# Networks:
# spike-triggered synaptic transmission, events, and artificial spiking cells

1. Define the types of cells
2. Create each cell in the network
3. Connect the cells

# Communication between cells

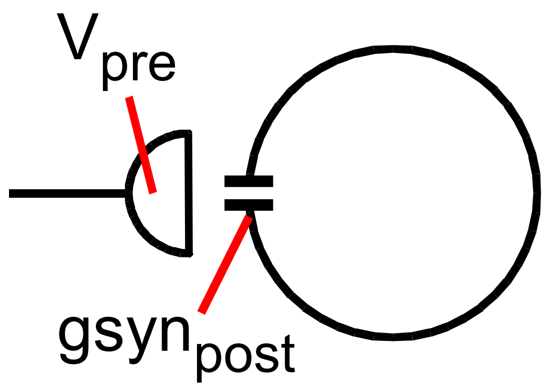
- Gap junctions
- Synaptic transmission
  - graded
  - spike-triggered

# Graded synaptic transmission

Physical system:

A presynaptic variable governs continuous transmitter release

Transmitter modulates a postsynaptic property




$gsyn_{post} = f(V_{pre})$

Problem: how does postsynaptic cell know $V_{pre}$?

# Graded synaptic transmission *continued*

Answer: use POINTER to link postsynaptic variable to the presynaptic variable

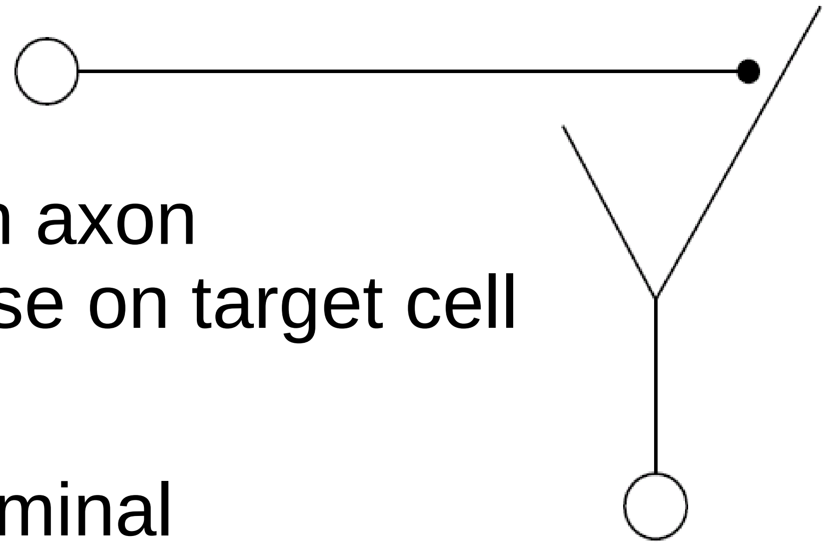
NMODL specification of synaptic mechanism:

```
NEURON {
    POINT_PROCESS Syn
    POINTER v_pre
}
```

hoc usage

```
objref syn
dend syn = new Syn(0.5)
setpointer syn.v_pre, precell.axon.v(1)
```

# Spike-triggered synaptic transmission



Physical system:

Presynaptic neuron with axon
that projects to synapse on target cell

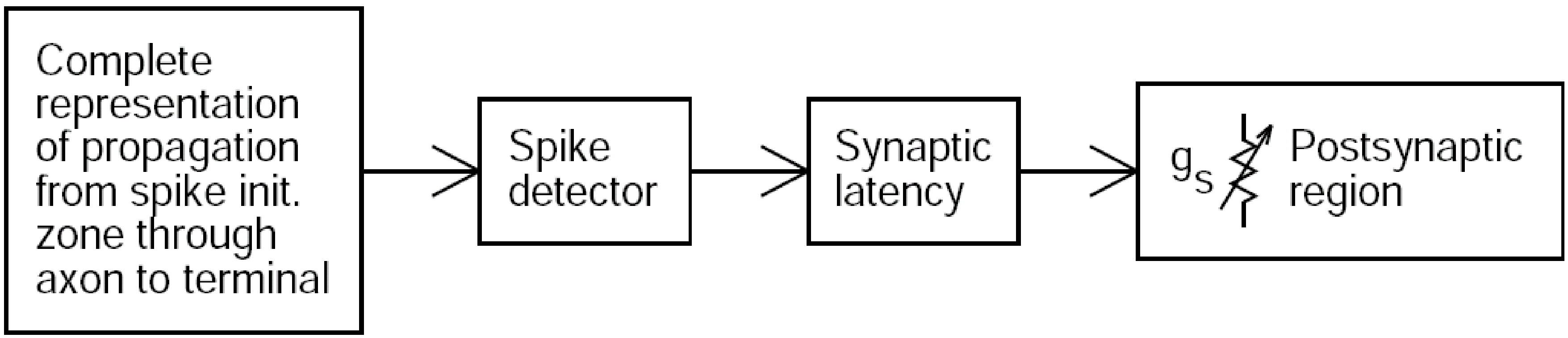
Conceptual model:

Spike in presynaptic terminal
triggers transmitter release;
presynaptic details unimportant

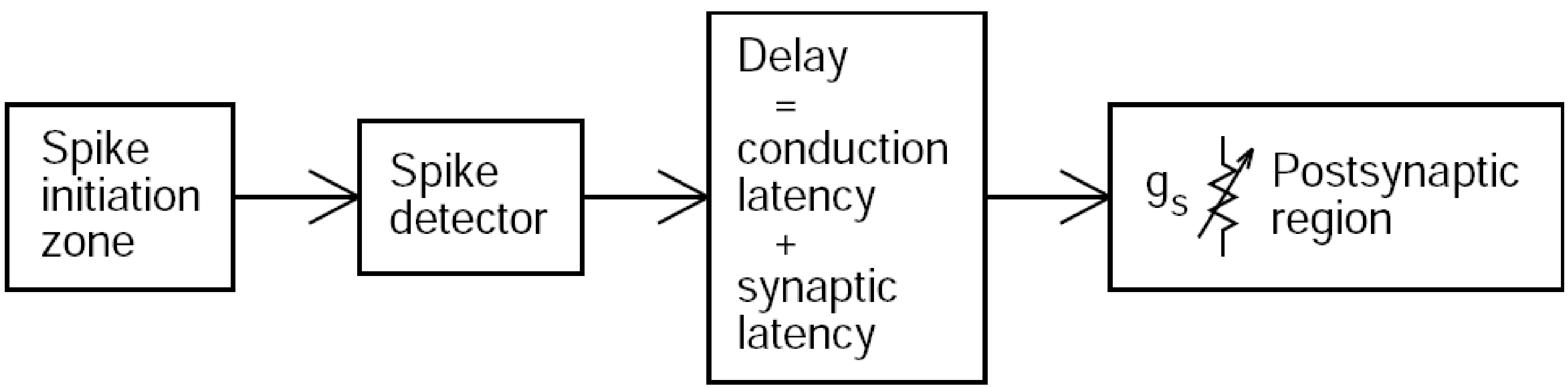
Postsynaptic effect described by
DE or kinetic scheme that is perturbed by
occurrence of a presynaptic spike

# Spike-triggered transmission: computational implementation

## Basic idea




## More efficient: "virtual spike propagation"



# The NetCon class

Python usage

```
nc = h.NetCon(source, target)
nc = h.NetCon(source_ref_v, target
     [, threshold, delay, weight,
     sec = section])
```

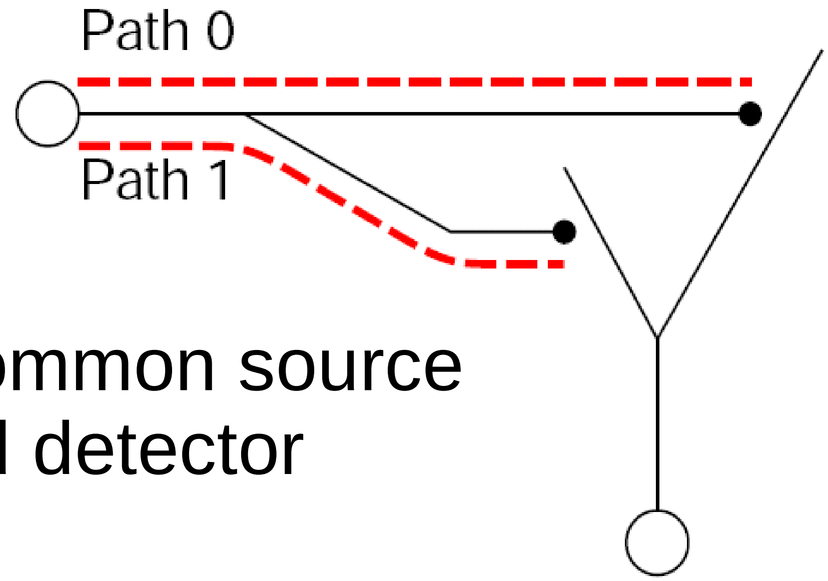
Defaults

```
nc.threshold = 10
nc.delay = 1 # must be >= 0
nc.weight[0] = 0 # weight is an array
```

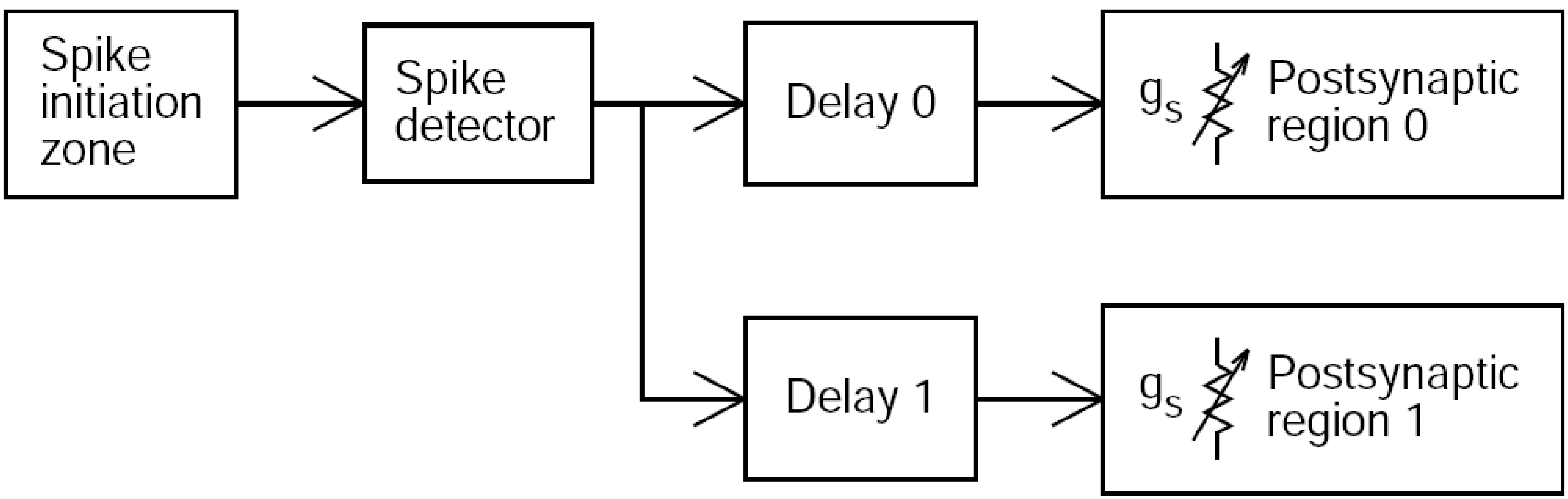
NMODL specification of synaptic mechanism

```
NET_RECEIVE(weight(microsiemens)) {
    . . .
}
```

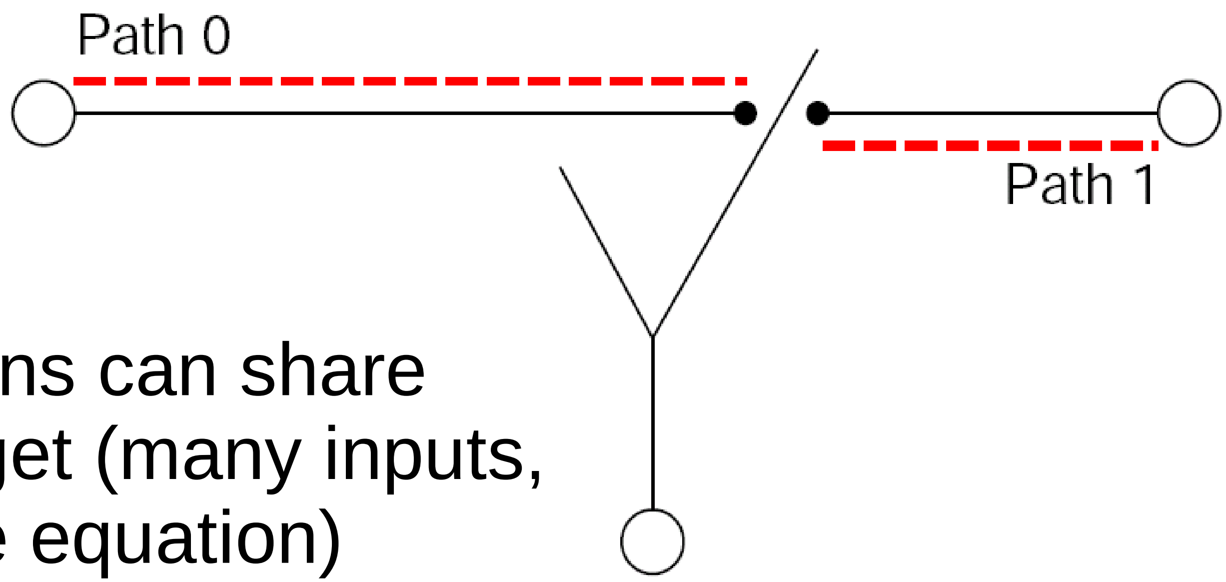
# Efficient divergence



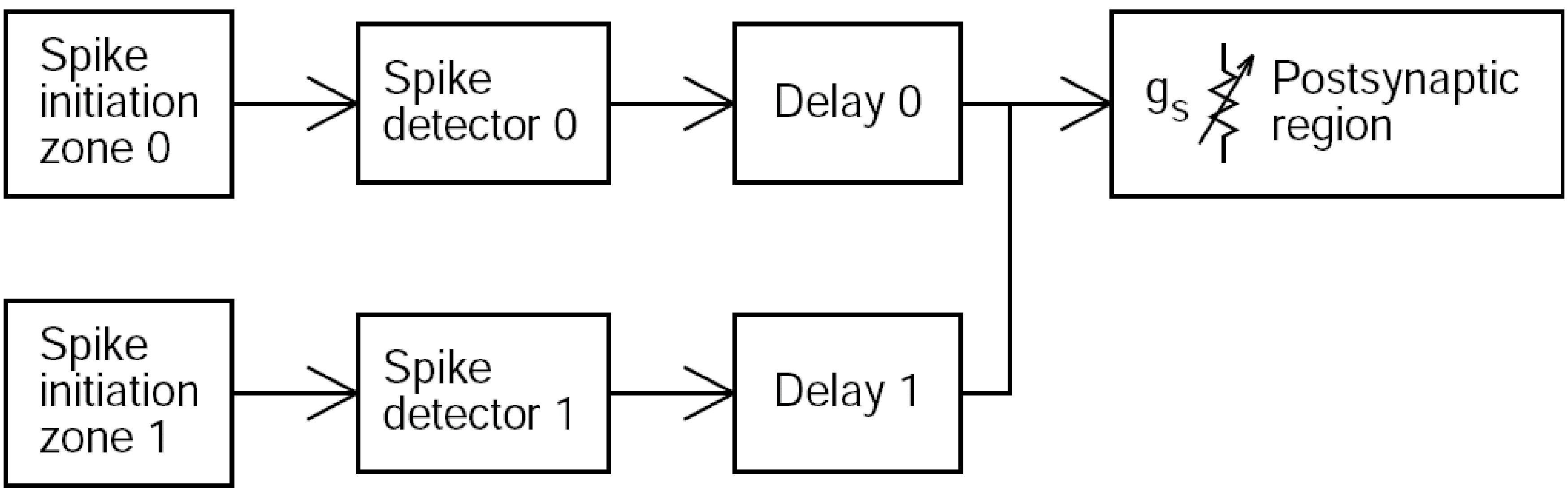

Multiple NetCons with a common source share a single threshold detector



# Efficient convergence




Multiple NetCons can share
a single target (many inputs,
but only one equation)

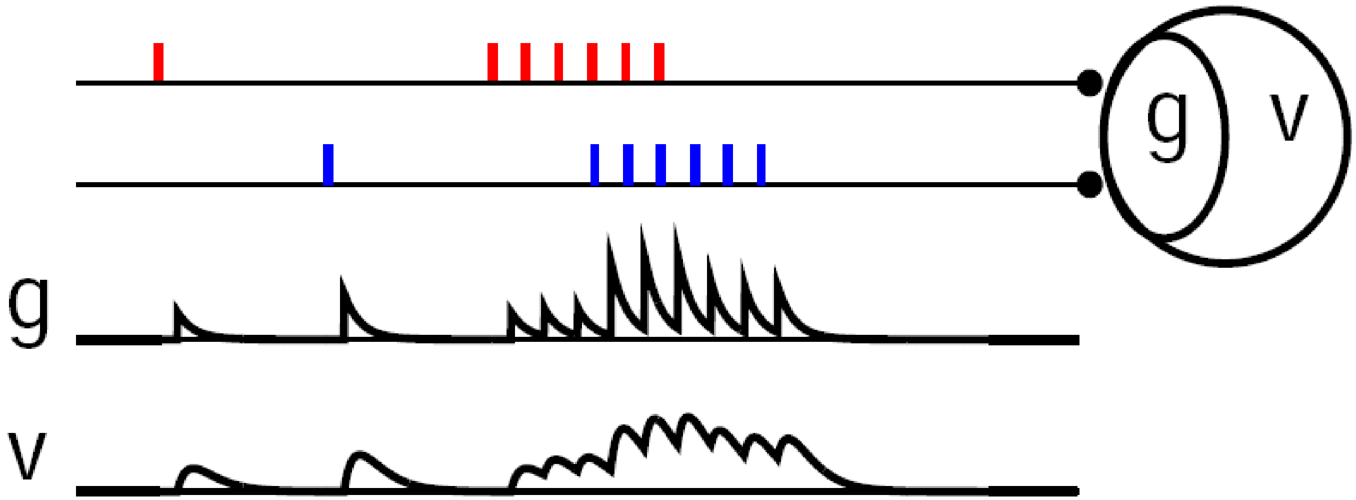


# Example: $g_s$ with fast rise and exponential decay

```
NEURON {
  POINT_PROCESS ExpSyn
  RANGE tau, e, i
  NONSPECIFIC_CURRENT i
}
  . . . declarations . . .
INITIAL { g = 0 }
BREAKPOINT {
  SOLVE state METHOD cnexp
  i = g*(v-e)
}
DERIVATIVE state { g' = -g/tau }
NET_RECEIVE(w (uS)) { g = g + w }
```

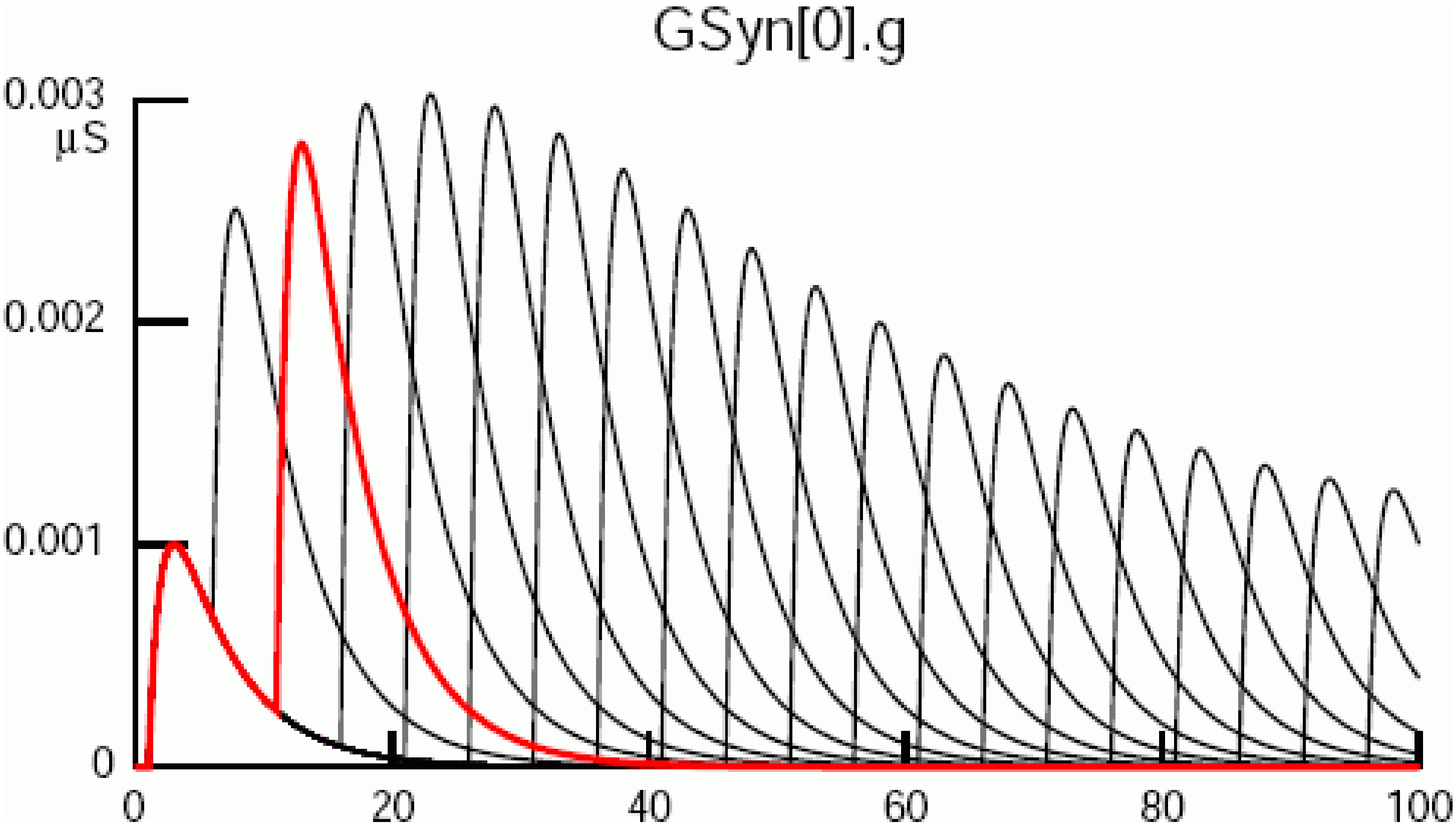
# $g_s$ with fast rise and exponential decay

*continued*



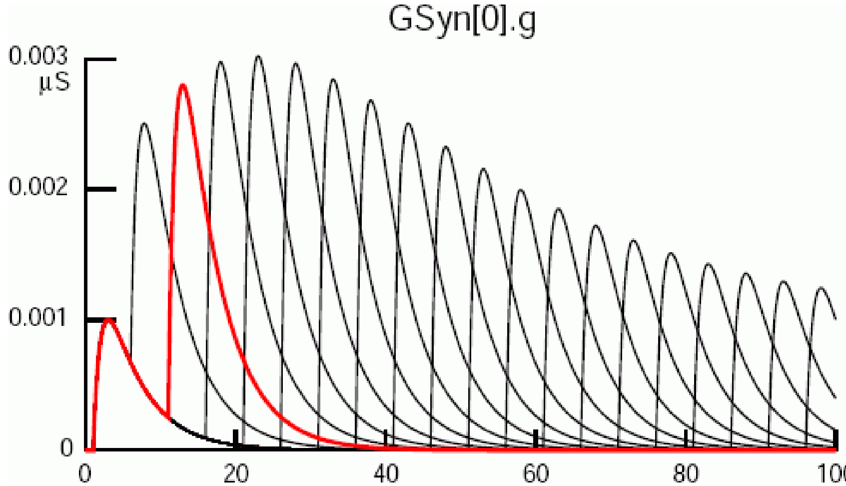

```
BREAKPOINT {
  SOLVE state METHOD cnexp
  i = g*(v-e)
}
DERIVATIVE state { g' = -g/tau }
NET_RECEIVE(w (uS)) { g = g + w }
```

# Example: use-dependent synaptic plasticity



# Use-dependent synaptic plasticity *continued*

```
BREAKPOINT {
  SOLVE state METHOD cnexp
  g = B - A
  i = g*(v-e)
}
DERIVATIVE state {
  A' = -A/tau1
  B' = -B/tau2
}
```




```
NET_RECEIVE(weight (uS), w, G1, G2, t0 (ms)) {
  INITIAL {w=0 G1=0 G2=0 t0=t}
  G1 = G1*exp(-(t-t0)/Gtau1)
  G2 = G2*exp(-(t-t0)/Gtau2)
  G1 = G1 + Ginc*Gfactor
  G2 = G2 + Ginc*Gfactor
  t0 = t
  w = weight*(1 + G2 - G1)
  g = g + w
  A = A + w*factor
  B = B + w*factor
}
```

# Artificial spiking cells

## "Integrate and fire" cells

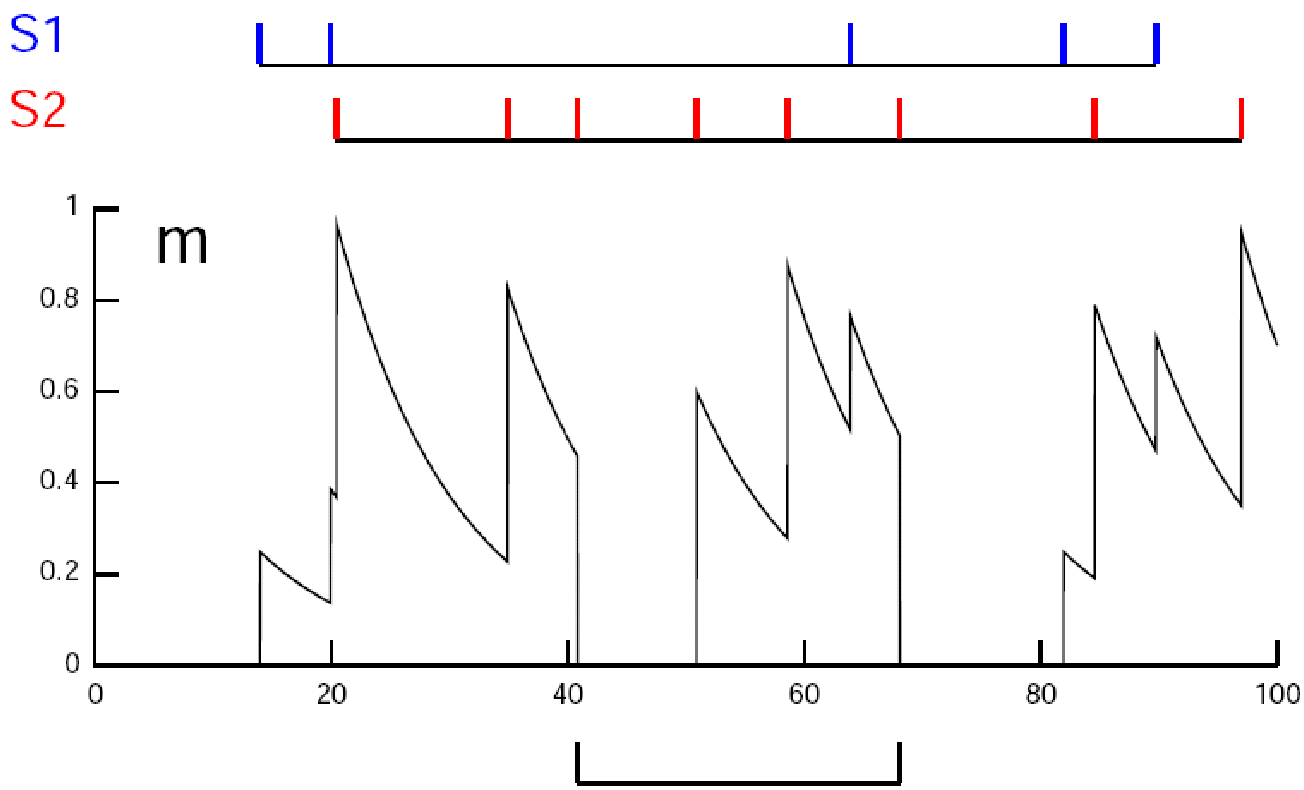
Prerequisite: all state variables must be
analytically computable from a new initial condition

Orders of magnitude faster than numerical integration

Event-driven simulation run time is
- *proportional* to # of received events
- *independent* of # of cells, # of connections, and problem time

Hybrid networks

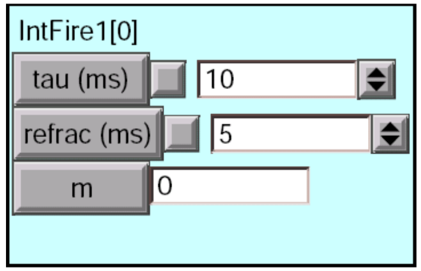
# Example: leaky integrate and fire model

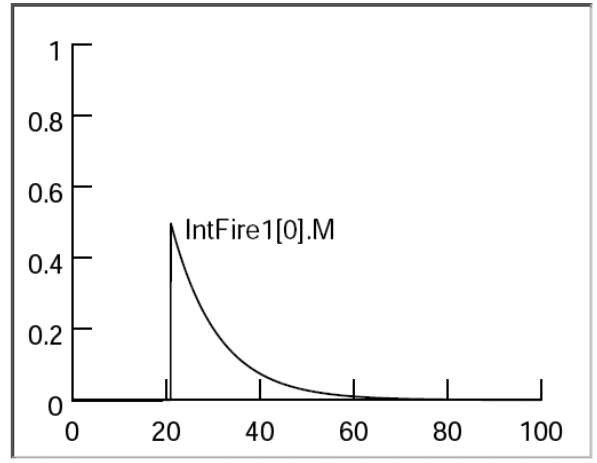


# Leaky integrate and fire model *continued*

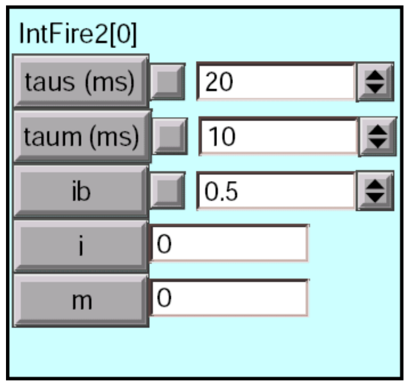
```
NEURON {
  ARTIFICIAL_CELL IntFire
  RANGE tau, m
}
  . . . declarations . . .
INITIAL { m = 0   t0 = t }
NET_RECEIVE (w) {
  m = m*exp(-(t-t0)/tau)
  t0 = t
  m = m + w
  if (m > 1) {
    net_event(t)
    m = 0
  }
}
```

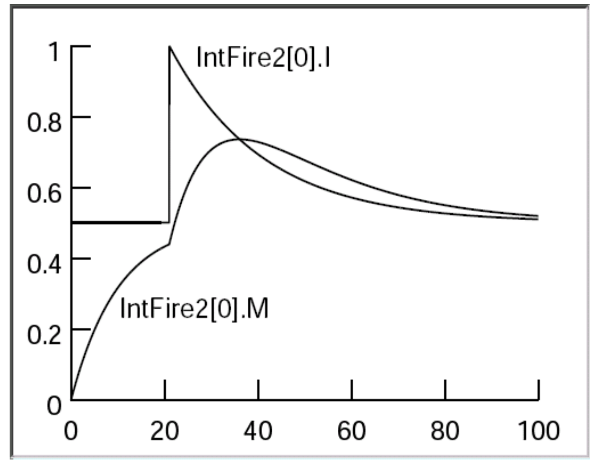
# IntFire1



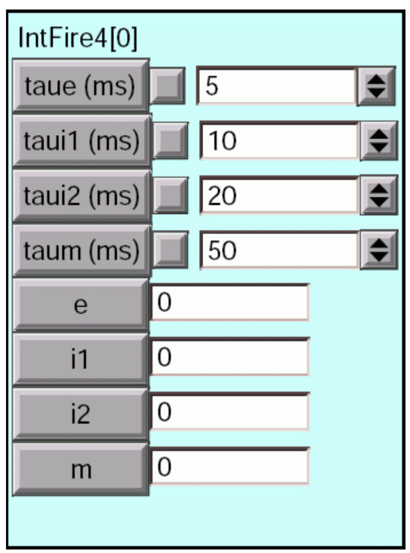



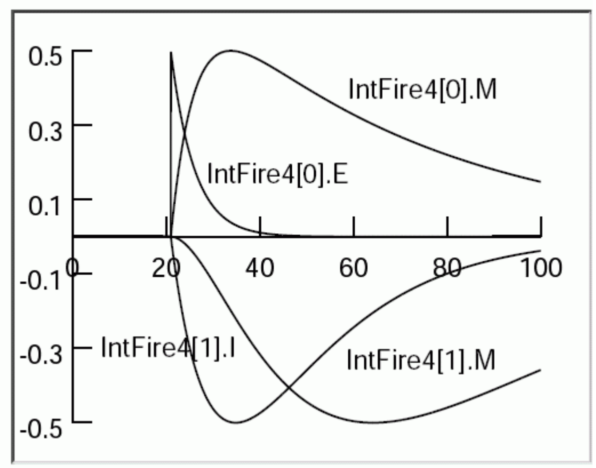

# IntFire2




# IntFire4



# Defining the types of cells

**Artificial spiking cells**

- `ARTIFICIAL_CELL` with a `NET_RECEIVE` block that calls `net_event`
- `NetStim`, `IntFire1`, `IntFire2`, `IntFire4`

**Biophysical model cells**

- "Real" model cells
- Sections and density mechanisms
- Synapses are `POINT_PROCESS`es that affect membrane current and have a `NET_RECEIVE` block, e.g. `ExpSyn`, `Exp2Syn`

# Defining types of biophysical model cells

## Encapsulate in a class

Export hoc class definition from CellBuilder or Network Builder

or

write your own in Python.

```
class Cell:
  def __init__(self)
    # specify geom, topol, biophys
    soma = h.Section(name='soma')
    self.soma = soma
    ... etc. ...

cells[]
N = 1000
for i in range(N):
  cell = Cell() # h.Cell() if Cell is defined in hoc
  cells.append(cell)
```

# Connecting cells

Which setup strategy is more efficient?

Iterate over sources

```
for each cell {
  connect this cell to its targets
}
```

or iterate over targets?

```
for each cell {
  connect sources to this cell
}
```

# Connecting cells

For a net distributed over multiple CPUs,
it is most efficient to iterate over targets first.

```
for each cell {
  connect sources to this cell
}
```