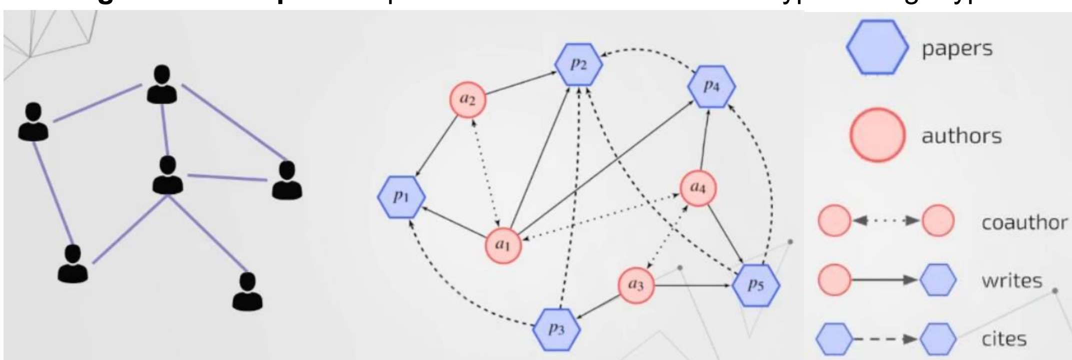
Divergence measures and message passing
Thomas Minka, 2005

Explores using **message-passing algorithms** to approximate complex **Bayesian Networks** with a simpler network, while **minimising information divergence**

- This is done by minimising the **local divergence**, for each node in the network
  - Very parallelisable, and each calculation is of much lower complexity
- This approach works because belief networks benefit from the **averaging effect**
  - **Averaging Effect -** a big, complex network behaves similarly to a simpler network
- We can use **variational methods** to approximate a complex network **p** with a simple network **q**
  - We can split a large network into **smaller parts**, each of which are **estimated variationally**
- **Message Passing -** a distributed method for fitting variational approximations
- **Homogeneous -** of the same kind; alike
- **Heterogeneous -** diverse in character or content
- **Homogeneous Graph -** graphs in which the nodes in a graph are of a single type
  - The edges of connecting the nodes also belong to a single type
  - For example, all edges are undirected
  - For example, in a social network, the only node type is people, and only edge type is friendship
- **Heterogeneous Graph -** Graphs with more than one node type or edge type
- 

Entropy - The average **surprise** that we get per sample

- We average out the surprise by summing up the product of the surprise and probability for each class
- $$\text{Entropy} = \sum \log\left(\frac{1}{p(x)}\right)p(x)$$
  Surprise
  The probability of the **Surprise.**
- **Surprise =** $\text{Surprise} = \log\left(\frac{1}{\text{Probability}}\right)$
  - We do log, so that when we plug in 1 for probability, we get 0
  - Also, when we plug in 0 for probability, we get undefined
  - The base of the log should be the number of classes we have

We **don't normalise distributions**, because we don't know what is the **integral** of the target distribution, and our estimation distribution **helps us estimate it**