A branching and recombination model of technological innovation

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Outline

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Scope and motivation

Main focus: the dynamics of technological transitions:

- What endogenous forces drive technological change?
- How technological innovation and technology adoption interact?

More specific questions:

- To what extent **externalities** are important, beyond intrinsic quality, in technology adoption decision?
- What is the role of switching **costs**?
- How important are technological **links**?
- what is the effect of **recombinant** innovation on adoption dynamics?
- How an innovation **policy** can maximize social welfare?

Positive externalities

For many adoption processes, positive externalities render the utility of an adopter to increase with the number of fellow adopters. Examples:

- technologies,
- social norms,
- scientific ideas

For technology adoption the positive externality is particularly strong because of technological standards.

Positive externalities cause **path-dependence** of technology diffusion. The extreme outcome is technological **lock-in**, where agents are stuck in one technology.

Literature

- On positive externalities, path-dependence and lock-in: David (1985), Arthur (1989).
- On technological graphs: Vega-Redondo (1994).
- On technology selection: Bruckner et al. (1996).
- On technological modularity and recombinant uncertainty: Fleming (2001), Ethiraj and Levinthal (2004).
- On recombinant innovation: van den Bergh (2008) and van den Bergh and Zeppini-Rossi (2008)

Main ingredients of the model

An agent-based model, with two entities:

- Technologies
  - have an intrinsic quality
  - exhibit positive externalities
  - form a directed technology graph
- Agents (say entrepreneurs or firms)
  - are homogeneous in their preferences
  - in every period they use one and only one technology
  - they incur switching costs when switching from one to another technology
  - they can invent new technologies

Agents' utility and technology adoption

The utility from using technology α in period t is

$$u_{\alpha,t} = l_\alpha + e n_{\alpha,t} \tag{1}$$

where l_α is the intrinsic **quality** of technology α, $n_{\alpha,t}$ is the **population** of technology α in period t and $e \in [0,1]$ is the **strength** of agents' externalities

Agents choose the technology that gives higher utility to them. **Switching** from technology α to β entails a **cost** equal to the technology **distance** $d_{\alpha\beta}$. Then one agent switches if:

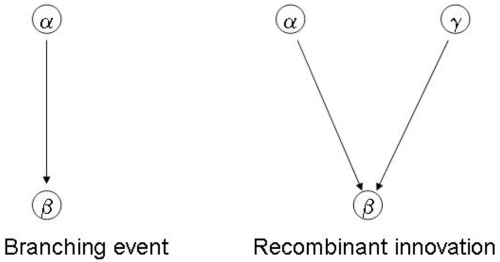
$$u_{\beta,t} - d_{\alpha\beta} > u_{\alpha,t} \tag{2}$$

Assumption: adjacent technologies have equal distance $d_{\alpha\beta} = 1$.

Two ways to innovations

At each time step t any agent can be drawn as **innovator** with probability p, introducing a **new technology** which is an improvement with respect to its previous one. Two cases:

1. innovators come from the same technology: *branching innovation*
2. innovators come from different technologies: *recombinant innovation*



Technological progress

Every time step with innovators witnesses a quality improvement.

- In case of branching the improvement is a unitary step up:

$$l_\beta = l_\alpha + 1 \qquad \textit{branching} \tag{3}$$

- When recombinant innovation arises, the quality of the innovation is a unit higher than the maximum quality of parents. If α and γ recombine to give the innovation β,

$$l_\beta = \max\{l_\alpha, l_\gamma, \dots\} + 1 \qquad \textit{recombination} \tag{4}$$

Timing of agents' actions

At each time step t, two stages take place:

1. **innovation stage**: a drawn is made and innovator(s) create the new technology
2. **decision stage**: remaining agents choose technology by maximizing utility

Assumption: innovators stick to their innovation for one period.

Assumption: in case of tie $(u_\beta - d_{\alpha\beta} = u_\gamma - d_{\alpha\gamma} = \dots)$, agents keep their technology if involved, otherwise choose randomly.

Assumption: agents are myopic, not considering their utility contribution. Moreover they are not strategic, missing to anticipate the actions of other agents.

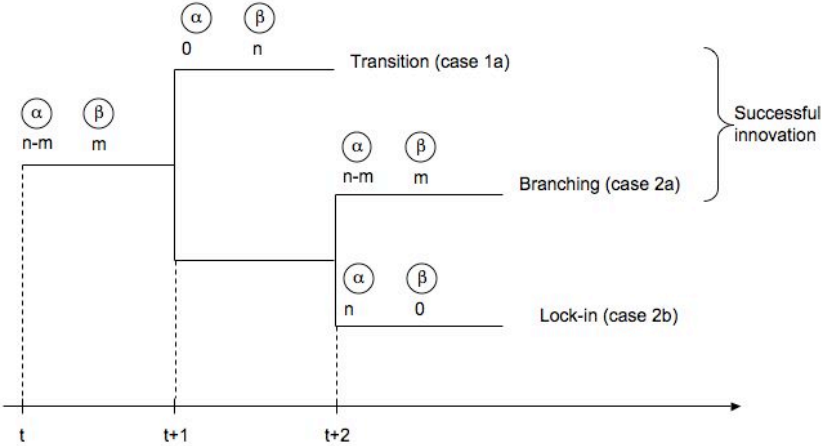
Successful innovations

Question: how many agents have to "co-invent" for a *successful innovation* (when non-innovators follow suit)?

Say n agents use technology α at time t, and $m < n$ agents co-invent technology β in that period. Three cases are possible:

1. if $m > \frac{n}{2}$ we have a *transition* (all agents follow)
2. if $\frac{n}{2} > m > \frac{n}{2} - \frac{1}{e}$ we have a *branching* event ($n - m$ agents remain with technology α, the m innovators remain with β)
3. if $m < \frac{n}{2} - \frac{1}{e}$ we have *lock-in* into technology α (no escape)

Technological transitions, branching and lock-in



Simulation set-up

We first explore qualitatively the effect of the probability of innovation p, with the following setting:

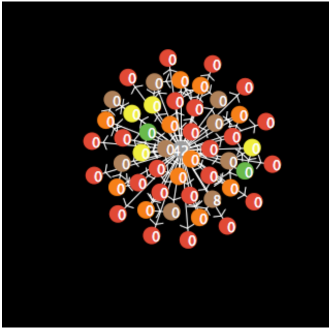
- 50 agents
- externalities $e = 0.5$
- time horizon $T = 50$ steps

We build up the technology graph and look at the dynamics of quality levels.[1]

[1] the model has been implemented in Netlogo.

Lock-in regime

$p = 0.1$



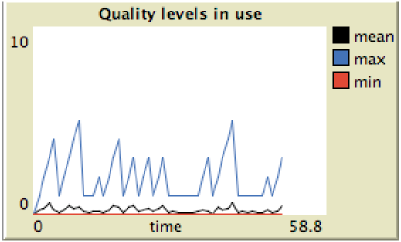
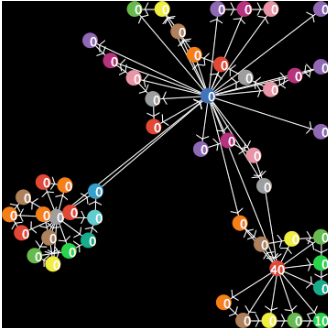


Figure: Left: technology graph. Right: Minimum quality level of used technologies (red line), maximum level (blue line) and mean level (black line).

Punctuated growth

$p = 0.2$



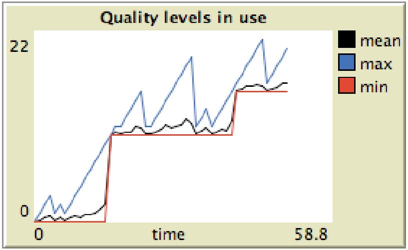


Figure: Left: technology graph. Right: Minimum quality level of used technologies (red line), maximum level (blue line) and mean level (black line).

Linear growth

$p = 0.5$

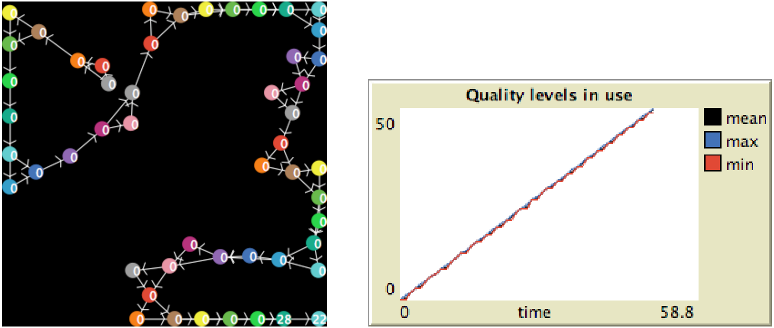


Figure: Left: technology graph. Right: Minimum quality level of used technologies (red line), maximum level (blue line) and mean level (black line).

Simulation set-up

With a **simulation experiment** we search quantitatively the parameter space. Here we have set the following conditions:

- Agents' **population** $N = \{2, 5, 10, 20, 50\}$
- **externalities** $e \in [0, 1]$ with 0.1 steps
- **probability of innovation** $p \in [0, 1]$ with 0.1 steps

We have chosen a **time horizon** of $T = 50$ time periods, and for each condition we have **repeated** the simulation 10 times.

Then we average resulting values over these 10 repetitions:

- accumulated quantities (over 50 periods):
  number of recombinations, **entropy**
- final values (after 50 periods):
  technologies' **minimum quality**, agents' **mean utility**

Results

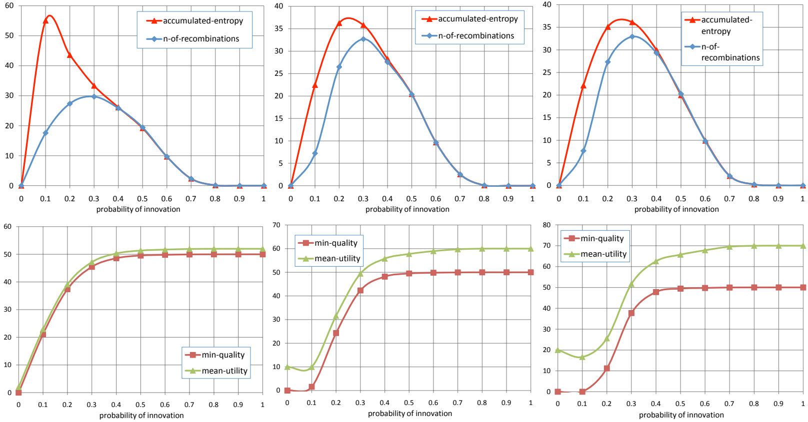


Figure: Simulation with $N = 20$. Top: entropy and number of recombinations. Bottom: Minimum quality of used technologies and mean utility across agents. Left: $e = 0.1$. Centre: $e = 0.5$. Right: $e = 1$

Including the cost of innovation

Think of p as the innovation policy investment, i.e. its cost.

$$w = < u(p) >_N - cp \qquad \textit{welfare measure} \tag{5}$$

where $< u(p) >_N$ is agents' mean utility, p is the probability of innovation and c is a cost factor for innovation policy.

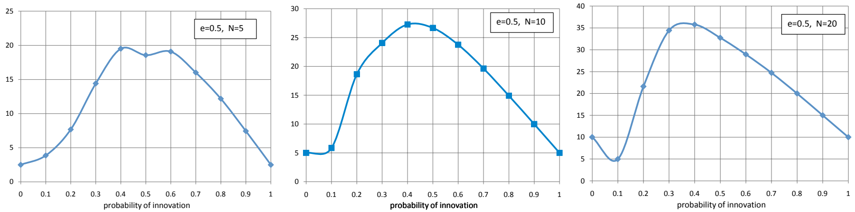


Figure: Measure of welfare w. Left: $N = 5$. Centre: $N = 10$. Right: $N = 20$.

Conclusion

Three main messages:

- Technological **recombination** matters: it represents a short-cut to higher quality. Recombinations trigger transitions and consequently boost technological progress. Similar virtue to random rewiring of "small-world networks".
- There's a **saturation effect** in the innovation probability: above a certain level, the marginal increase in utility is negligible. This means there is an internal optimum for innovation policy effort (p). This optimum is highly correlated with the number of technological recombinations.
- We obtain an **S-shaped utility** when the number of agents becomes large. This translates into an internal minimum for welfare: either do not invest in innovation at all (corner solution) or go for the internal optimum.