Modelling the Spread of Energy Innovations in Cities

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UNIVERSITY OF BATH

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Energy and the Design of Environments

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With: Catherine Bale, Timothy Foxon, William Gale, Alastair Rucklidge. (Leeds)

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  - by 2050: 60%–80%

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- Cities are expanding:
  - Over 50% people living in cities,
  - by 2050: 60%–80%

- Buildings consume 20%–40% of total energy.
- Local authorities can influence residents/businesses to reduce energy demand.
- Decision-making tools are needed to support their potential contribution to energy and climate change targets‡.

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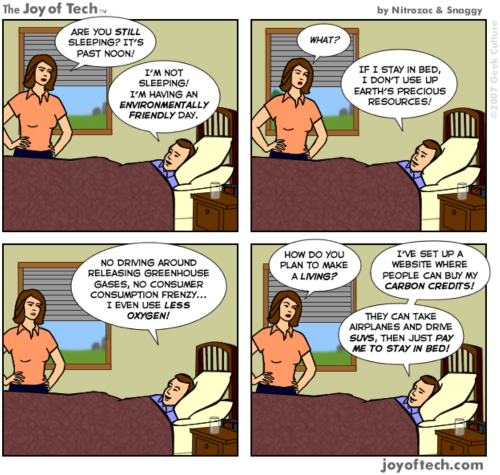
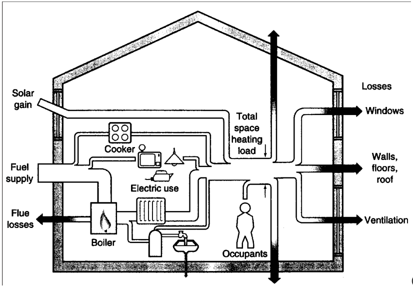
‡: Bale, et al. *"Strategic energy planning within local authorities in the UK: A study of the city of Leeds."* Energy Policy (2012)

Understanding energy behaviour



Domestic energy use

- Energy use depends on both technology and behaviour:



©BRE

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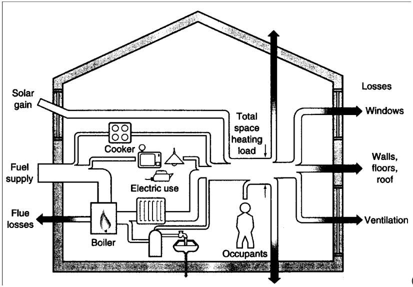
- Energy use depends on both technology and behaviour:

- use of installed tech & decisions to install.



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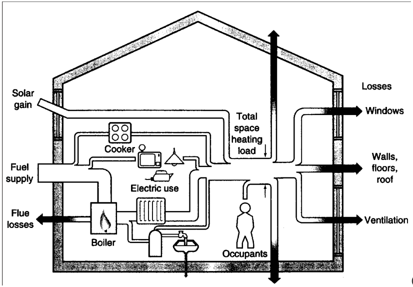

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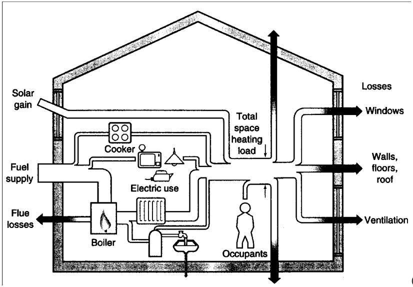

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- can we create models of energy innovation uptake?

Why is energy different?

- Model of uptake of technology.
- E.g. Smart-phones:
  - visible and socially desirable,
  - mediated by social contacts between individuals.

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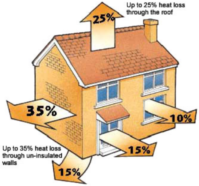
http://www.greendayrenewables.com

Why is energy different?

- Model of uptake of technology.
- E.g. Smart-phones:
  - visible and socially desirable,
  - mediated by social contacts between individuals.
- Energy technologies:
  - sometimes visible (solar panels).
  - can be hidden (e.g. loft insulation),
  - decisions based on individual benefit.

http://www.greendayrenewables.com



http://www.homeinsulationgrants.com

Complex systems

- System of many *interacting* components,
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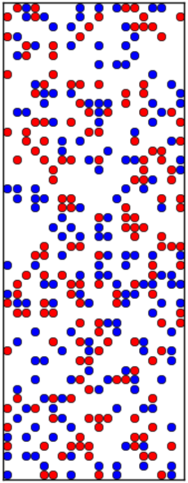
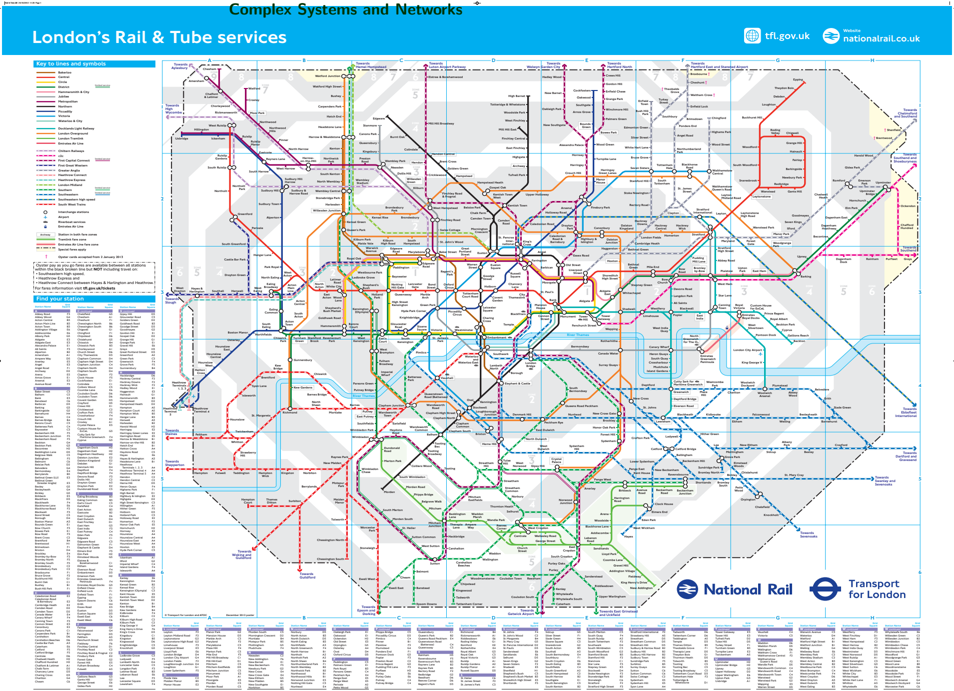
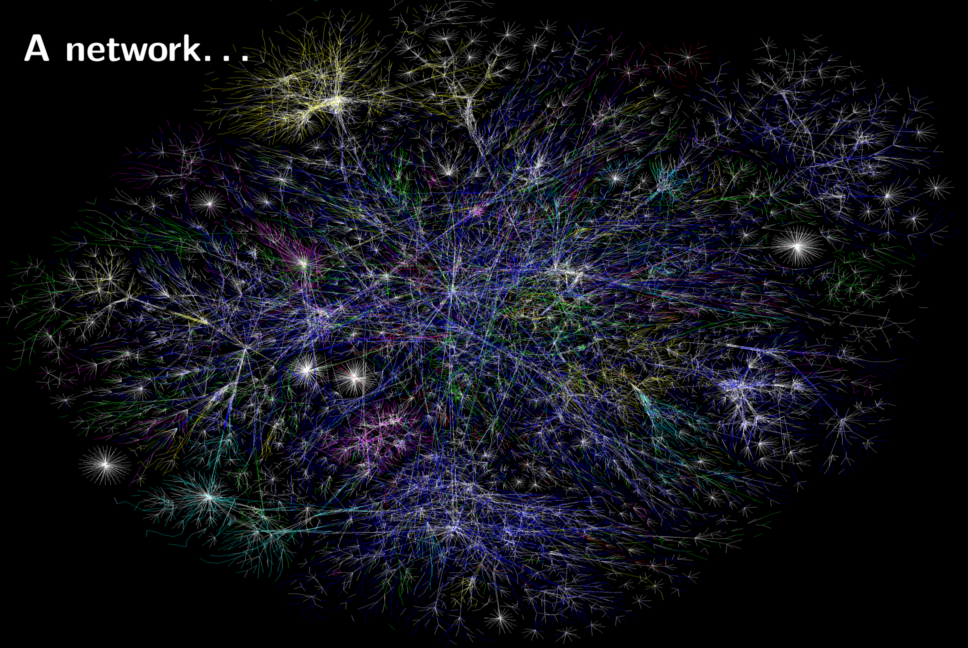
- **interactions** are important,
- dynamics governed by *rules* or equations of interaction,
- behaviour of whole system emerges naturally through interactions:
  - *"emergent properties"*.



Complex Systems and Networks

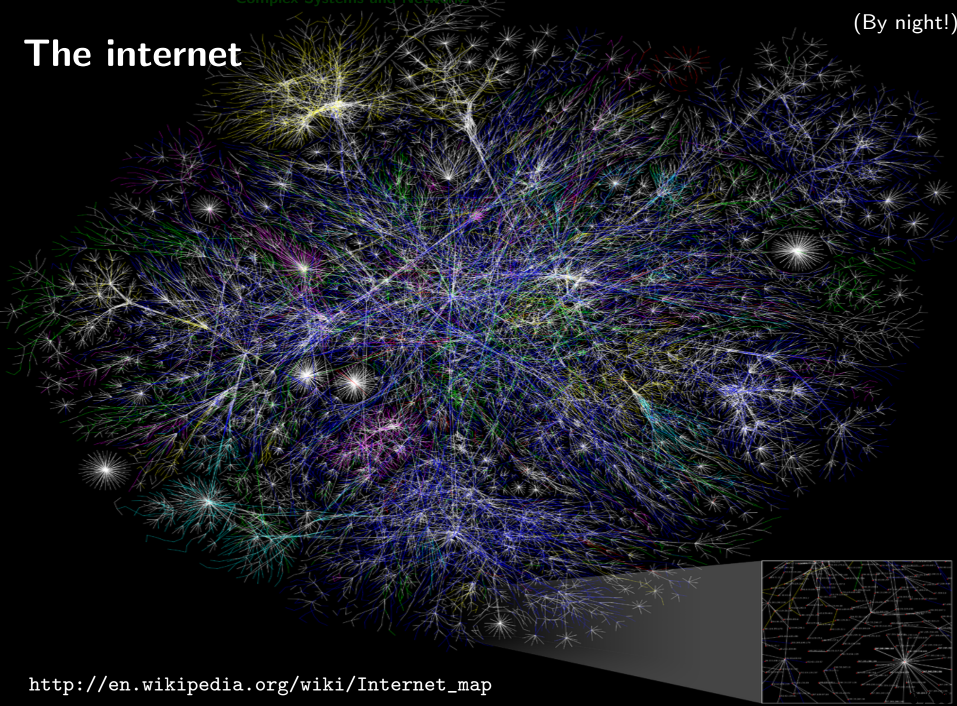


A network. . .



The internet

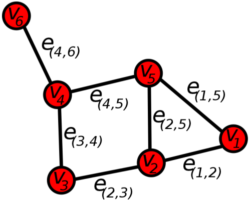
(By night!)



http://en.wikipedia.org/wiki/Internet_map

Network models

- Individuals are considered as *nodes* ('vertices') on a network.
  - Properties of nodes are associated with variables.
- *Links* ('edges'): interactions between individuals.



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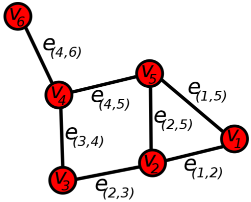

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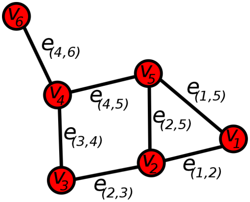

$$A = \begin{pmatrix} 0 & 1 & 0 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 & 1 \\ 1 & 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \end{pmatrix}$$

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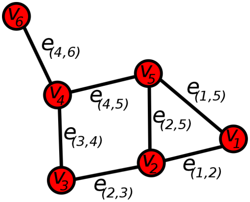

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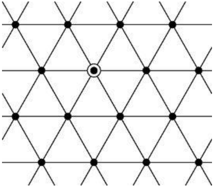
- *Adjacency matrix* can be used to give information about importance of nodes/links — "*centrality* measures"
  - Google's *PageRank*© uses eigenvectors.

Types of network model

- Regular lattice:



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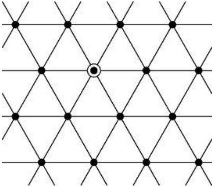

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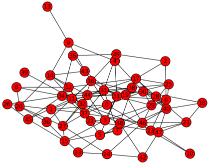
- Random (Erdős Renyí):



⊕ short path lengths $l \propto \frac{\log N}{\log \bar{k}}$,

⊖ no *clustering* $(N \to \infty)$.

"Complex" networks

- Different models reproduce different features.

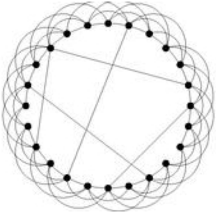
(a) 

Figure: (a): A *small world* network with random *rewiring* of a regular lattice.

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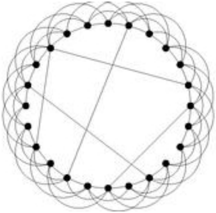
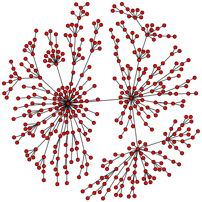
(a)  (b) 

Figure: (a): A *small world* network with random *rewiring* of a regular lattice. (b): A preferential attachment graph which has a *scale-free* degree distribution.

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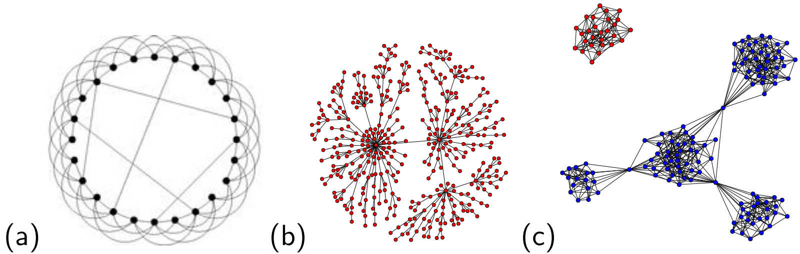

Figure: (a): A *small world* network with random *rewiring* of a regular lattice. (b): A preferential attachment graph which has a *scale-free* degree distribution. (c): A simple model of weakly-connected communities.

Why do networks matter?

"Braess' paradox" for traffic flow:

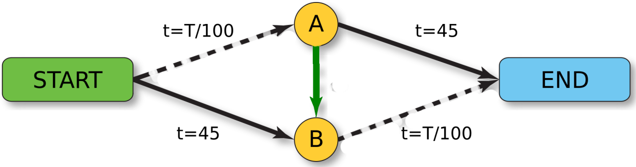

Figure: From: `http://en.wikipedia.org/wiki/Braess's_paradox`

- Solid lines: Constant (slow) roads.
- Dashed lines: Variable (fast) lines, depends on traffic density.

Real-world relevance

- Mathematical results have shown that Braess' paradox is about as likely to occur as not occur in random additions to random networks.

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- In Seoul a motorway closure resulted in traffic speeding up around the city.
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- Simulations have shown the effect in decentralized generation power transmission networks.

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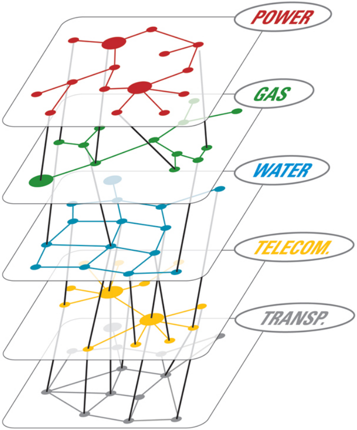
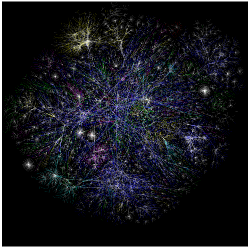
Interconnected Urban Networks





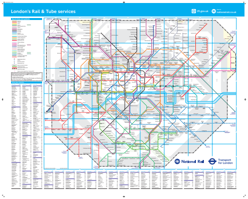


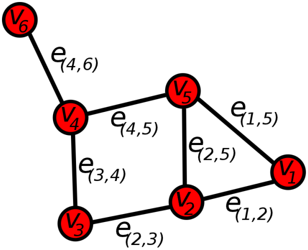
Figure: © Leonardo Dueãs–Osorio.
From: https://simonsfoundation.org/features/science-news/treading-softly-in-a-connected-world/

Modelling innovation diffusion on networks

- Households are *nodes* on a network.
  - Innovation adoption or not are the variables.

Modelling innovation diffusion on networks

- Households are *nodes* on a network.
  - Innovation adoption or not are the variables.
- *Links*: interactions where people communicate information with each other about energy.
  - Behaviour *rules* determine uptake dynamics.



Threshold model dynamical rules

- Current adoption state, $x_i = 0, 1$.
- Uptake based on perceived *"usefulness"* crossing a threshold:

$$\text{future state: } x_i' = \begin{cases} 1 & \text{if } x_i = 1, \\ 1 & \text{if } x_i = 0 \text{ and } u_i > \theta_i, \\ 0 & \text{otherwise.} \end{cases} \tag{1}$$

- θ_i: threshold (barriers, costs etc.)

Factors influencing uptake

Decisions to adopt can be based on various factors:

a) rational decision-making with regards to the intrinsic value of a product;

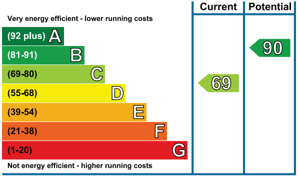
b) social spreading of technology or ideas induced by peer-to-peer communication of information;

c) interaction with the "mainstream" via a global feedback:

- e.g. via media, markets etc.

Intrinsic benefit

Energy Efficiency Rating



The graph shows the current energy efficiency of your home.

The higher the rating the lower your fuel bills are likely to be.

The potential rating shows the effect of undertaking the recommendations on page 3.

The average energy efficiency rating for a dwelling in England and Wales is band D (rating 60).

Top actions you can take to save money and make your home more efficient

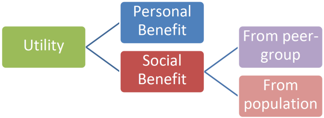
Recommended measures	Indicative cost	Typical savings over 3 years	Available with Green Deal
1 Increase loft insulation to 270 mm	£100 - £350	£87	✓
2 Floor insulation	£800 - £1,200	£123	✓
3 Add additional 80 mm jacket to hot water cylinder	£15 - £30	£69	✓

See page 3 for a full list of recommendations for this property.

To find out more about the recommended measures and other actions you could take today to save money, visit **www.direct.gov.uk/savingenergy** or call **0300 123 1234** (standard national rate). The Green Deal may allow you to make your home warmer and cheaper to run at no up-front cost.

Social aspects of decision-making

- Decision of to adopt based on combination of factors:
  - personal + social benefit[1].



1: Delre et al., *"Will it spread or not? the effects of social influences and network topology on innovation diffusion."* Journal of Product Innovation Management (2010).

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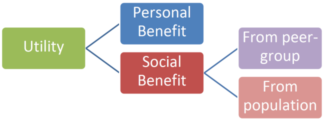

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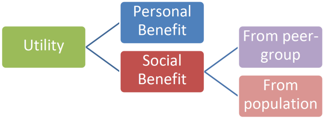
Social aspects of decision-making

- Decision of to adopt based on combination of factors:
  - personal + social benefit[1].
- Intrinsic benefits to individual.
- Social benefit combination of both[2]:
  - personal social network – friends & neighbours,
  - mainstream social norm (society as a whole).



1: Delre et al., *"Will it spread or not? the effects of social influences and network topology on innovation diffusion."* Journal of Product Innovation Management (2010).

2: Valente, *"Social network thresholds in the diffusion of innovations."* Social networks (1996).

Mathematical model

- Total *utility* to individual♠:

$$u_i = \alpha_i p_i + \beta_i s_i + \gamma_i m \tag{2}$$

- p_i, s_i, m: personal, peer-group and societal influence.
- $\alpha_i, \beta_i, \gamma_i$: relative weightings given to each factor,

♠ McCullen et al., *"Multi-parameter models of innovation diffusion on complex networks"*, SIADS (2013).

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- $\alpha_i, \beta_i, \gamma_i$: relative weightings given to each factor,
  - Different types of people have different $\alpha_i, \beta_i, \gamma_i$ — *"archetypes"*

♠ McCullen et al., *"Multi-parameter models of innovation diffusion on complex networks"*, SIADS (2013).

Real-world social networks

- Real networks have many features, including:
  - local connections, distant ties, wide spread in degrees, community structure. . .

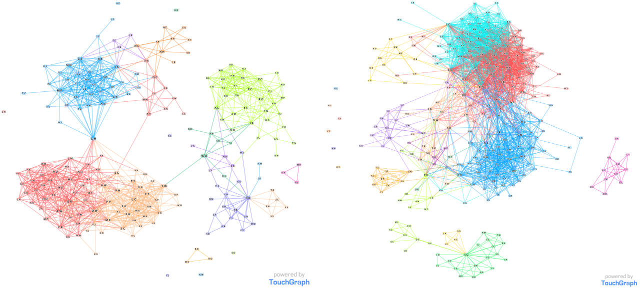
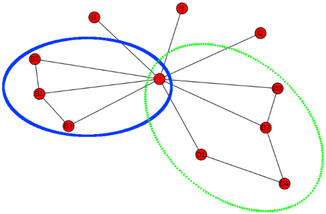


Figure: Inter-friend contacts on the *Facebook* website.

Random clustered model*

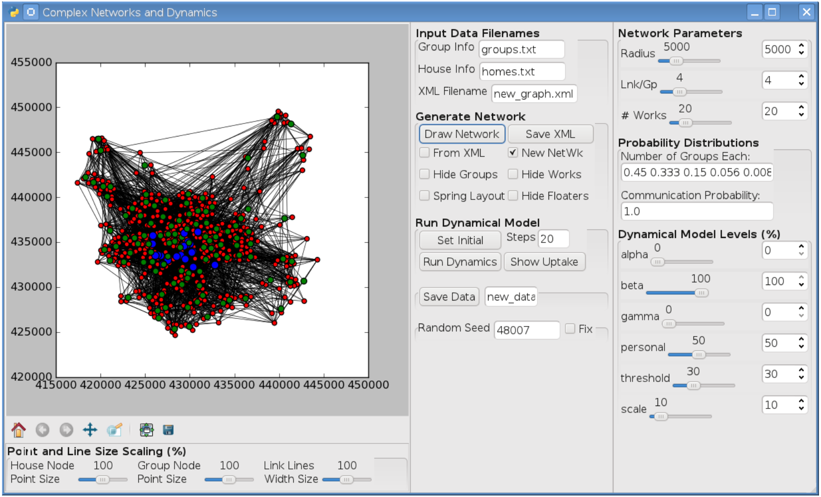
- Each node associated with G *groups*.
- Linked to L others in each group.



- Can also be linked to individuals in wider network.
- Can also impose geography.

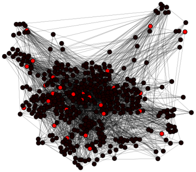
⋆: Newman *"Properties of highly clustered networks."* Physical Review E (2003).

Simulation demonstration



Outcomes — homogeneous archetypes

Expected chance of success depends on details:



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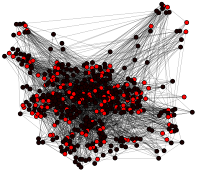

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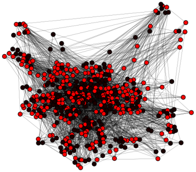

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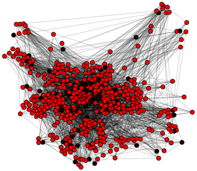

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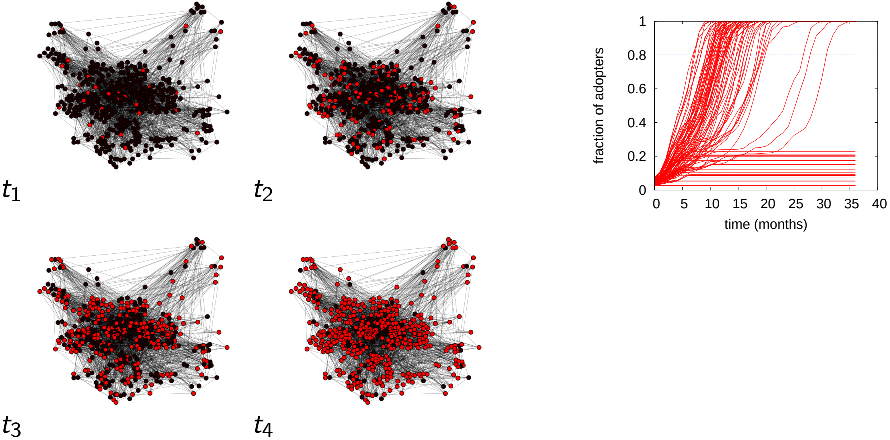

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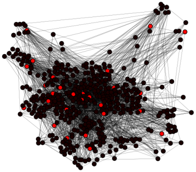

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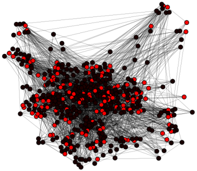

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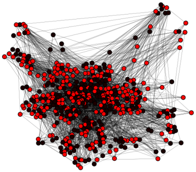
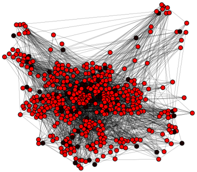


t_3



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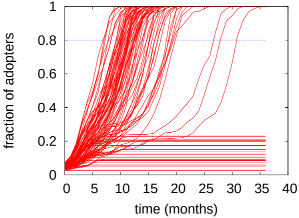

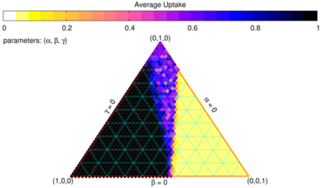

Analysis of Results

- Given individuals have a certain $\theta, p, \alpha, \beta, \gamma$ and m, require critical fraction of *active* neighbours:

$$s^* = \frac{\theta - \alpha p - \gamma m}{\beta}, \tag{3}$$

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- combining (3) and (4) gives X^* regions of *beta*, γ plots...

Comparison with Watts-Strogatz

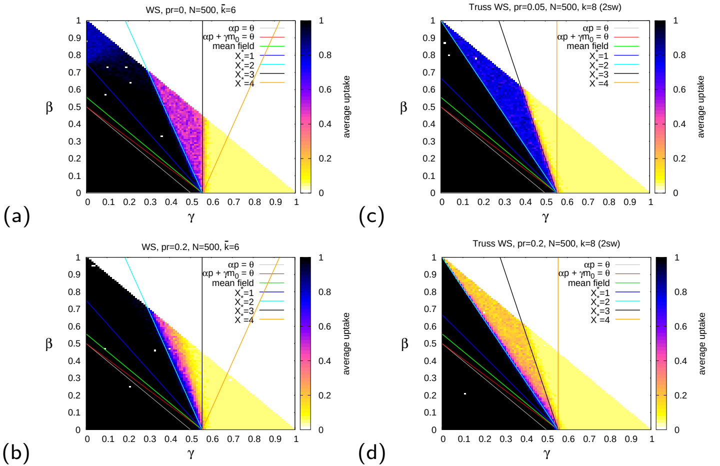
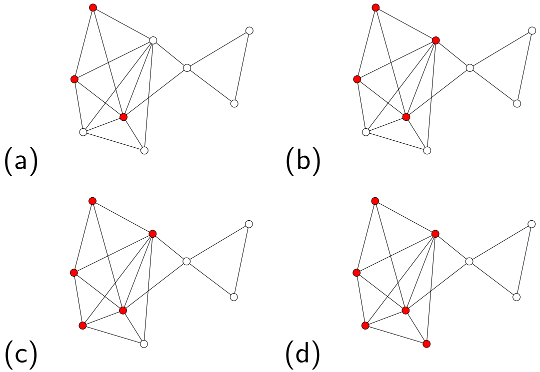


Figure: **(a)** 1D $\bar{k} = 6$, $p_r = 0$, **(b)** 1D $\bar{k} = 6$, $p_r = 0.2$; **(c)** truss $k = 8$, $p_r = 0.05$, **(d)** truss $k = 8$, $p_r = 0.2$.

The Effect of Clustering

Clustering creates non-independent neighbourhoods:



- Only one "success" required in network for spreading to occur.

Clustering and Communities

Enhances expected uptake:

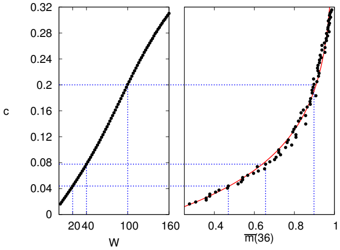


Figure: Expected uptake for clustered random network, with number of *groups* W determining level of clustering c.

- Only one "success" required in network for spreading to occur.

Inputting real data

- Survey data including info on behaviours.
  - Over 1050 valid responses received from residents of Leeds.
- Data used as a guide rather than definitive source,
  - used to narrow choice of structure and parameter values,
  - also to illustrate potential applications.

Model element	Parameter	Question / Data
Network	number of active individual / group connections.	Q. on who talks to whom about energy.
Threshold	θ	Q. on house type, tenancy and income.
Node archetypes	α, β, γ	Defra types of pro-enviro. behaviour

Bale, McCullen et al., Complexity (2014)

Parametrising the models

Model Feature	**Parameters**	**Data (if used)**
Network structure	N, G, M | W, L	Survey | Assumption
Individual connections	I | L	Survey | Assumption
Group connections	G | L	Survey | Assumption
Archetypes	$A_i = (\alpha_i, \beta_i, \gamma_i)$, $P(A_i)$	Simulation
Threshold	θ | $P\theta$	Survey | Assumption

Modelling scenarios

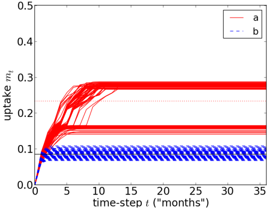
- Different **scenarios** studied by varying *dynamical model* and *network parameters*.

	Baseline	**Seeded**	**Community**	**Incentives**	**Snowball**
Model Param.	Do Nothing	Give efficiency measure to some (random) individuals	Give efficiency measure to whole communities.	Advertise a money off scheme.	Recommend-a-friend discount voucher scheme.
Links	Data based	–	–	–	**Increase**
Threshold	Data based	–	–	**Lower**	**Lower**
Initial Seed	Unforced	**Random**	**Target**	–	–

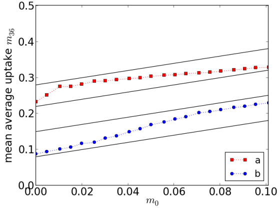
Bale, McCullen at al., Energy Policy (2013)

Comparison of model scenarios

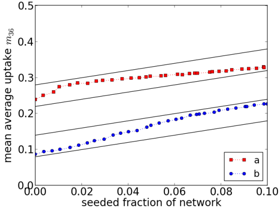
Baseline



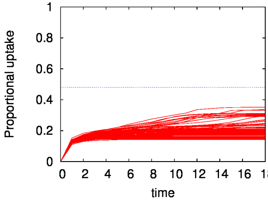
Seeded



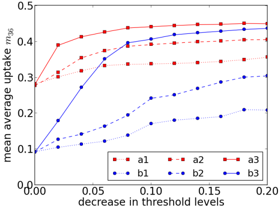
Communities



Incentives



Snowball



Further reading

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Multiparameter Models of Innovation Diffusion on Complex Networks*

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Key words. innovation diffusion, networks, threshold models, uptake of energy efficiency measures

AMS subject classifications. 91-04, 91F99

DOI. 10.1137/120885371

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What Math Can Tell Us About Technology's Spread Through Cities

EMILY BADGER   APR 10, 2013   COMMENTS

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