# Lecture 3 - System Modeling

July 8, 2015

# Outline

# Introduction

We can derive the mathematical model of a dynamic system in **two ways** mainly:

1. Physical Modeling:
   Applying the laws of physics, chemistry, thermodynamics,...
   Also called modeling from *First Principles*
   - Sometimes these are non-linear. Lots of methods of this course require linear systems. Therefore **linearization** is needed.
     e.g. $\sin(\theta) \sim \theta, \theta \to 0$

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   - Sometimes these are non-linear. Lots of methods of this course require linear systems. Therefore **linearization** is needed.
     e.g. $\sin(\theta) \sim \theta, \theta \to 0$
2. System identification or *Empirical Modeling*:
   Developing models from observed or collected data

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**Black box identification**: based on experimentation.
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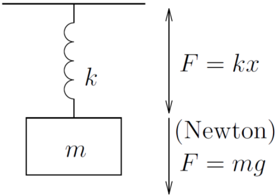
Most popular approaches are forms of black box identification.

# Outline

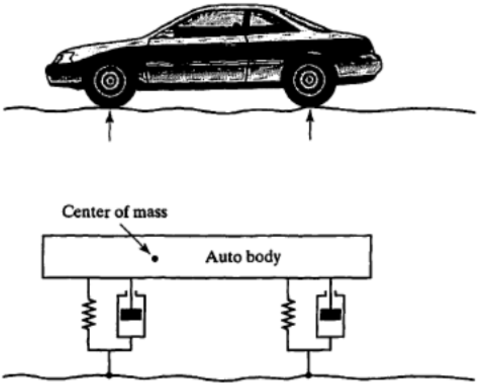
# Example 1: Mass-Spring System

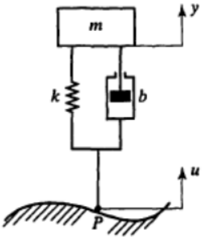



If spring is at rest at $x = 0$:

$$m \cdot \frac{d^2x}{dt^2} + k \cdot x = m \cdot g$$

# Example 2: Mass-Spring Damped

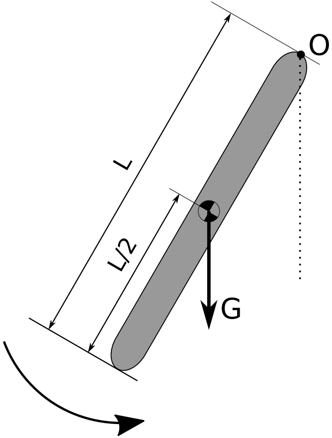



Force excerted by damper: $F = b\dot{x}$

Differential equation can be found by writing force equilibrium and moment equilibrium around center of mass

# Example 3: Pendulum

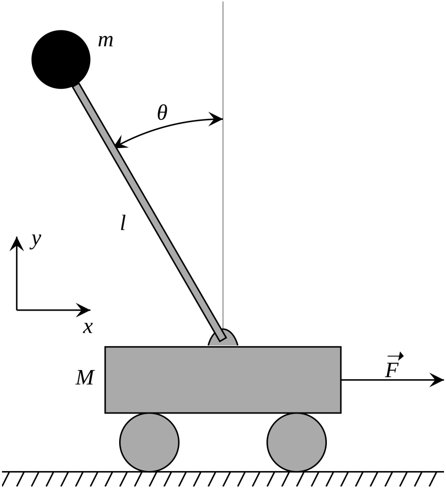



Dynamic equilibrium:

$$I\ddot{\theta}(t) = -mg\frac{L}{2}\sin(\theta(t)) \text{ with } I = \frac{mL^2}{3}$$
$$\ddot{\theta}(t) = -\frac{3g}{2L}\sin(\theta(t))$$

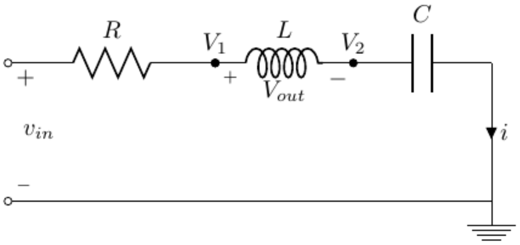
Small deviation of $\theta(t)$:
$$\ddot{\theta}(t) = -\frac{3g}{2L}\theta(t)$$
Solving the differential equation yields the general solution:
$$\theta(t) = A\cos(\omega_0 + \phi) \text{ with } \omega_0 = \sqrt{\frac{3g}{2L}}$$
and $\phi$ & $A$ to be determined with the initial condition

# Example 4: Inverted Pendulum




Analysis can be done with Newton like former example, but less tedious is using energy-methods (Lagrange)

# Example 5: RLC Circuit




Besides input $v_{in}$, two internal variables are needed to determine output $\Rightarrow$ Second-order System

| Inputs | Ouputs | Choosen States |
|---|---|---|
| $v_{in}$ | $v_{out}$ | $V_2$ |
| | | $i$ |

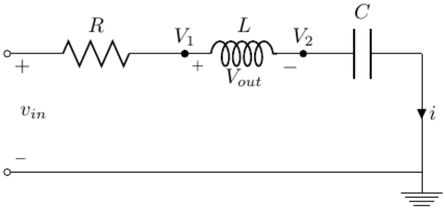
# Example 5: RLC Circuit

Equations for each component:

$$i = \frac{V_{in} - V_1}{R}$$

$$V_1 - V_2 = L \cdot \frac{di}{dt}$$

$$i = C \cdot \frac{dV_2}{dt}$$



# Example 5: RLC Circuit

- Writing derivatives of state variables in function of state variables and inputs: $\begin{cases} \frac{di}{dt} = \frac{V_1 - V_2}{L} = \frac{V_{in} - R \cdot i - V_2}{L} \\ \frac{dV_2}{dt} = \frac{i}{C} \end{cases}$
- Writing output in function of state variables and inputs: $V_{out} = V_1 - V_2 = V_{in} - Ri - V_2$

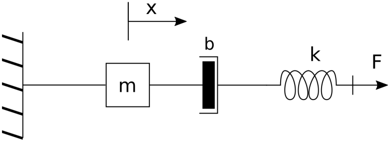
## State Space Representation

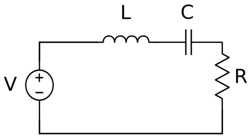
This yields the **State Space Representation** of the dynamic system. In Matrix form:

$$\begin{bmatrix} \frac{dV_2}{dt} \\ \frac{di}{dt} \end{bmatrix} = \begin{bmatrix} 0 & 1/C \\ -1/L & -R/L \end{bmatrix} \begin{bmatrix} V_2 \\ i \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} V_{in}$$

$$V_{out} = \begin{bmatrix} -1 & -R \end{bmatrix} \begin{bmatrix} V_2 \\ i \end{bmatrix} + V_{in}$$

# Force-Voltage Analogy



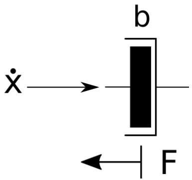

Let:

$$\begin{array}{ccc} F & \leftrightarrow & V \\ \dot{x} & \leftrightarrow & i \\ x & \leftrightarrow & q \end{array}$$

# Force-Voltage Analogy

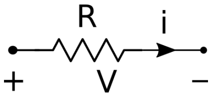
The analogy between the other quantities follows from comparing the physical laws.

Damping:




$$F = b\dot{x}$$

Resistance:




$$V = Ri$$

$$\boxed{b \leftrightarrow R}$$

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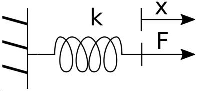
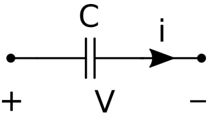
Spring:




$$F = kx$$
$$\Rightarrow \frac{dF}{dt} = k\frac{dx}{dt}$$

Capacitor:




$$\frac{dV}{dt} = \frac{i}{C}$$

$$\boxed{k \leftrightarrow \frac{1}{C}}$$

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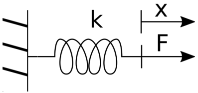


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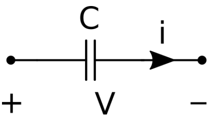


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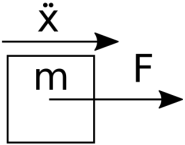
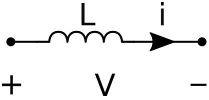
Newton:




$$F = m\ddot{x}$$
$$= m\frac{d\dot{x}}{dt}$$

Coil:




$$V = L\frac{di}{dt}$$

$$\boxed{m \leftrightarrow L}$$

# Example 6: Hoover dam

Define:

- Inflow of water: $u(t)$
- Current volume of water: $x(t)$
- Outflow of water: $y(t)$
- Water level: $h(t)$

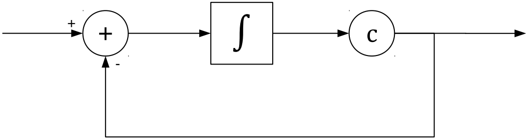
Assume that $x(t) = c_1 \cdot h(t)$

What will happen when we open the gate?

# Example 6: Hoover dam

- Outflow depends on height:
  $$y(t) = c_2 \cdot h(t)$$
- The state of the system is defined by the contained volume of water:
  $$\dot{x}(t) = u(t) - y(t) = u(t) - c_2 \cdot h(t)$$
- Thus a **State Space Representation** is, with $c \triangleq \frac{c_2}{c_1}$:

$$\dot{x}(t) = u(t) - c \cdot x(t)$$
$$y(t) = c \cdot x(t)$$



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2. First Principles Modeling
3. Nonlinear systems & linearization
4. System Identifcation
    - Grey box identification
    - Black box identification

# Nonlinear systems

In this course we focus on the linear state-space representation:

$$\begin{cases} \dot{x}(t) = Ax(t) + Bu(t), \\ y(t) = Cx(t) + Du(t). \end{cases} \qquad \begin{cases} x[k+1] & = Ax[k] + Bu[k], \\ \quad y[k] & = Cx[k] + Du[k]. \end{cases}$$

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Most real life systems involve nonlinearity:

$$\begin{cases} \dot{x}(t) = f\big(x(t), u(t)\big), \\ y(t) = g\big(x(t), u(t)\big), \end{cases}$$

where $f$ and/or $g$ contain some nonlinearity, such as:

- *powers*: e.g. $\dot{x}(t) = Ax(t) + Bu(t) + \gamma u(t)^2$,
- *interactions*: e.g. $\dot{x}(t) = Ax(t) + Bu(t) + \gamma x(t)u(t)$,
- *clipping*: e.g. $\alpha \leq x(t) \leq \beta$.

# Linearization around equilibrium point

Nonlinear systems have (several) equilibrium points $x_e$, $u_e$, $y_e$:

$$\begin{cases} \dot{x}_e = f\left(x_e, u_e\right) = 0, \\ y_e = g\left(x_e, u_e\right). \end{cases}$$

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Linearizing in the region of $(x_e, u_e, y_e)$:

$$x = x_e + \Delta x, \quad u = u_e + \Delta u, \quad y = y_e + \Delta y,$$

with $\Delta x$, $\Delta u$ and $\Delta y$ *sufficiently* small.

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$$\begin{cases} \frac{dx}{dt} = \frac{d(x_e+\Delta x)}{dt} = \frac{d\Delta x}{dt} = f(x,u) = f(x_e+\Delta x, u_e+\Delta u), \\ y_e + \Delta y = g(x,u) = g(x_e+\Delta x, u_e+\Delta u). \end{cases}$$

We write the *vectors* $x$ and $u$ in their individual components to simplify interpretation:

$$\begin{aligned} \dot{x}_1 &= f_1(x_1, ..., x_n, u_1, .., u_l) \\ &\vdots \\ \dot{x}_n &= f_1(x_1, ..., x_n, u_1, .., u_l) \\ \dot{y}_1 &= h_1(x_1, ..., x_n, u_1, .., u_l) \\ &\vdots \\ \dot{y}_l &= h_l(x_1, ..., x_n, u_1, .., u_l) \end{aligned}$$

# Example: decalcification plant

Used to reduce concentration of calcium hydroxide in water:

- chemical reaction: $Ca(OH)_2 + CO_2 \rightarrow CaCO_3 + H_2O$
- reaction speed: $r = c[Ca(OH)_2][CO_2]$
- rate of change of concentration:

$$\frac{d[Ca(OH)_2]}{dt} = \frac{k}{V} - \frac{r}{V},$$
$$\frac{d[CO_2]}{dt} = \frac{u}{V} - \frac{r}{V},$$

  with inflow rates $k$ and $u$ in mol/s and tank volume $V$ in L.
- input $u$: inflow of $CO_2$, output: $[Ca(OH)_2]$

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with two state variables: $x_1 = [Ca(OH)_2]$ and $x_2 = [CO_2]$.

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$$\frac{k_{eq}}{V} - \frac{c}{V}[Ca(OH)_2]_{eq}[CO_2]_{eq} = 0,$$
$$\frac{u_{eq}}{V} - \frac{c}{V}[Ca(OH)_2]_{eq}[CO_2]_{eq} = 0.$$

# Linearization of the decalcification plant

For small deviations near the equilibrium:

$$\frac{d\Delta x_1}{dt} = -\frac{c}{V}[CO_2]_{eq}\Delta x_1 - \frac{c}{V}[Ca(OH)_2]_{eq}\Delta x_2,$$
$$\frac{d\Delta x_2}{dt} = -\frac{c}{V}[CO_2]_{eq}\Delta x_1 - \frac{c}{V}[Ca(OH)_2]_{eq}\Delta x_2 + \frac{\Delta u}{V},$$
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\Delta y &= \Delta x_1.
\end{aligned}$$

The resulting linear state-space model is $\begin{cases} \dot{x}(t) = Ax(t) + Bu(t) \\ y(t) = Cx(t) + Du(t) \end{cases}$:

$$\begin{bmatrix} \frac{d[Ca(OH)_2]}{dt} \\ \frac{d[CO_2]}{dt} \end{bmatrix} = -\begin{bmatrix} \frac{c}{V}[CO_2]_{eq} & \frac{c}{V}[Ca(OH)_2]_{eq} \\ \frac{c}{V}[CO_2]_{eq} & \frac{c}{V}[Ca(OH)_2]_{eq} \end{bmatrix} \begin{bmatrix} [Ca(OH)_2] \\ [CO_2] \end{bmatrix} + \begin{bmatrix} 0 \\ \frac{1}{V} \end{bmatrix} u(t)$$

$$y(t) = [Ca(OH)_2]$$

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"*All models are wrong, but some are useful.*" - George E. P. Box

# Linear regression

Consider input matrix $\mathbf{X}$, output vector $\mathbf{y}$ and residuals $\epsilon$:

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A common estimation approach is ordinary least squares (OLS):

$$\begin{aligned}(\mathbf{X}^T\mathbf{X})\hat{\theta}_{OLS} &= \mathbf{X}^T\mathbf{y},\\ \hat{\theta}_{OLS} &= (\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T\mathbf{y}.\end{aligned}$$

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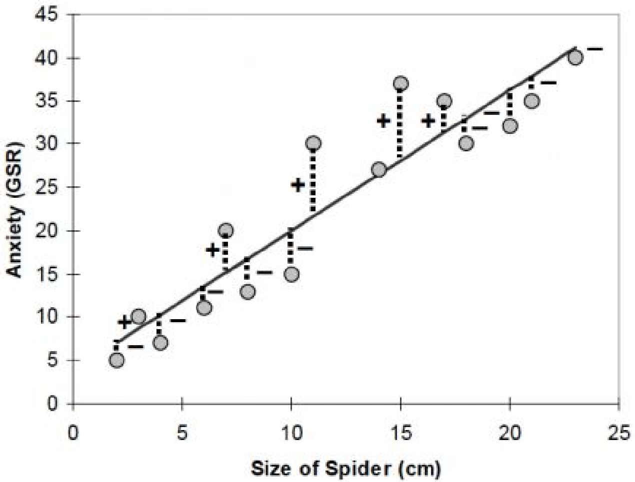
The OLS estimate minimizes the sum-of-squares of errors, i.e.:

$$\hat{\theta}_{OLS} = \arg\min_{\theta} \sum_{i=1}^{N} \left(y(i) - \sum_{j=1}^{d} X(i,j)\theta(j)\right)^2$$

# Linear regression with ordinary least squares



# Maximum likelihood estimation

The maximum likelihood estimate $\hat{\theta}_{ML}$ is the parameter vector that maximizes the likelihood $\mathcal{L}(\cdot)$ of observing the (known) outputs $\mathbf{y}$, given the (known) inputs $\mathbf{X}$:

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**Example**: least squares estimators are the maximum likelihood estimators if the associated residuals $\epsilon$ are normally distributed.

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Bayes' theorem: $P(A \mid B) = P(B \mid A) \cdot P(A) \;/\; P(B)$.

If a prior distribution $p(\cdot)$ is available for $\theta$, then the posterior distribution for $\theta$ becomes:

$$\theta \mapsto \mathcal{L}(\theta \mid \mathbf{y}, \mathbf{X}) = \frac{\mathcal{L}(\mathbf{y}, \mathbf{X} \mid \theta) p(\theta)}{\int_{\vartheta} \mathcal{L}(\mathbf{y}, \mathbf{X} \mid \vartheta) p(\vartheta) d\vartheta}.$$

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Bayesian: maximum likelihood estimation with a *prior* $p(\theta)$.
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Bayes' theorem: $P(A \mid B) = P(B \mid A) \cdot P(A) \; / \; P(B)$.

If a prior distribution $p(\cdot)$ is available for $\theta$, then the posterior distribution for $\theta$ becomes:

$$\theta \mapsto \mathcal{L}(\theta \mid \mathbf{y}, \mathbf{X}) = \frac{\mathcal{L}(\mathbf{y}, \mathbf{X} \mid \theta) p(\theta)}{\int_{\vartheta} \mathcal{L}(\mathbf{y}, \mathbf{X} \mid \vartheta) p(\vartheta) d\vartheta}.$$

The MAP estimate is the mode of the posterior distribution of $\theta$:

$$\hat{\theta}_{MAP} = \arg\max_{\theta} \mathcal{L}(\mathbf{y}, \mathbf{X} \mid \theta) p(\theta).$$

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# Outline

# Black box identification

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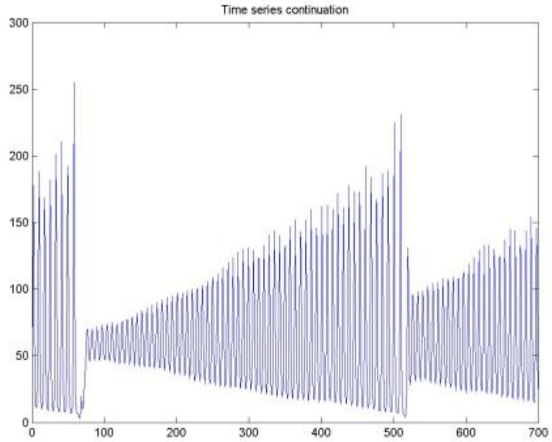
# Time series: Santa Fe laser



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This laser can be treated as an autonomous discrete time system:

$$\begin{cases} x[k+1] = f\big(x[k-N+1], \ldots, x[k]\big), \\ y[k] = x[k]. \end{cases}$$

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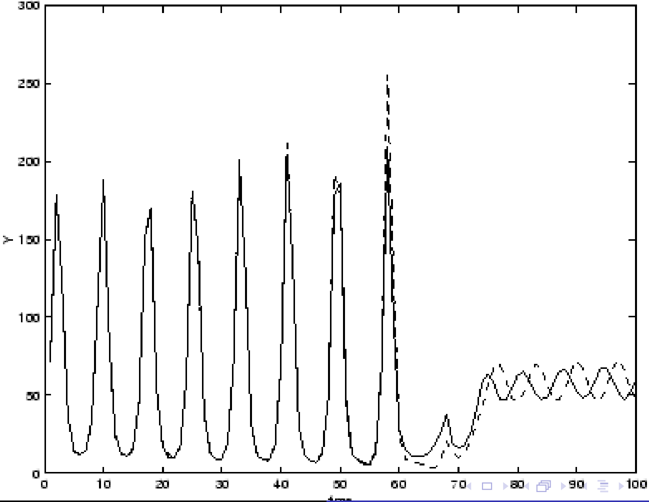
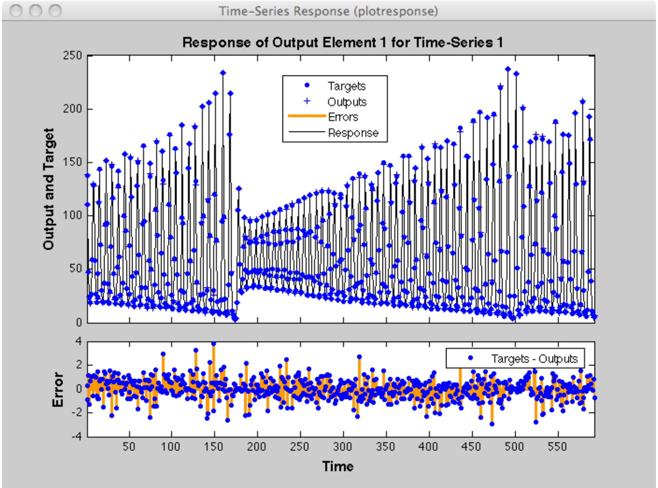
Nonlinear models can be obtained via machine learning methods.
$\rightarrow$ neural networks, support vector machine, random forest, ...

# Predictions of a least-squares support vector machine



# Predictions of an artificial neural network



# Neural network: biological

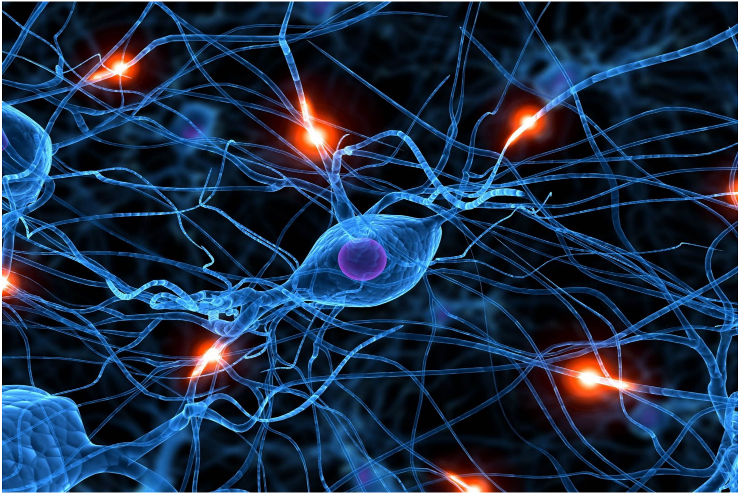


Image taken from http://www.extremetech.com/wp-content/uploads/2013/09/340.jpg.

# Structure of a single neuron

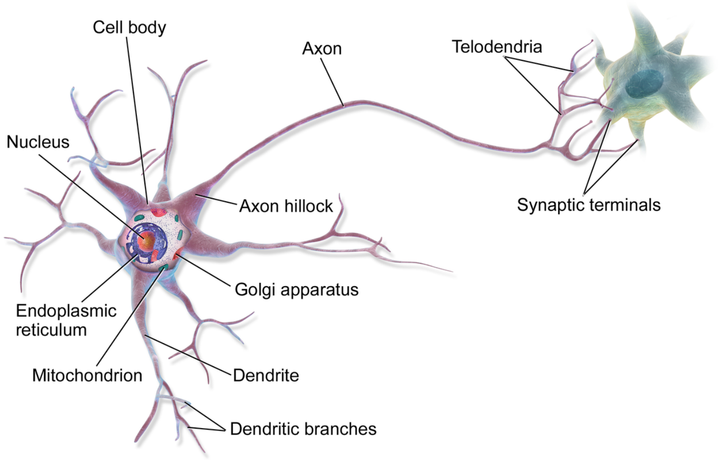



Image taken from http://en.wikipedia.org/wiki/File:Blausen_0657_MultipolarNeuron.png.

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