# Modelling swarms

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We shall investigate swarming models from the perspective of hybrid multi-agent control/consensus.

# Consensus

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# Flocking models

The modelling of flocks has been an active area of applied mathematics for the past twenty years. One of the first breakthroughs occurred in the 1980's, when Craig Reynolds used a simple set of algorithms to generate realistic computer models of flocking agents, which he called *boids*.

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Vicsek et al. developed *self-propelled particle models* which incorporated disturbances/noise to the swarms whereas Kennedy and Eberhart focussed on optimisation models to simulate the complex choreography of flocking animals.

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- track your neighbours
- don't crash

- go somewhere
- stay there

# Networks

We shall couch our discussion in the language of *complex network theory*. A *network* is a weighted graph, that is, a set of elements called *nodes* or *vertices*, which may be connected to one another via relational links (*edges*). To each node we assign a *state* and to each edge a weight (or *gain*), $\sigma_{i,j}$.

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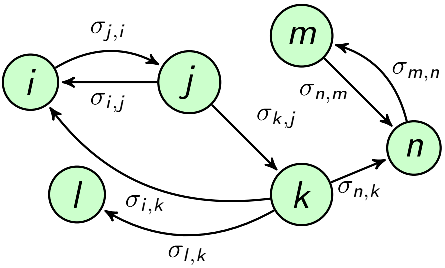

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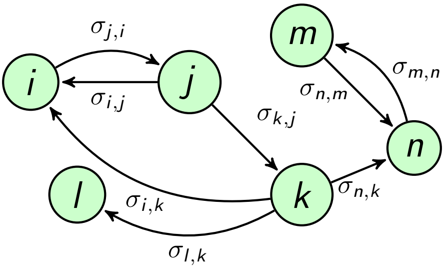


We want our states and gains to evolve until some “configuration” or consensus is achieved.

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$$\dot{\sigma}_{i,j} = \xi(\mathbf{s}_i, \mathbf{s}_j, \Omega_i) \tag{2}$$

where $\Omega_i$ is the local neighbourhood of agent $i$ containing $n$ members and $\xi$ is some function of the respective states.

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# References


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