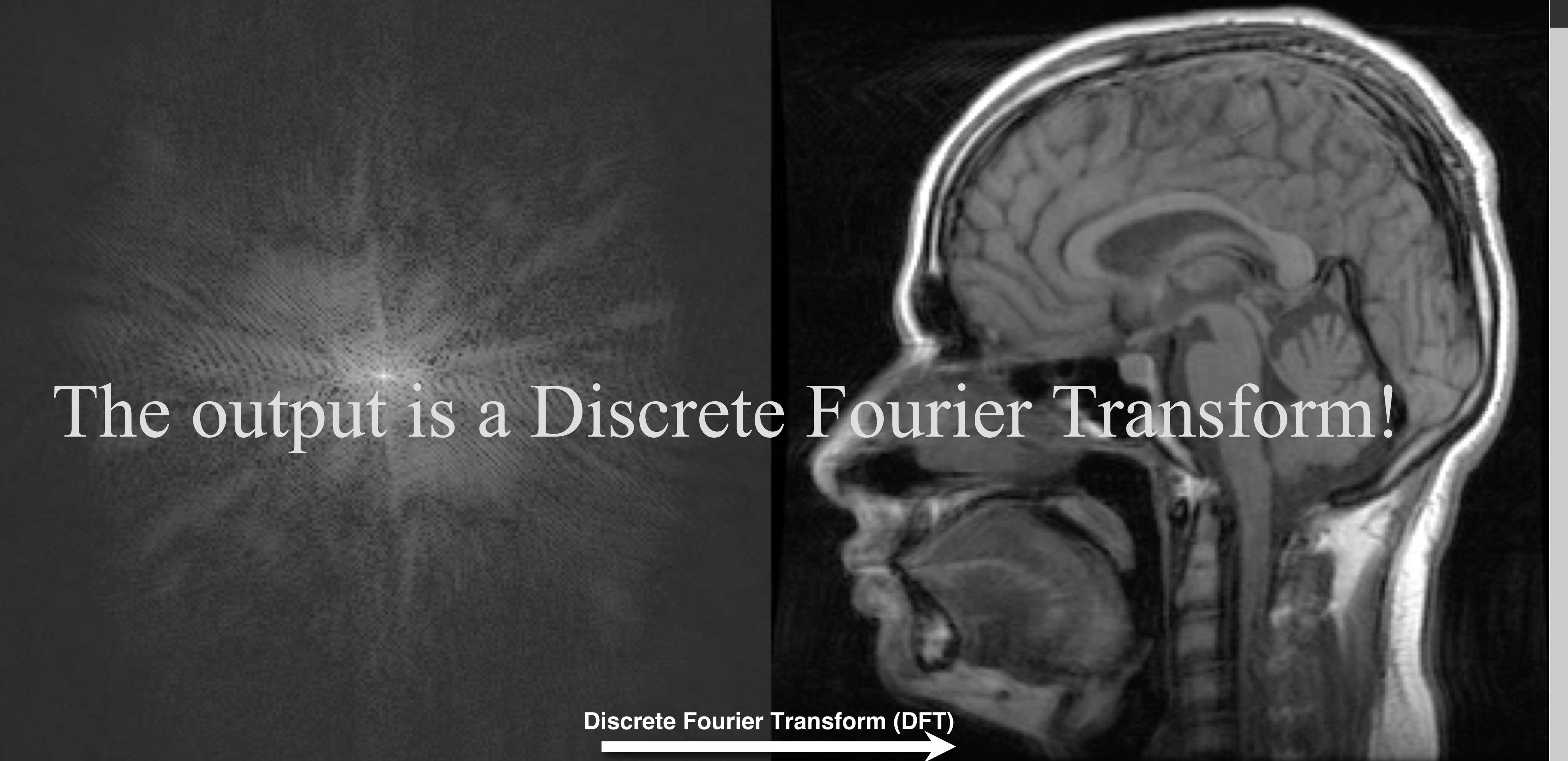
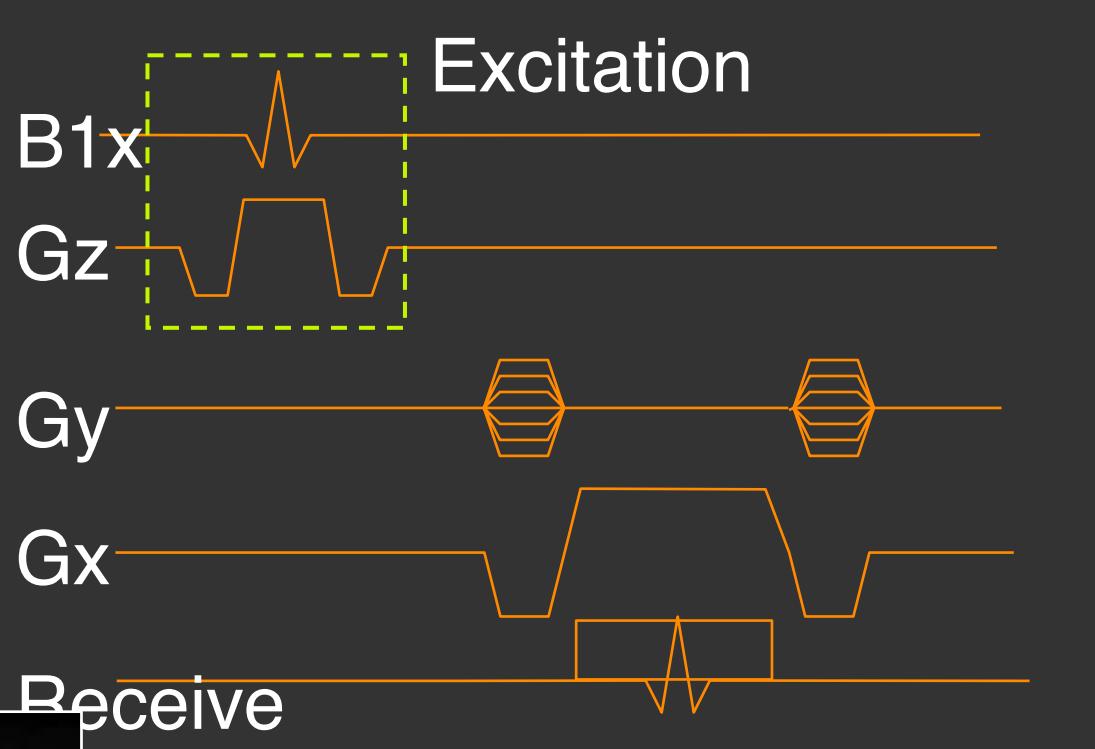
$$C = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$



# Fourier Reconstruction

$$y(t) = \int_R M_x(r, t) + jM_y(r, t) dr$$

 Data (showing just magnitude)



The output is a Discrete Fourier Transform!

Discrete Fourier Transform (DFT)