Agent-Based Models in Practice

EES 4760/5760

Agent-Based and Individual-Based Computational Modeling

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Ways to use models

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1. Detailed predictions
2. Theory-building
3. What-if analysis

Detailed Predictions

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Detailed Predictions

- Develop model:
  - Theory-driven
    - Use existing theory
  - Data-driven
    - Need *lots* of observations/data
    - Look for patterns in data
    - Describe patterns mathematically
- Calibrate model
  - Mathematical theory has parameters
    - Adjust parameters to make model agree with past observations
- Validate & Verify

Validation & Verification

- **Cross-validation** (for comparing theories):
  - Divide data into k parts: $1 \ldots k$
    - Each part has a turn as t̀est set’’:
      - Fit model parameters to the other parts
      - Compare predictions to test set.
  - Choose model that performs best over the k comparisons.
- **Hold-out testing** (for estimating predictive accuracy):
  - Divide data into *hold-out* and *training* data:
    - Divide *training* data into k parts
    - Use *cross-validation* to choose best model
    - Calibrate best model on full *training* set
    - Test predictions against *hold-out* set to estimate predictive power

Theory-Building

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Theory-Building

- Similar to detailed prediction
  - Detailed prediction often uses very complicated models to capture all the relevant details of the real world
  - Theory-building often uses simplified models to capture just the most important aspects of what makes the real-world system tick.

What-if analysis

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What-if analysis

- Does not necessarily need data
- Start with simple theory or hypothesis
- Explore implications

Robust Policy Analysis

- How to make policy under extreme uncertainty:
  - R. Lempert: Making policy for the next 100 years
    - planning for climate change, technological revolutions, etc.
  - You can’t predict what will happen
  - Division:
    - *policy variables* (things you can control),
    - *external variables* (things you can’t control).
  - Use ***lots*** of model runs (BehaviorSpace goes nuts)
    - Which sets of *policy variables* avoid catastrophic outcomes across the widest range of *external variables*?

Realistic Expectations

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Realistic Expectations

- Most ABM work ***does not*** aspire to make detailed predictions
- Much focuses on either theory-building or what-if analysis

Example of Detailed Predictions: 2014 Ebola Epidemic

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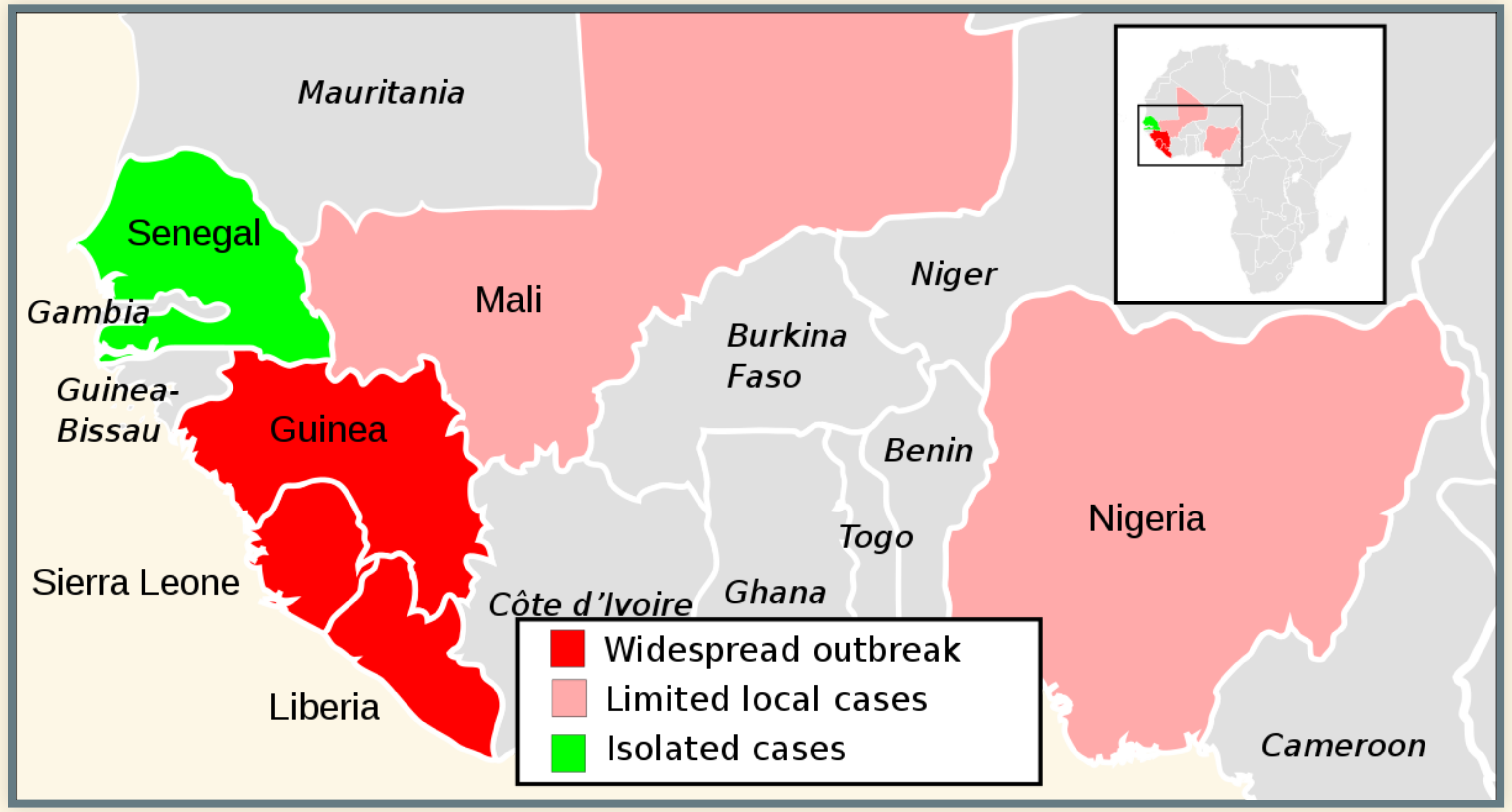
2014 Ebola Outbreak

- Ebola hemorrhagic fever is highly infectious through contact with blood or other bodily fluids
  - It also spreads from contact with infected fruit bats and non-human primates
  - 40–50% of infected people die
- Outbreak began in spring 2014 in Guinea
- By summer:
  - Spread to Sierra Leone and Liberia with additional cases in Mali, Nigeria, and Senegal



  - 100 new cases per week
  - In July, U.S. Government asked computational biologists to develop models of outbreak.

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M.M. Waldrop, Special agents offer modeling upgrade,'' PNAS **114**, 7176–7179 (2017). doi: 10.1073/pnas.1710350114{target="_blank"}

Agent-Based Modeling of Ebola Outbreak

- Goals of model:
  - Determine how bad the outbreak will become
  - Provide guidance on number and location of field hospitals
  - Develop plan to field-test experimental vaccine
- Challenges
  - Simple equations can predict general properties of disease spread
  - Spread of Ebola also depended on:
    - Detailed geography and transportation networks
    - Human behavior and social/familial relationships
  - These required agent-based models
- Relief agencies needed answers in *weeks*

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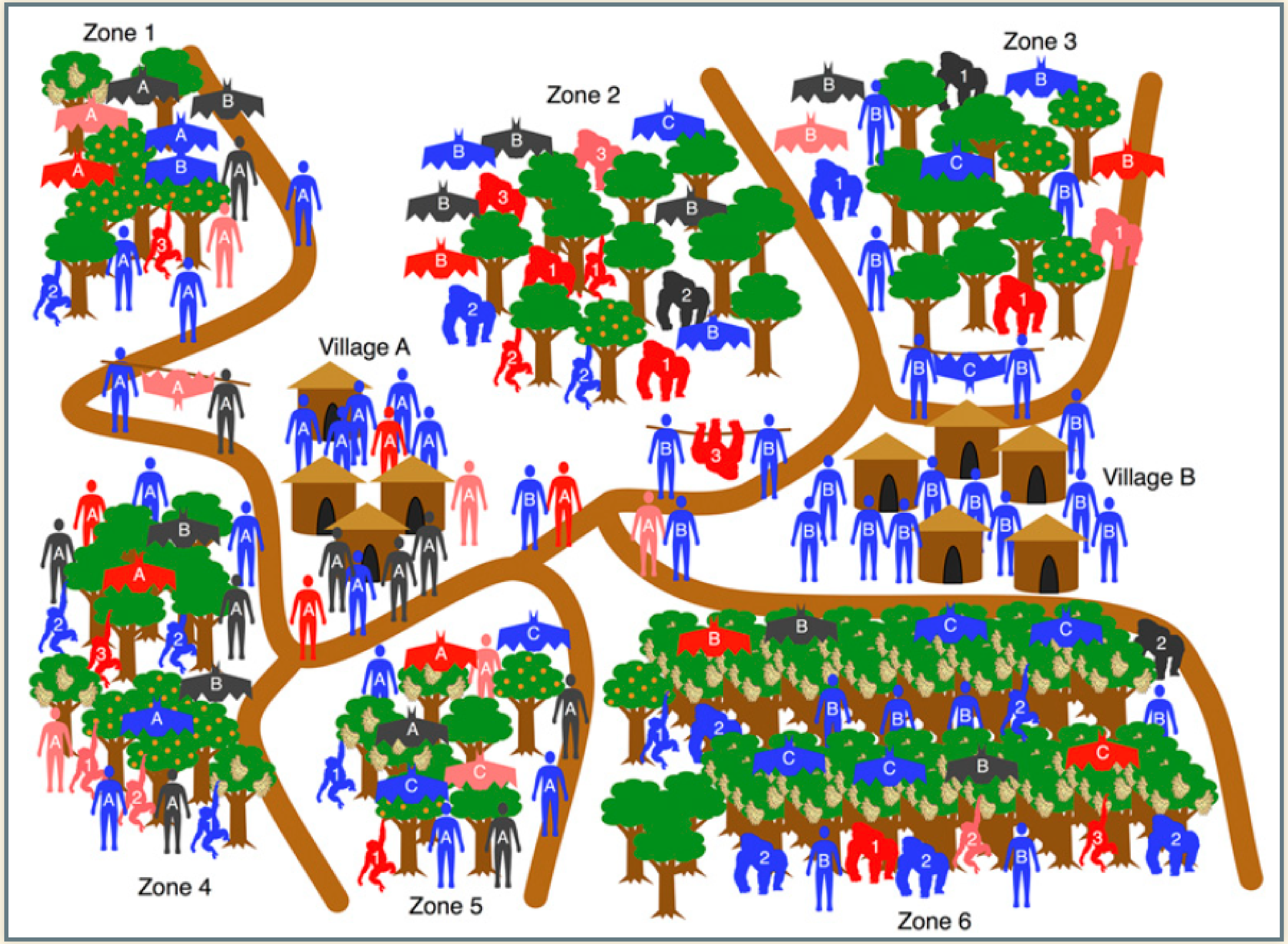
Schematic structure of model



K.A. Alexander *et al.*, “Modeling Wildlife-Associated Zoönoses: Applications and Caveats,” Vector-Borne and Zoönotic Diseases **12**, 1005–1018 (2012). doi: 10.1089/vbz.2012.0987

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Parameterizing and Calibrating the Model

- The models needed detailed data that was hard to get
  - At first the team had a high-school student doing a summer internship get up early every morning to look up data on the Facebook page of the Sierra Leone public health ministry
  - An undergraduate student intern would enter the data into a computer.
  - Later, they assigned a graduate student to work full time on gathering and entering the data.
- The models were tracking millions of people. They needed powerful supercomputers to run.
- This initial modeling let them forecast that if the epidemic was not controlled, there would be between 500,000 and 1,400,000 cases by January 2015.
- This was the decisive factor in President Obama’s decision to send U.S. military to help.

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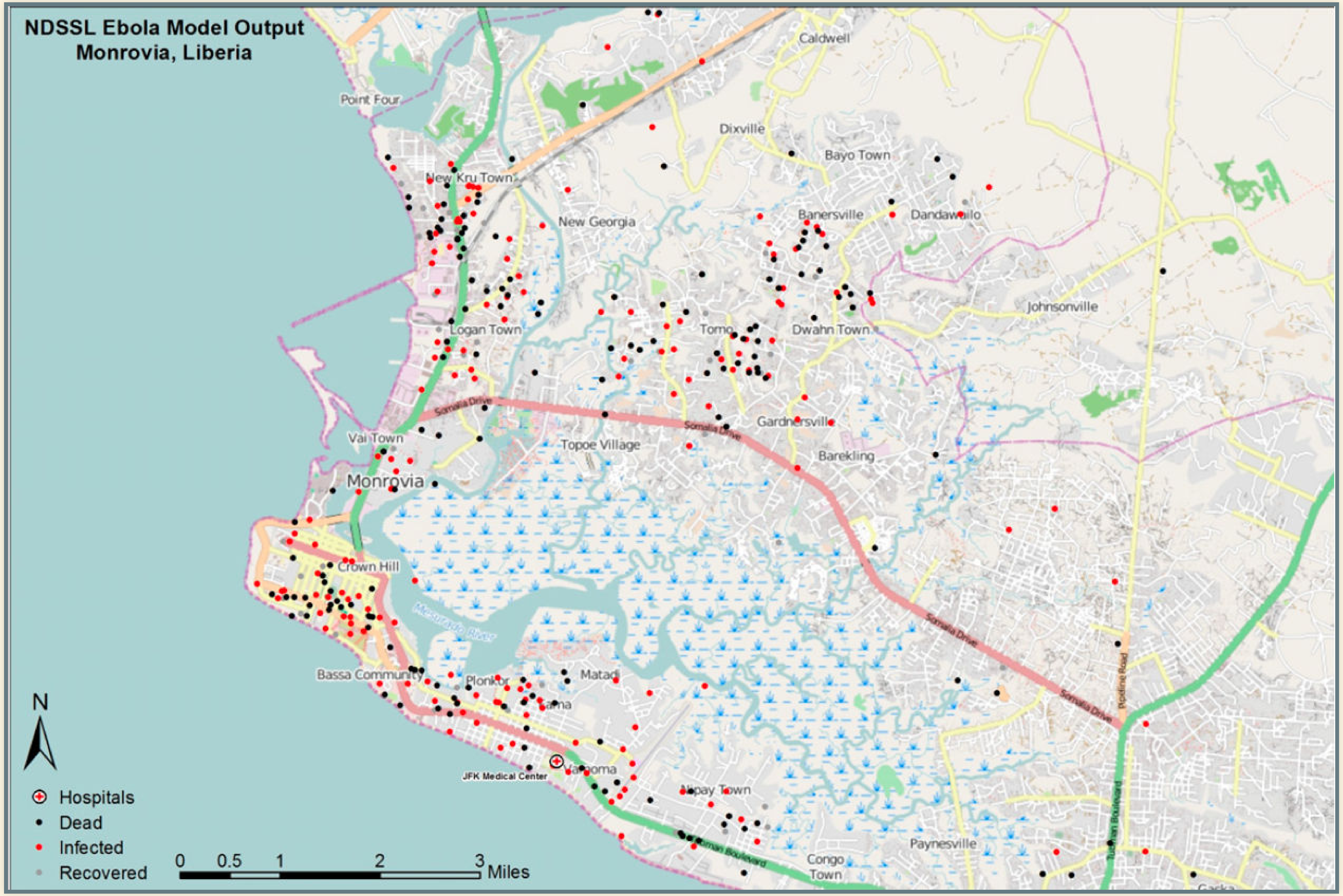
What-If Modeling for Policy Guidance

- The next steps were to use the model to guide policy decisions in responding to the epidemic.
  - By October, health workers were providing better data and the model was doing well at tracking the spread of the epidemic.
  - One Friday in October, the government asked the modelers to tell them where to put mobile hospitals.
    - Cargo planes would be taking off Monday morning
  - This required predicting not just the size of the epidemic, but the detailed locations of where sick people would be over the next several weeks and months.
  - The team worked all weekend and produced the necessary predictions.

Model Predictions



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The Role of Human Behavior

- Another important aspect of the spread of the disease is behavioral:
  - Traditional mourning practices include washing and touching the body of the deceased.
    - This spreads infection
  - Agent-based models predicted that changing these behaviors would dramatically reduce the spread of disease.
  - Public health experts were skeptical that people would change their behaviors
  - In the end, people *did* change behavior to adopt quarantine and safer burial practices.
- The epidemic ended in January 2016.
  - The final toll was 28,000 cases and 11,000 deaths
  - This was far less than would likely have occurred if the epidemic had gone untreated.

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Vaccine Testing

- At the time of the epidemic, there was a new experimental vaccine for Ebola, but it had not been tested on people.
- The agent-based models were used to design the field tests.
- Question: How fast would the disease spread?
  - Would it be necessary to vaccinate everyone in the area?
  - Or could health workers use a “ring” strategy?
    - Vaccinate only the people who had first- or second-degree contact with a victim.
  - The model said that a ring strategy would work.
- The vaccine was tested and proved up to 100% effective at preventing Ebola.
- Agent-based models played several important roles in guiding the international response.

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Example Research Model

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J.J. Jordan *et al.*, “Third-party punishment as a costly signal of trustworthiness,” Nature **530**, 473 (2016). doi:10.1038/nature16981

- Cooperation and Cheating
  - Common situation:
    - Everyone is better off if everyone cooperates than if everyone cheats.
    - Once everyone else has chosen their action, any individual is better off cheating than cooperating.
    - *Nash equilibrium*: Everyone making the best choice for himself produces the worst outcome for everyone.
    - Opposite of the “invisible hand” in economics.

Prisoner's Dilemma

	B Cooperates	**B Defects**
A Cooperates	5, 5	0, 7
A Defects	7, 0	1, 1

- No matter what player A does, player B is better off defecting
- No matter what player B does, player A is better off defecting
- If both players defect, both are worse off than if both cooperated.

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Tragedy of the commons

- Ten farmers share a pasture.
- A pasture can support 100 cows.
- If $N_{\text{cows}} \le 100$, each cow produces $1,000 worth of milk per month.
- If $N_{\text{cows}} > 100$, each cow produces $\$1,000 \times \left(1 - \frac{(N_{\text{cows}} - 100)}{100}\right)$ worth of milk per month.
- Each farmer has 10 cows, each farmer earns $10,000 per month.
- One farmer adds 1 cow: total 101.
  - Each cow produces $\$1000 \times (1 - (101 - 100)/100) = \$990$.
  - First farmer earns (11 $990 = $10,890),
  - Everyone else earns $9,900.
- Each farmer adds 1 cow: total 110.
  - Each cow produces $900. Each farmer earns $9,900.

Iterated games

- If only playing once, best strategy is to cheat, because it is rational for everyone else to cheat.
- If playing multiple turns, threat of punishment in future rounds promotes cooperation.
- It is generally costly to punish people.
- If someone cheats against you, it's often worthwhile to punish them.
- If you see someone cheating against another person and you aren't affected, is it worth your while to punish the cheater, even if it costs you?
- Does tragedy of commons inhibit people from punishing?

Game Theory

- Punishment sends a signal:
  - Deters cheaters.
  - Signals that you are trustworthy.

Game

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Game

- Player has two roles: **Signaler** and **Chooser**
- **Signaler** can be either *Trustworthy* or *Exploitative*.
- Two kinds of signals: *Helping* or *Punishing* a third party.
- Two stages:
  1. **Signalers** can pay costs to send signals.
  2. **Choosers** decide whether to accept **Signalers** as partners.
- Cost of signaling can be either small (s) or large (ℓ)

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Payoffs

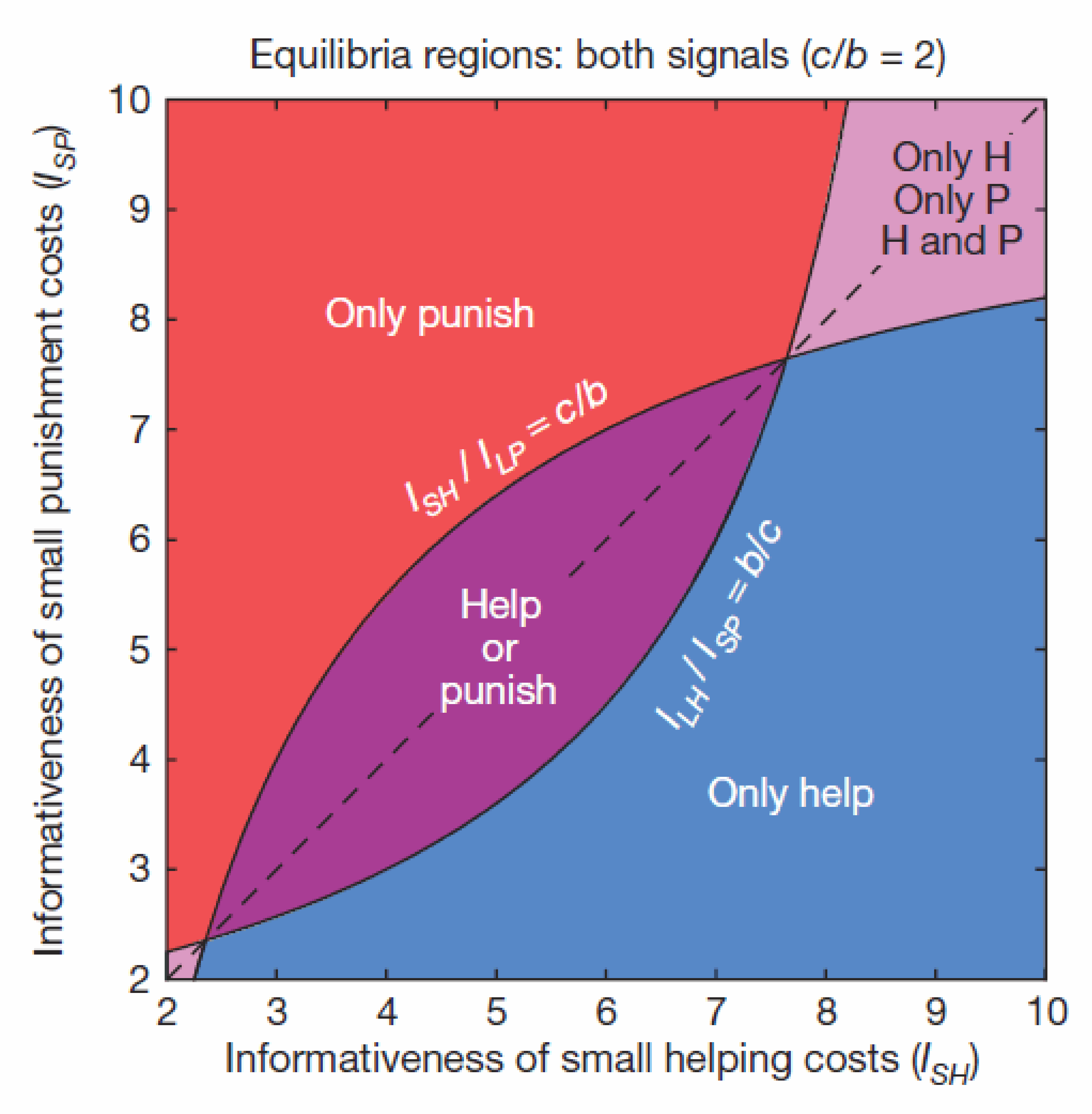
- Payoffs after second stage are:

	Trustworthy Signaller	**Exploitative Signaller**
Chooser Accepts	m, r	-e, r
Chooser Rejects	0, 0	0, 0

- m is benefit of mutual cooperation,
- r is reward for being trustworthy,
- e is harm from exploitation.

J.J. Jordan *et al.*, “Third-party punishment as a costly signal of trustworthiness,” Nature **530**, 473 (2016). doi:10.1038/nature16981

Rational strategies



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Agent-based model

Agent-based model

- Signaler randomly chosen to be Trustworthy or Exploitative.
- Chooser does not know Signaler type
- Evolution of strategies:
  - Each agent plays a certain number of turns (a generation)
  - Agents have probability of reproducing based on earnings from game.
    - Offspring inherit strategy with some random “mutations”

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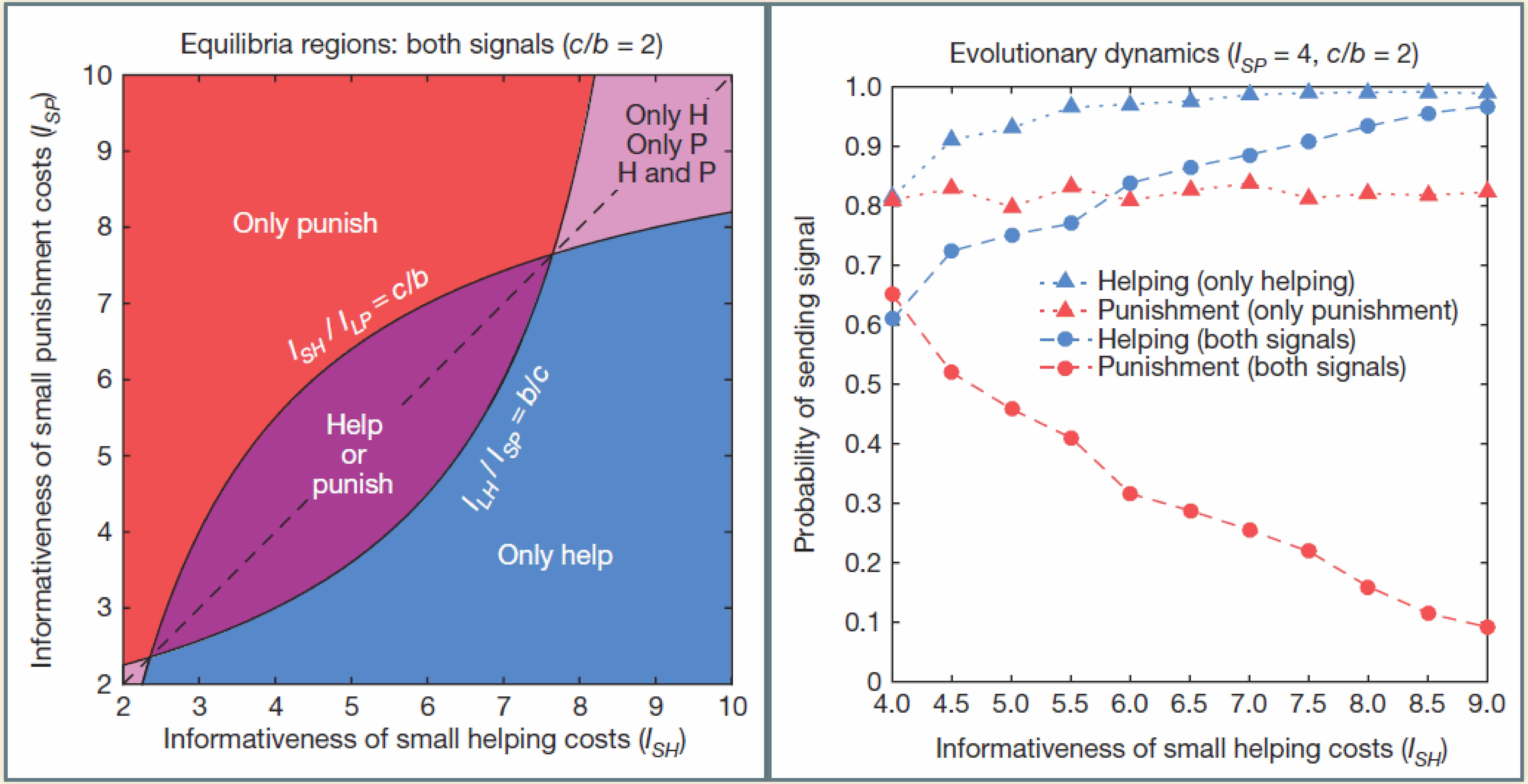
Outcome of evolution



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Human Game

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Human Game

- Amazon Mechanical Turk (Internet)
- Human players assigned to one of three games:

1. Signaler can only punish.
2. Signaler can only help.
3. Signaler can help and punish.

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Trust Game

- To check whether signals are interpreted accurately by Chooser agents, run a second game:
  - Chooser gets some money M.
    - Chooses how much to *send* to Signaler (x).
  - Money sent to Signaler is tripled (Signaler get $3x$)
  - Signaler decides how much of the $3x$ to *return* to Chooser.

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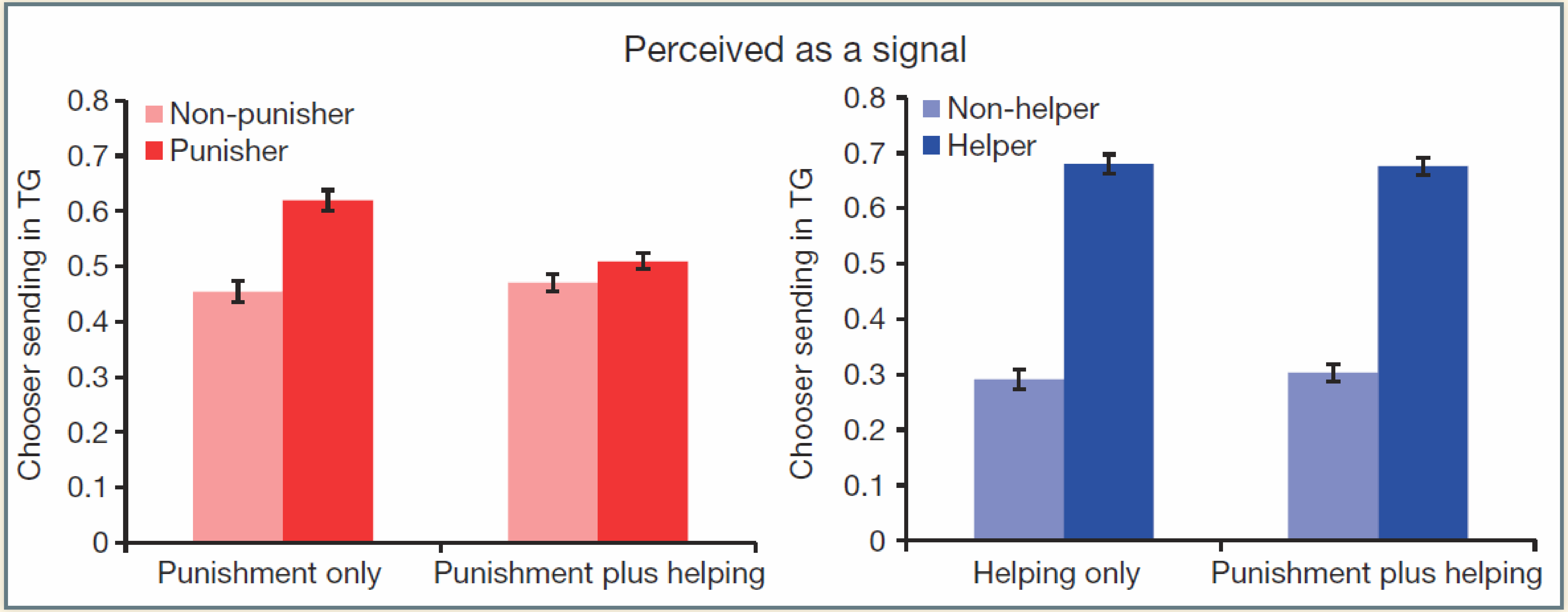
Perception of signaling:



- Chooser shows trust by sending more money to Signalers who punish and who help.
- Helping is a more powerful signal to Chooser than punishing.
- This matches theory of rational behavior.

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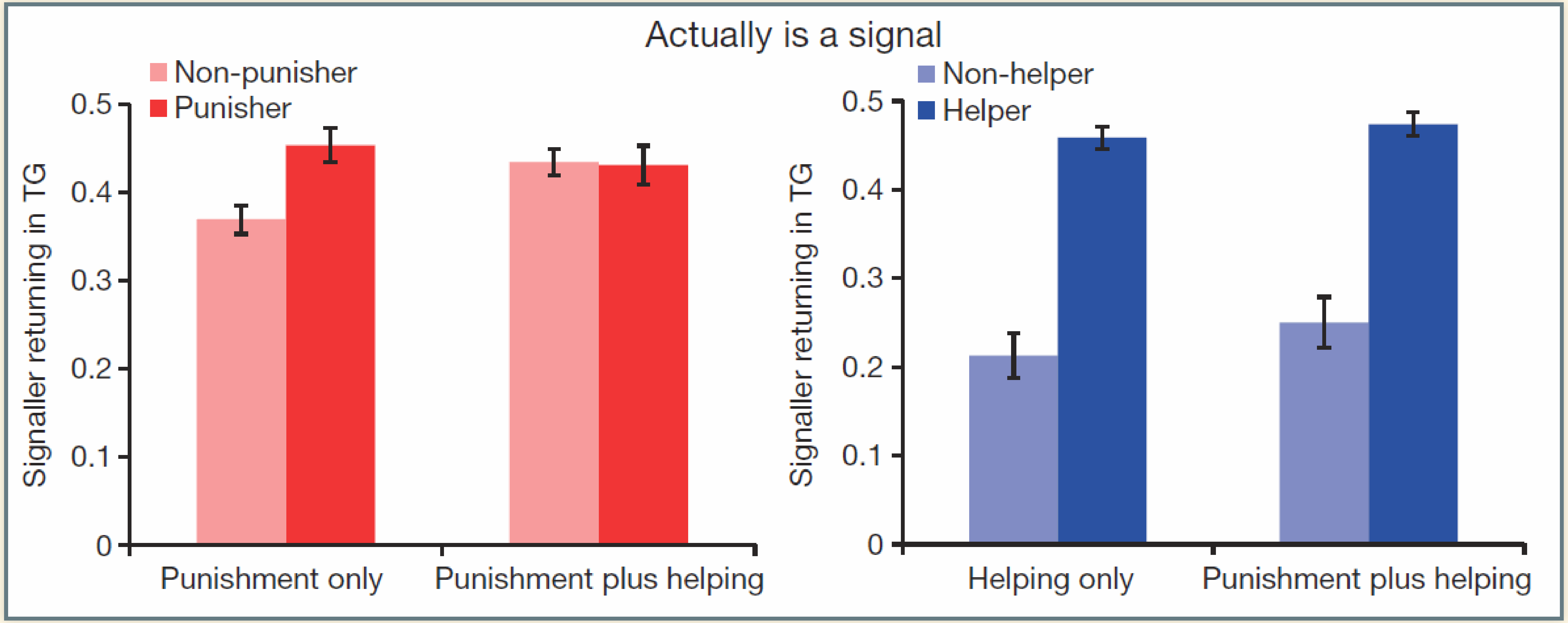
Actual signaliing



- Signalers who punish are more trustworthy: return more money to Chooser.
- Helping is indeed a more accurate signal of trustworthiness.

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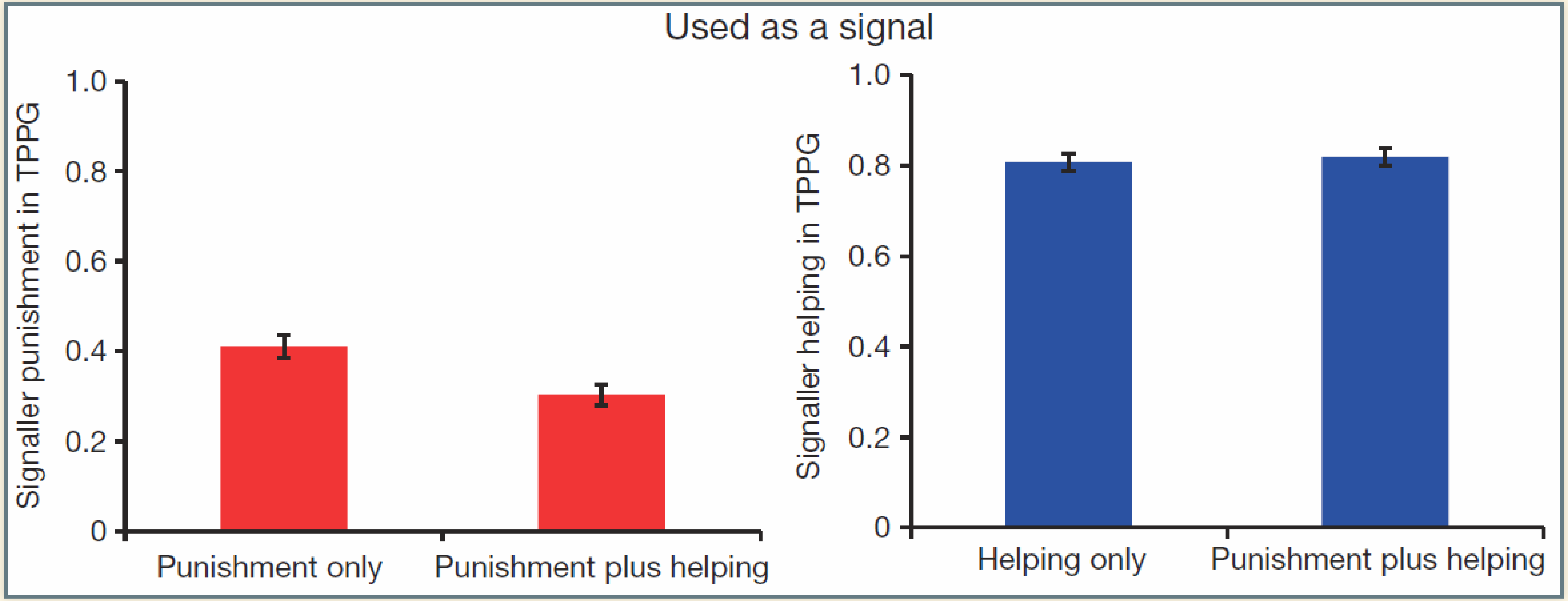
Signaler Choice



- Signaler is less likely to punish when helping is an option.

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Conclusions

- Evolved strategies of agents match both pure theory (rational strategy) and experimental results.
- It is advantageous for third parties to carry out costly punishments when the punishments can signal trustworthiness to others in the community.
- When there are less costly or more effective ways to signal trustworthiness, third parties are less likely to punish.

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