THEORETICAL MODELING, ICPSR SUMMER II 2024 HOMEWORK 3

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August 2024

1 Learning from others

1.1

```
globals [
  environA? ;;is the environment in state A?
]
turtles-own [
  payoff
  consensus-learner? ;;am I a consensus learner?
  behaviorA? ;;do I have behavior A?
  old? ;;am I in the old generation
  location
]

;;;;;;--------SET UP PROCEDURES ---------------------------

to setup
  clear-all
  set environA? one-of [true false]
  ask patches[
    sprout 1 [
      set shape "circle"
      set consensus-learner? ifelse-value (random-float 1 < init-freq-consensus-learners) [true] [false]
      set behaviorA? environA?
      set payoff baseline-fitness + adaptive-fitness-diff ;;start everyone wiht max fitness.
      set location random num-location
    ]
  ]
  recolor
  reset-ticks
end

to recolor
  ask turtles[
    set color ifelse-value consensus-learner? [sky] [pink]
  ]
end
```

Figure 1: code for setting location with probablity m

1.2

```
;;;;;;--------DYNAMICS PROCEDURES ----------------------------

to go
  reproduction
  recolor
  environ-change      ;;the environment changes
  learning            ;;agents learn
  move
  calculate-payoffs
  tick
end

;;agents reproduce with probability proportionate to their fitness
to reproduction
  ask turtles [set old? true]
  let num-olds (count turtles with [old?])
  let max-fit max [payoff] of turtles
  while [(count turtles with [not old?]) < num-olds]
  [
    ask one-of turtles with [old?] [
      let p (payoff / max-fit) ;;probability of reproduction.
      if random-float 1 < p [
        hatch 1 [
          set old? false
          ifelse (random-float 1 < mutation-rate)
          [set consensus-learner? one-of [true false]]
          [set consensus-learner? ([consensus-learner?] of myself)]
          if (any? other turtles-here with [not old?])
          [move-to one-of patches with [not any? turtles-here with [not old?]]]
        ]
      ]
    ]
  ]
end
```

Figure 2: rest of code for consensus-learning - part a

```
to move
  ask turtles [
    if random-float 1 < move-prob [
      set location random num-location
    ]
  ]
end

to environ-change
  if random-float 1 < environ-change-rate
  [set environA? (not environA?)]
end

to learning
  ask turtles with [not old?][
    ifelse not consensus-learner? ;;if individual learner
    [
        set behaviorA? environA?
    ]
    [ ;;if consensus learner
      let teacher one-of turtles with [not consensus-learner?]
      print  count turtles with [consensus-learner?]
      print  count turtles with [not consensus-learner?]

      if count turtles with [consensus-learner?] > count turtles with [not consensus-learner?][
        set teacher one-of turtles with [consensus-learner?]
      ]
      set behaviorA? ([behaviorA?] of teacher)
    ]
  ]
  ask turtles with [old?] [die] ;; kill the old
end
```

Figure 3: rest of code for consensus-learning - part b

1.3

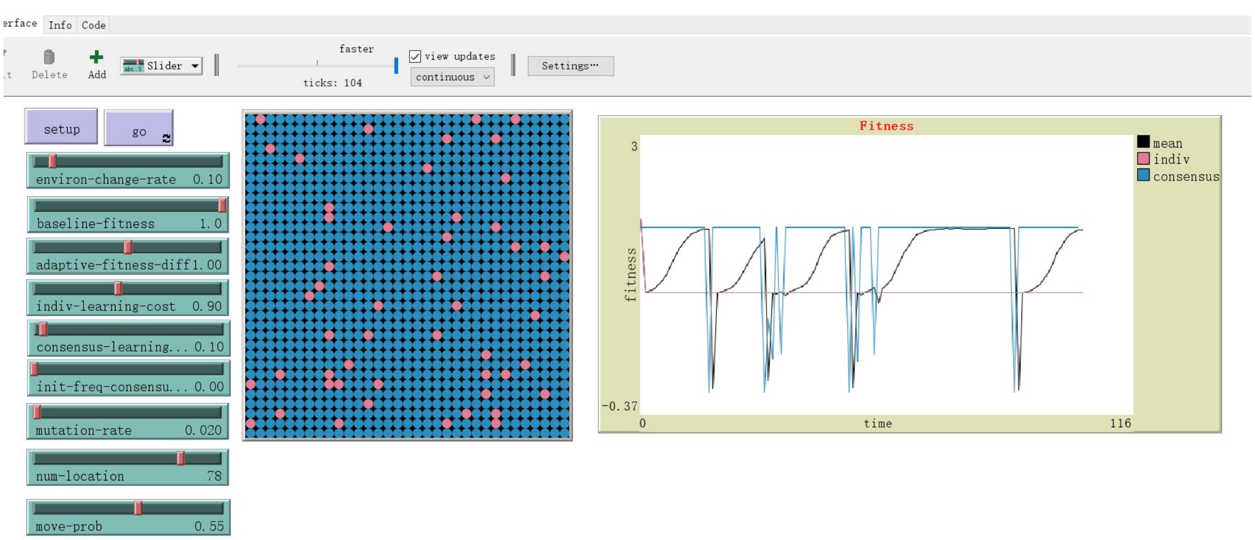


Figure 4: consensus-learning simulation

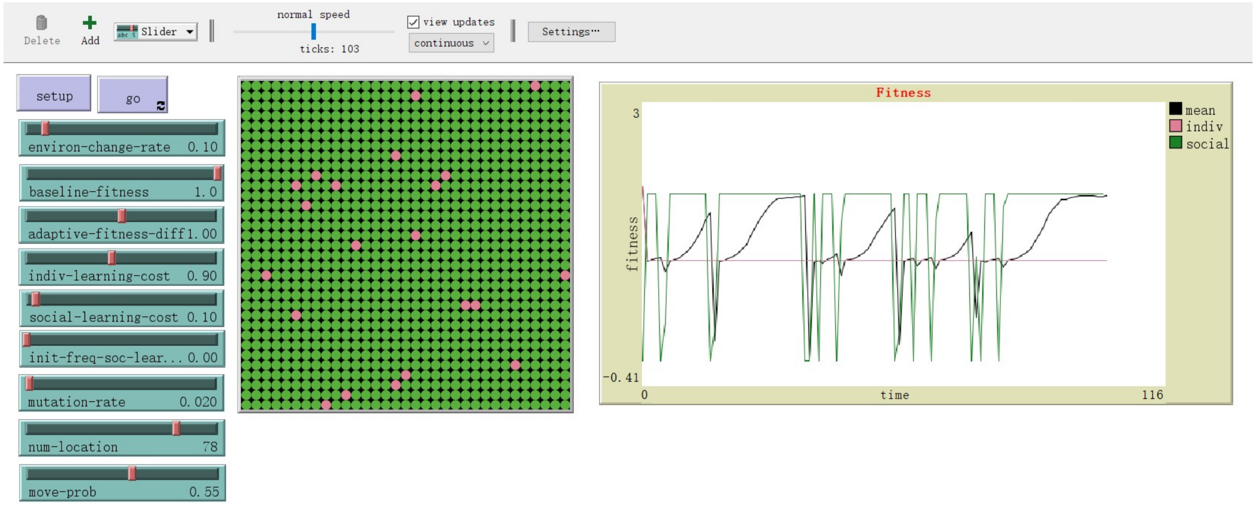


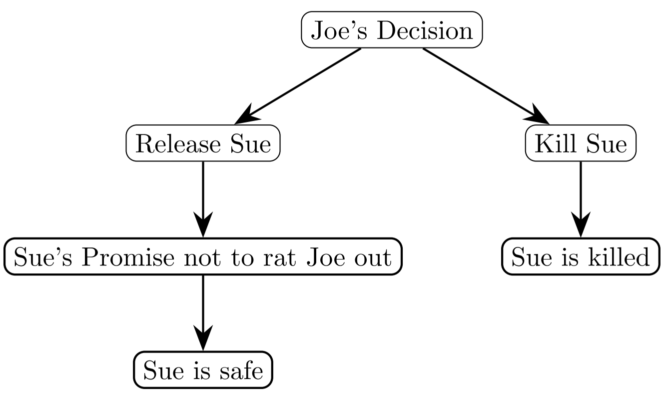
Figure 5: social-learning simulation

From the simulation it can be clearly seemed that under the same parameters, setting the m to 0.55 (high but not too high), the fitness curve of consensus-learning performs better and more stable fitness to social-learning, indicating that consensus learning out performs unbiased social learning and costly individual learning.

2 Guilty by association

2.1

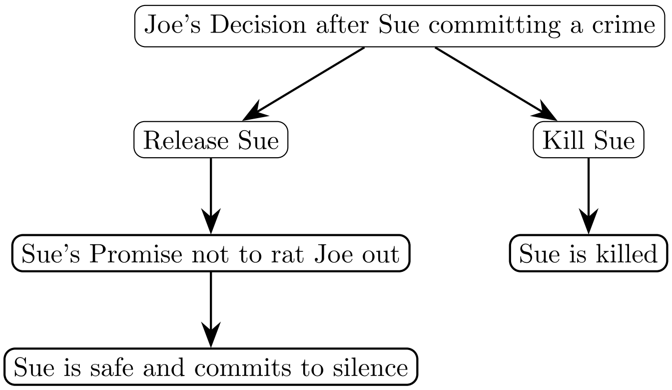
Game Tree



Backward Induction

- **If Joe Releases Sue:**
  Sue has promised not to rat Joe out, but she can still identify him. Joe risks being caught.
- **If Joe Kills Sue:**
  Joe avoids the risk of being identified and apprehended. Therefore, this option is preferable.

2.2



Backward Induction

- **If Joe Releases Sue:**
  Sue will either keep silent or rat Joe out. For the former Joe avoids the risk of being apprehended. For the latter it will also make Sue less credible as Joe witnessed her committing a crime.

- **If Joe Kills Sue:**
  Joe avoids the risk of being identified and apprehended.

  In summary, Schelling's idea relies on Sue's act of committing a crime to make her testimony less credible, thus ensuring that Joe avoids the risk of capture.

3 I want to believe

3.1

Because the reverse scenario, assigning a low probability of truth to a true hypothesis, is far less likely in reality. Therefore it make more sense to study how publication bias leads to accepting false facts as true. The model is concerned with false positives, not false negatives.

3.2

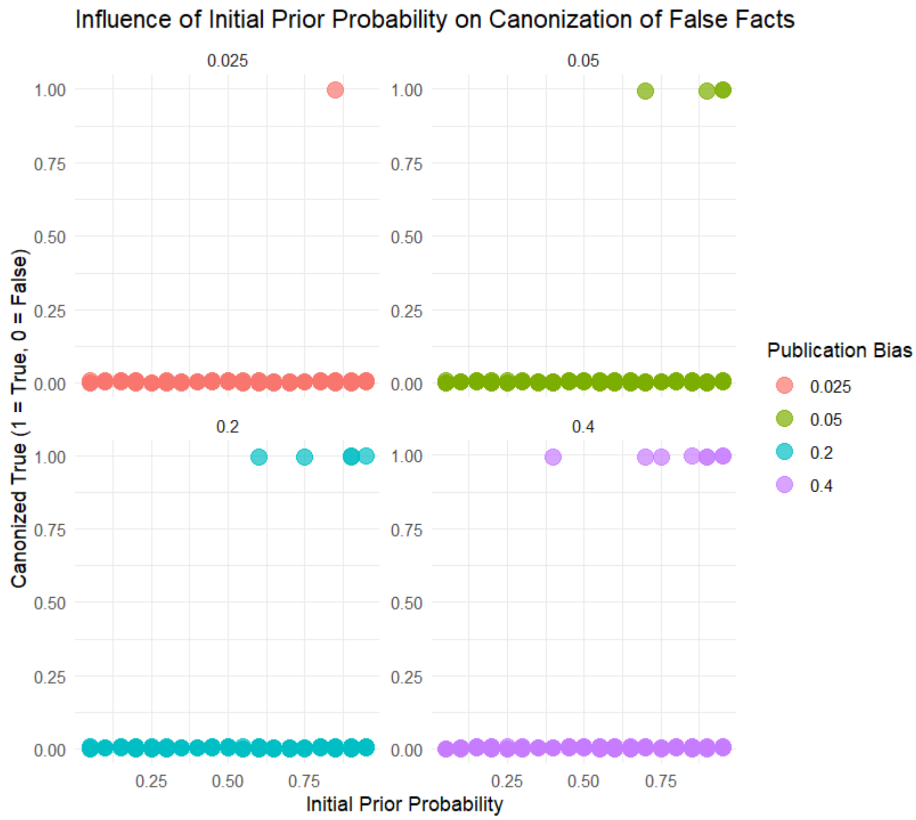


Figure 6: Influence of Initial Prior Probability on Canonization of False Facts

Clearly higher initial prior probablity leads to a higher probablity of canonization of a false fact as true.

4 The plot thickens

4.1

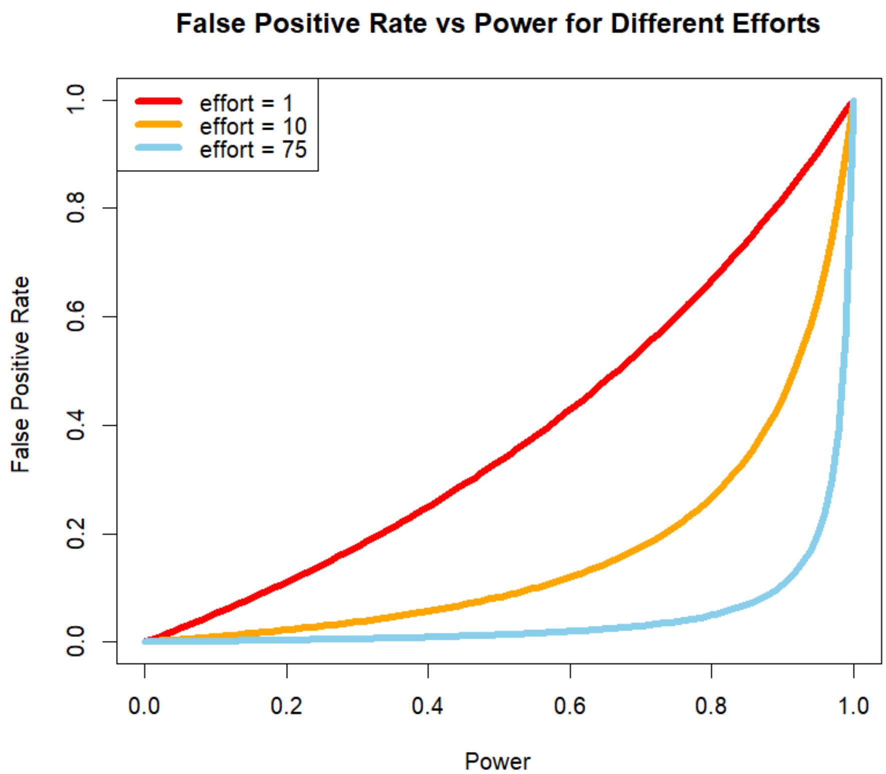


Figure 7: False Positive Rate vs Power for Different Efforts

As power goes up, so does the false positive rate, but increasing effort will decrease the false positive rate for a given power.

4.2

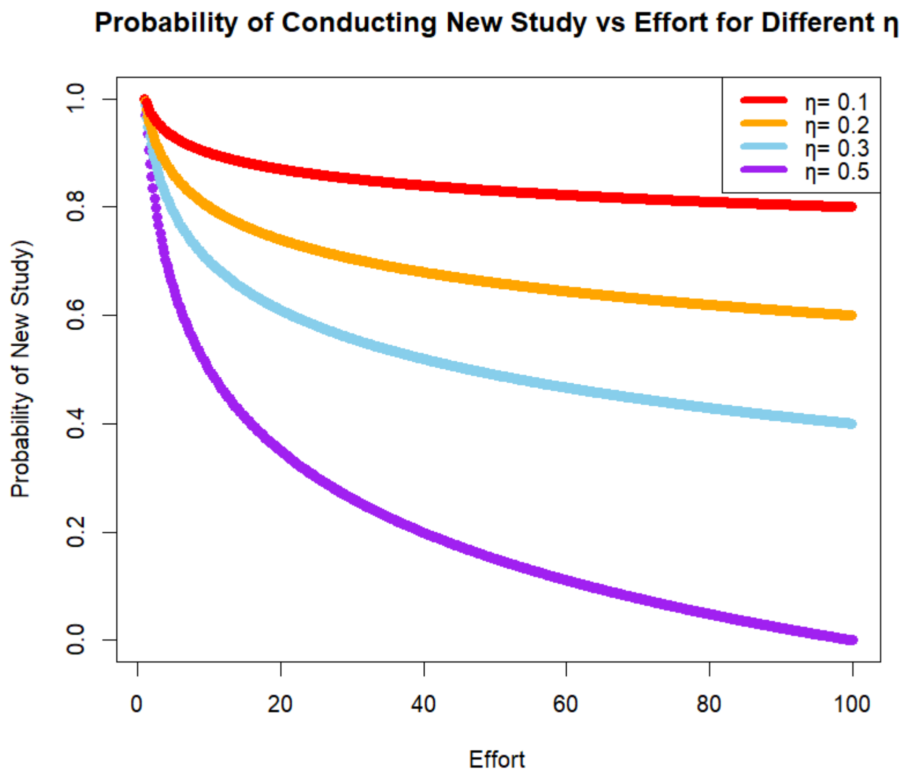


Figure 8: Probability of Conducting New Study vs Effort for Different η

Labs exerting more effort should have a lower probability of starting a new study than labs exerting less effort. When the influence.

4.3

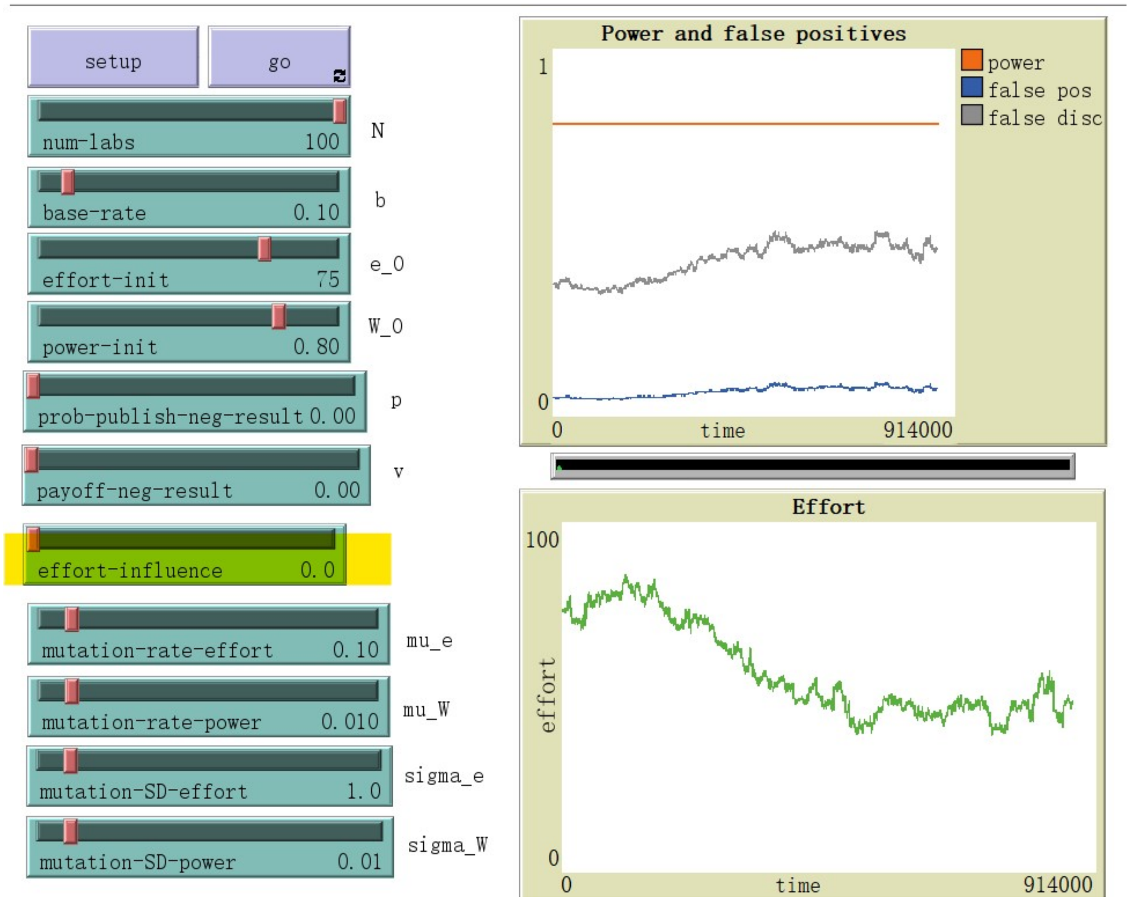


Figure 9: Effort evolves with constant power and $\eta = 0$

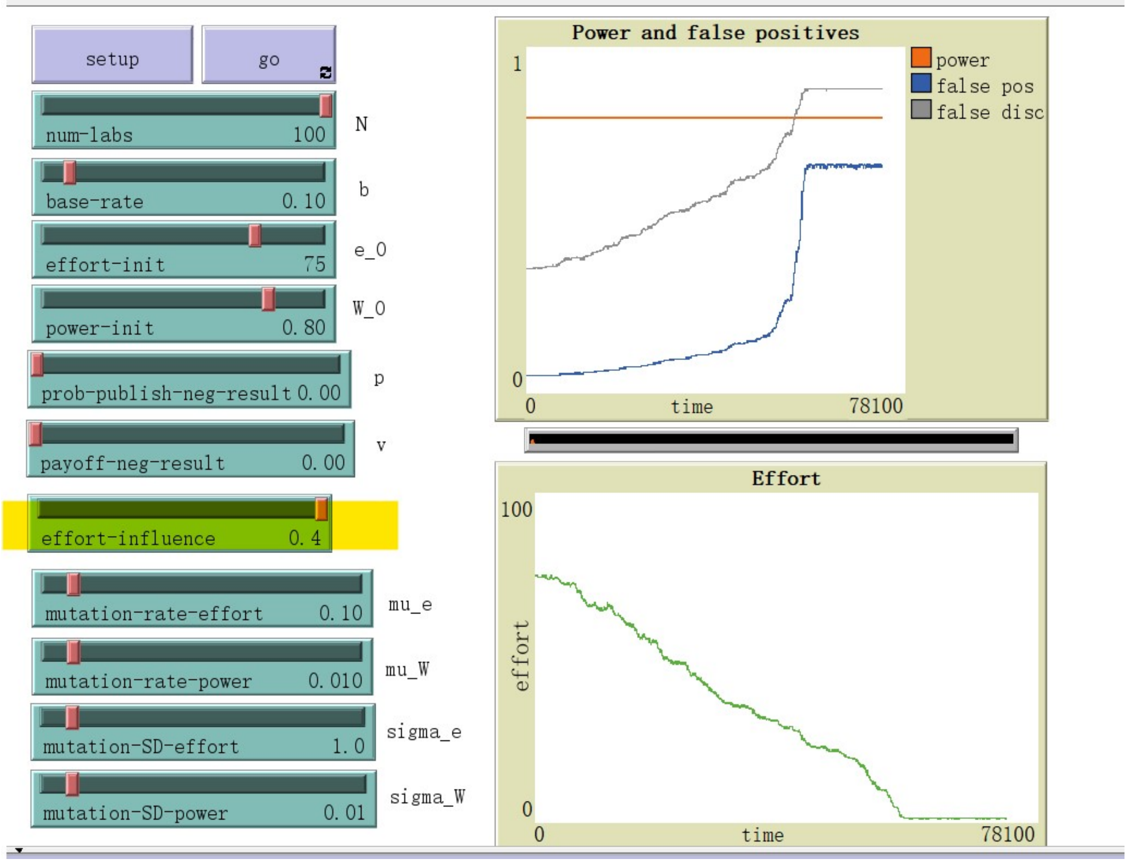


Figure 10: Effort evolves with constant power and $\eta = 0.4$

When $\eta = 0$, meaning there is no effect of effort on productivity, when power is held constant but effort evolves, the effort of researches decreases moderately and false discoveries maintain stable.

When $\eta = 0.4$, meaning there is a strong effect of effort on productivity, when power is held constant but effort evolves, all researches exhibit minimal effort and false discoveries soar.

5 Getting attached, preferentially

5.1

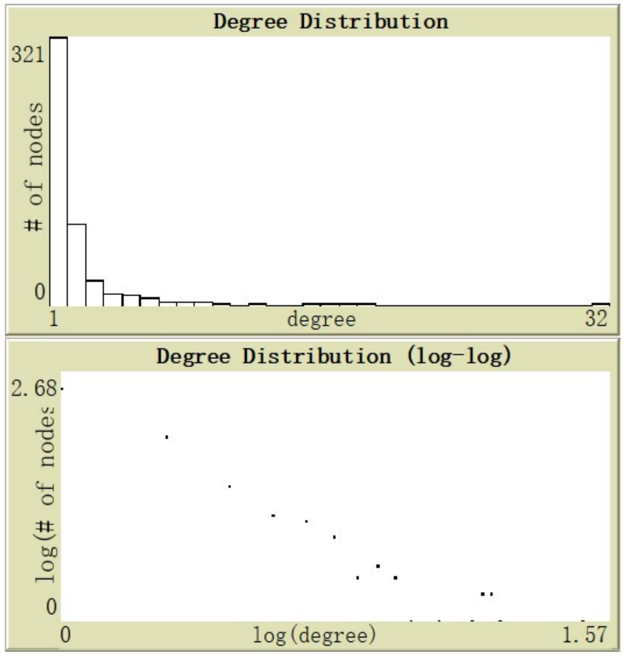


Figure 11: degree distribution

The highest degree is 31. The lowest degree is 1.

5.2

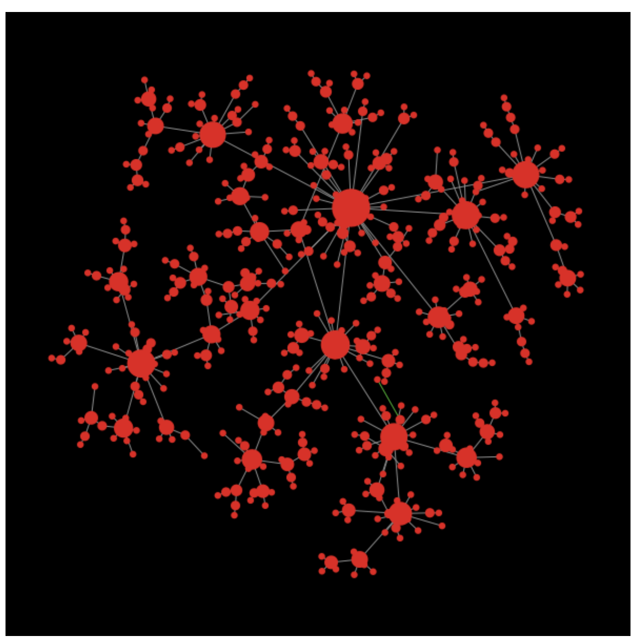


Figure 12: Old money powers

Clearly older nodes have more degree, indicating the power of capalisim accmulation.

5.3

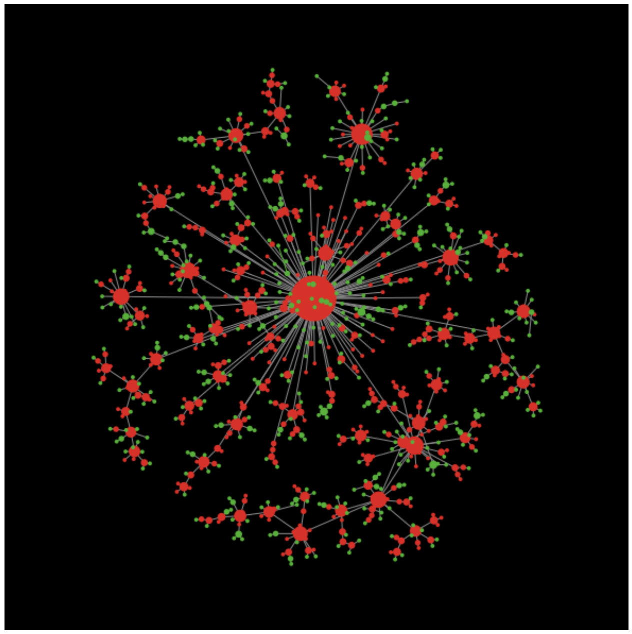


Figure 13: Old money still power

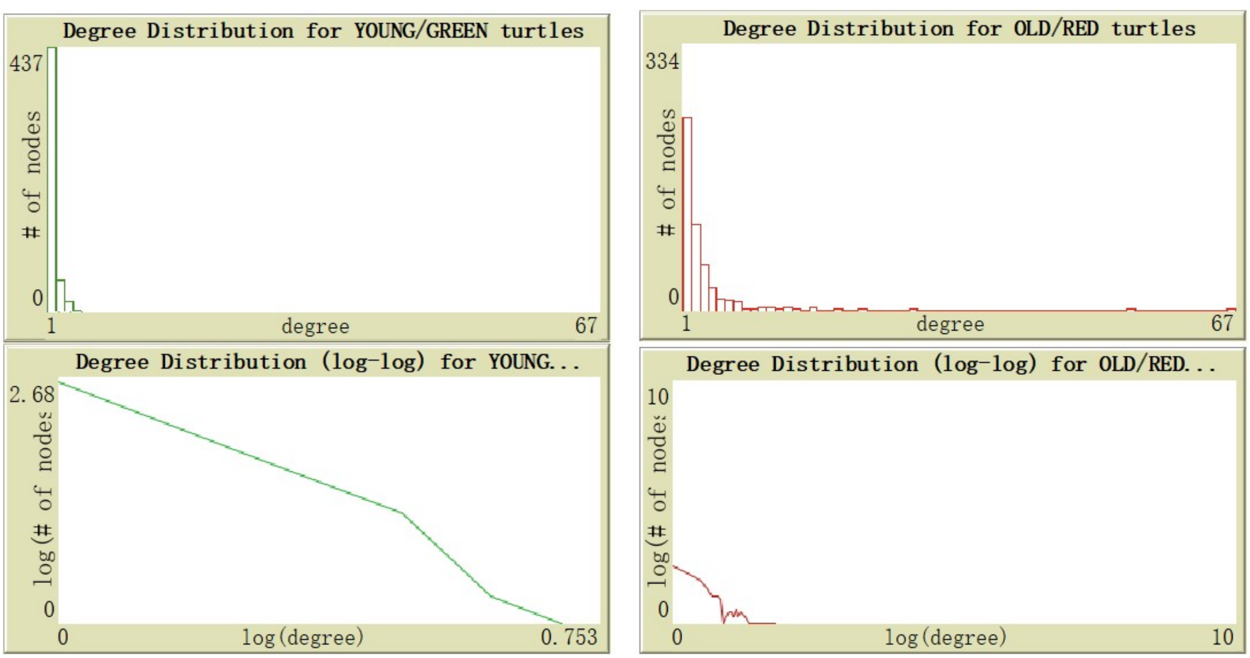


Figure 14: degree distributions of old and young money

For old/red turtles,the highest degree is 67. The lowest degree is 1. For young/green turtles,the highest degree is 6. The lowest degree is 1. Early birds get worm. Old money get richer.

6 Are complex contagions really so hard to spread?

6.1

```
to go
  ;; stop if every agent has already been infected
  if all? turtles [infected?]
    [stop]

  ask turtles with [ infected? = true ]
  [
    ;; infect neighbors
    ask link-neighbors with [not infected?]
      [
        if (((not complex-contagion?) or (count link-neighbors with [infected? = true] > 1)))  ;; infect with probability p
        [
          set infected? true
          set color yellow
          set size infected-size

          ;; color the link with the node doing the infection for viz purposes only
          ask link-with myself [set color yellow]
        ]

        if ((complex-contagion?) and (count link-neighbors with [infected? = true] = 1) and (random-float 2 <= prob-spread-one))
        [

          set infected? true
          set color yellow
          set size infected-size
          ask link-with myself [set color yellow]
        ]

    ]
  ]
  set num-infected count turtles with [infected? = true]
  tick
end
```

Figure 15: code with prob-spread-one

6.2

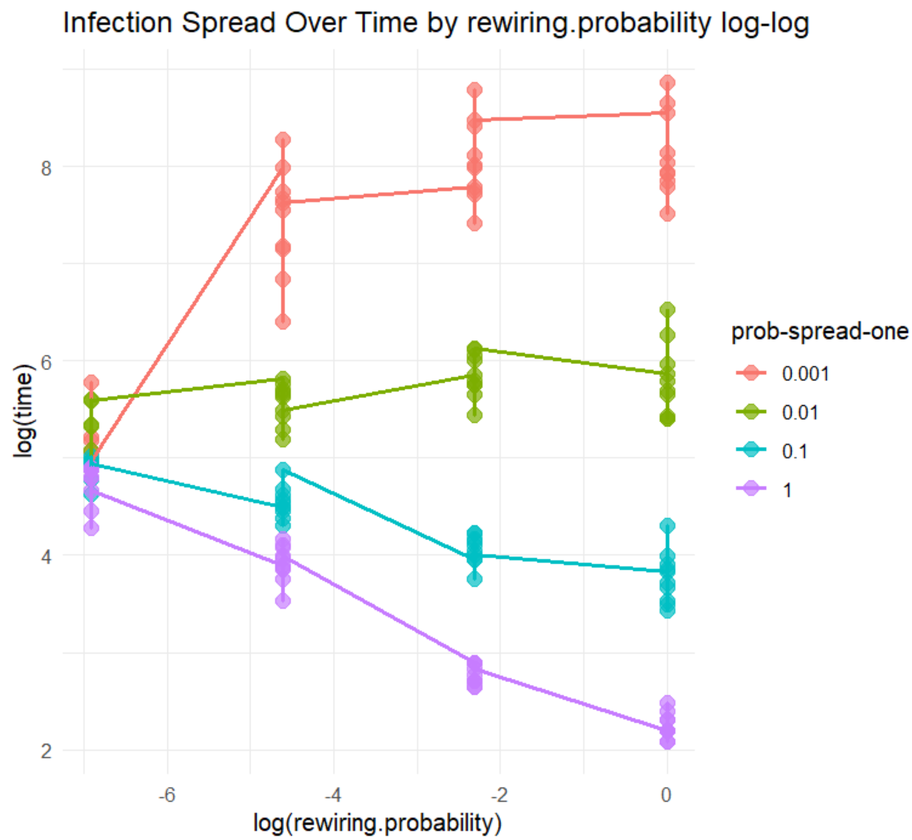


Figure 16: Infection Spread Over Time by rewiring probability log-log

When prob-spread-one = 0.1 and 1, the higher the rewiring probablity, the less time it takes to fully thread through the network. While when prob-spread-one = 0.001 and 0.01, the higher the rewiring probablity, the more time it takes to fully thread through the network.

6.3

The modified complex contagion model shows that behaviors can spread more easily than we thought. Even one infected neighbor can sometimes cause spread if they are persuasive enough. This means complex contagions are not as hard to spread as we believed. They can spread faster, especially in networks that are not highly connected.