

Behavioral Voting Models and an Evolution of Voting Theory

Presented by
Jeremy Gilmore

University of San Francisco

EITM: Houston 2015



Overview

History of Voting Theory

- Models
- Implications
- Limitations

Behavioral Voting Models

- Bendor, Diemeier, Ting
- Fowler

Modeling the Models

- R
- The Code
- Simulations

Why does voting matter?

Human Behavior

- We always look to answer 'Why' questions
- Why do we do what we do?

Fundamental Right

- Foundation upon which our society is governed
- We also have the right *not* to vote

Freakonomics Podcast

Stephen Dubner

Greg Rosalsky

<http://freakonomics.com/2015/06/04/should-we-really-behave-like-economists-say-we-do-a-new-freakonomics-radio-podcast/>

Featuring

- Brian Caplan- econlog.econlib.org
- Mancur Olson

"'Rational' Theories of Voting Turnout"

by Benny Geys

of *Wissenschaftszentrum Berlin für Sozialforschung*

Originally published:

Political Studies Review: 2006 Vol 4, 16-35

The Voting Paradox

Does your vote count?

- No
- A single individual will not impact the outcome of an election

People still vote

- Rational Choice Theory predicts large scale abstention from voting

Conclusion

- Individuals are not rational
- There must be some other reason people vote

Voting Turnout

Not only quantity of votes, but account for

- ‘First-order’ elections (national) have higher turnout than ‘second-order’ elections (local or regional)
- Some people have a higher likelihood of voting at polls
- Younger voters and elderly are less likely to vote
- Those who feel alienated tend not to participate in part because no party represents their concerns
- Strategic voters

Creating Voting Models

In theory, all models should

- account for each voting segment mentioned
- correlate with actual election results
- make fundamental sense
- ...
- should have predictive capability

Progression of Voting Models

1. 'Pure' rational (instrumental) voting model
2. adding consumption benefits
3. Ethical/altruistic preferences
4. Minimax regret
5. Game theory
6. Group-based models
7. Voter's information level
8. Adaptive (or reinforcement) learning

Instrumental Voting

The instrumental view of rationality holds that an action has value only if it affects outcomes

A voter calculates the expected utility of voting or abstention and will vote if benefits exceed costs

$$R = PB - C > 0$$

$$R = PB - C > 0$$

R -> Expected utility of voting

B -> Difference in expected utilities from the policies
between candidates

P -> Probability that one's vote affects outcome

C -> Cost of voting

Expected Outcome

$$R = PB - C$$

Based on the parameters as defined above:

- P is close to zero
- Therefore PB is close to zero
- With even minuscule C...
- costs will be greater than benefits and **no vote**

Types of Costs

Sunk costs before election day

- Information costs about candidates and policies
- Registration costs (time, etc.)

Election day costs

- Shoe leather costs
- Opportunity costs for time spent voting

Results

- Implausible that this model explains the *level* of voting
- Hence the Paradox
- Explains how voting levels change as costs increase or for more important elections (first-order vs. second-order)

Consumption Benefits of Voting

$$R = PB - C + D$$

D -> Benefit of expressing oneself

- Civic duty
- Preference amongst candidates

Recall,

- PB still near zero
- Reduced to $R = D - C$

Implications:

- Turnout related to events unrelated to election
- No predictive power unless we understand *why* individuals choose to express themselves

The Ethical Voter

Individuals care about others in addition to themselves

Voters have two sets of preferences

- Their own preferences
- Ethical or altruistic preferences

$$W_i = U_i + \alpha \sum_{i \neq j} U_j$$

$$W_i = U_i + \alpha \sum_{i \neq j} U_j$$

W -> Overall utility for individual i

U -> Selfish preferences

α -> Weight individual attaches to others' happiness
where $\alpha \in (0, 1)$

Theoretical Implications

Because PB is near zero, ethical considerations dominate

Further distinction:

- 'pure' altruism- dependent on recipients increased happiness (inflates B)
- 'warm-glow' altruism- personal satisfaction from altruistic behavior (similar to D from the consumption benefits model)

Benefits of voting may counterbalance costs

Model Extended:

- 'discriminating altruists'- participate for benefit of group
- 'unconditional altruists'- care equally among all others
- 'rule utilitarians'- receive warm-glow payoff following a rule that if followed by everyone would maximize social utility

Minimax Regret

Decision to vote not related to risk, but uncertainty

- Voter will choose an action that will minimize regret given worst-case scenario
- R_{ij} is the regret the individual feels after action a_i in the state of the world S_j
- Basically, the difference in what the individual would have attained had the individual known the true state of the world at the time decision a_i was made

Implications

- This model outperforms the expected utility model
- Do individuals account for regret in decision making process?
- People rationalize wrong decisions

Minimax Regret Extended

Incorporation of ‘remorse’ and ‘elation’

- Consider the feelings of gain and loss
- If the individual has no control over the event leading to gain or loss, then the individual will experience it's effects with magnitudes G or L
- If the individual can influence the outcome, they feel greater gain or loss. These additional magnitudes are remorse and elation
- Note: This still depends on probability P , which is near zero which makes these contributions negligible

Game Theoretic Approach

Voters take into account the actions of others

- Assume everyone is rational. Everyone realizes their vote won't impact election results therefore abstain
- In this situation a single vote may be decisive, causing the strategic individual to vote
- But everyone knows this, so everyone votes...
- Probability P is now endogenous to the model as the game is played

Multiple (mixed-strategy) equilibria

- Assumes all voters have perfect information about voting costs and preferences of others
- Only viable in small electorates (consider information costs)

Group-Based Models

Implications of group behavior in voting

- Group benefits may be higher than costs
- Groups likely to have larger benefits than individuals (extra benefits in exchange for votes)
- Political influence of a social group proportional to its size

Free Rider Problems

- Individuals have incentive cheat (not vote); no personal costs, yet retain group benefits

Group incentives

- Group enforcement of social norms
- Social pressure to induce voting- increase credibility or reputation

Characteristics

Factors Affecting Group Behavior

- Frequency of interaction
- Deterrent effect of social isolation
- Group enforcement easier if behavior among members is easily observed

'Rule Utilitarians'

(benefit derived if voting to maximize social utility)

- Turnout may be a result of inclusion in group and subsequent benefits
- Voting is not always the optimal objective:
For some small groups, minimizing cost may be advantageous

Implications

This model makes sense

Reflects real world

Turnout is rational in a group context

- to build reputation toward other group members
- or benefits resulting from 'discriminating' altruistic behavior or 'rule utilitarian' behavior

Social context matters

- Turnout increases with group identity
- Model accounts for strategic voters

Information Models

Premise of the model

- Individuals have limited capacity to analyze all information
- Individuals inherently cannot be utility maximizers, but utility 'satisficers'. They cannot choose best option, instead choose most satisfactory alternative
- Voting likely to increase as more information attained
 - B increases as individual gains confidence they are voting for right candidate
 - Ideological preferences influence decision to obtain information
- Uninformed voters have reason to abstain
 - Uninformed voters are assumed to only affect the outcome by voting for wrong candidate

Model Limitations

Predisposition is the key

Why are individuals predisposed to seek information?

Model can explain some turnout, but questions remain

Does not predict actual level of turnout, but instead the differences in the probability that a given individual votes

Learning Theory

People have the ability to learn ‘good’ strategies from observing what has happened in the past

- They can learn from their own past actions
 - Vote or abstention, election outcome, positive or negative reinforcement
 - If past action (or lack of) had benefit, then action repeated
- They can learn from others
 - Imitate what works for others
- Individuals are ‘adaptive satisfiers’- backward looking
 - Compared to ‘prospective optimizers’- forward looking in original model

People tend to have habitual behavior (vote or abstain)

How learning changes the model

Mainly affects D term ($R = PB - C + D$)

- Rewarded for vote if their candidate wins or punished for abstention if their candidate loses
Preference for voting is increased
- Rewarded for abstention if their candidate wins or punished for voting if their candidate loses
Preference for voting is decreased
- The consumption of voting itself is endogenous

Focus is on marginal effects of reinforcement (or punishment) of the individual's likelihood to vote in the next election

"A Behavioral Model of Turnout"

Jonathan Bendor

Graduate School of Business,
Stanford University

Daniel Diermeier

Kellogg School of Management,
Northwestern University

Michael Ting

Department of Political Science and SIPA,
Columbia University

American Political Science Review, Issue 2, May 2003, pp 261-280

‘Adaptive Rationality’

Citizens learn by trial and error

- repeat satisfactory actions, avoiding unsatisfactory ones

Aspiration levels are endogenous

- adjusting to experience

Setting Up the BDT Model

- N - population comprised of $n_d > 0$, and $n_r > 0$

$$n_d + n_r = N$$
- Each voter i will vote (V) or Abstain (A)
 If vote, vote for their own party (no strategic voting)
- Winner determined by most votes between parties
 If tie results, coin toss determines winner
- All members of winning party receive payoff b
 (whether they vote or abstain)
- Those who vote have fixed cost c
 Winning abstainers get b
 Winning voters get $b - c$
 Losing abstainers get 0
 Losing voters get $-c$

Setting Up the BDT Model

- Random shock $\theta_{i,t}$ added to each payoff
i.i.d. across all citizens and time periods drawn from mean 0 uniform distribution with support ω
- Each citizen i in period t has propensity to vote
probability of vote: $p_{i,t}(V) \in [0, 1]$
probability of abstention: $p_{i,t}(A) = 1 - p_{i,t}(V)$
- Aspiration is the payoff the voter hopes to achieve
- Each voter realizes an action $I \in [V, A]$
- Election winner determined and $\pi_{i,t}$ payoff for each citizen
- Propensity adjusted depending on whether or not outcome is successful

$$\pi_{i,t} \geq a_{i,t}$$

Update Functions

Successful outcome

- $p_{i,t+1}(I) = p_{i,t}(I) + \alpha(1 - p_{i,t}(I))$

Unsuccessful outcome

- $p_{i,t+1}(I) = p_{i,t}(I) + \alpha(p_{i,t}(I))$
- where $\alpha \in [0, 1]$ determines the speed in which propensities change in response to reinforcement and inhibition
- In other words, α represents the speed of learning

Aspirations updated too

- As individuals get more accustomed to winning, a increases
- As losing prevails, a decreases
- Aspiration assumed to be weighted average of previous aspiration and payoff

$$a_{i,t+1} = \lambda a_{i,t} + (1 - \lambda)\pi_{i,t}, \text{ where } \lambda \in [0, 1]$$

Technical Notes

- Some individuals are *inertial*
will not update their propensity or aspiration functions
Denoted as ϵ_p and ϵ_a , respectively
- BDT assume a finite space, so round results to three digits
Reinforcement rounded up, inhibition rounded down

Variables

For all i

$n_d = 5000$ (number of democrats)

$n_r = 5000$ (number of republicans)

$b = 1$ (benefit of winning)

$c = .25$ (cost of voting)

$\alpha = .1$ (pace of learning)

$\lambda = .95$ (pace of aspiration adjustment)

$\omega = .2$ (noise in the payoff)

$\epsilon_p = \epsilon_a = .01$ (non-responsive inertial individuals)

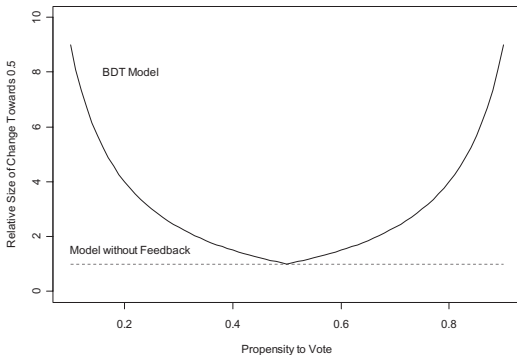
$p_{i,t=0} = .5$ (moderate initial propensity)

$a_{i,t=0} = .5$ (moderate initial aspirations)

Moderating Feedback

Bush-Mosteller Rule

- Explains aggregate behavior, but not for individuals
- Biases results towards BDT's main results
- BDT Model has a better prediction rate than those previous



Moderating Feedback

Consider the following

Reinforcement

$$p_{i,t+1}(l) = p_{i,t}(l) + \alpha(1 - p_{i,t}(l))$$

When propensity at t equals 0, propensity *increases* by α

When propensity near 1, reinforcement diminishes to 0

Inhibition

$$p_{i,t+1}(l) = p_{i,t}(l) + \alpha(p_{i,t}(l))$$

When propensity near 1, propensity *decreases* by α

When propensity equals 0, inhibition diminishes to 0

Reinforcement stronger than inhibition for propensities $< .5$

Inhibition stronger than reinforcement for propensities $> .5$

Moderating Feedback Example

Suppose $\alpha = .1$ and previous propensity $p_{i,t} = .1$

- If reinforced, the new propensity will increase by .09
- If inhibited, the new propensity will only decrease by .01
- For stable probability, every reinforcement must be matched by nine inhibitions

Moderating Feedback Example

- Suppose $\alpha = .1$ and previous propensity $p_{i,t} = .1$
- If probability of success $\Pr(\pi_{i,t} \geq a_{i,t}) = .5$
 - 50% chance propensity reinforced and will increase by .01
 - 50% chance propensity inhibited and will decrease by .09
- The expected change in propensity is the previous propensity plus the change due to reinforcement or inhibition weighted by the probability of success or failure:

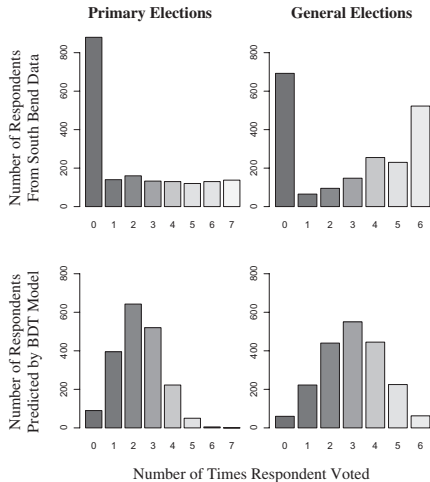
$$E(p_{i,t+1}) = p_{i,t} + \Pr(\pi_{i,t} \geq a_{i,t})\alpha(1 - p_{i,t}) + \Pr(\pi_{i,t} < a_{i,t})(-\alpha p_{i,t})$$

From the previous example: $E[p_{i,t+1}] = .14$
Propensities tend towards .5

Casual Voting in the BDT Model

Moderating feedback has implications

- Model explains and predicts *casual* voting where individuals sometimes vote, and sometimes abstain
- *Habitual* voting however reflects real world where individuals habitually vote or habitually abstain



"Habitual Voting and Behavioral Turnout"

James Fowler

Professor of Medical Genetics and Political Science
University of California San Diego

Journal of Politics, Vol. 68, No. 2, May 2006, pp 335-344

An Alternative Behavioral Model

Propensity adjustment rule

Successful outcome $p_{i,t} \geq a_{i,t}$ reinforces voting:

$$p_{i,t+1}(I) = \min(1, p_{i,t}(I) + \alpha)$$

Unsuccessful outcome $p_{i,t} < a_{i,t}$ inhibits voting:

$$p_{i,t+1}(I) = \max(0, p_{i,t}(I) - \alpha)$$

Previous example:

$\alpha = .1$, and $p_{i,t} = .1$

If voting satisfies, propensity increases by .1

If voting does not satisfy, propensity decreases by .1

Moderating feedback is removed from model

Implications

- While voters cannot have fixed 100% or 0% chance of participation, they can have very high, or very low propensities to vote that can persist over many elections
- This reinforces real-world behavior and *habitual* voting
- Suppose $\Pr(\pi_{i,t} \geq a_{i,t}) = .5$, then the expected change in propensity is:

$$\Pr(\pi_{i,t} \geq a_{i,t})\alpha + \Pr(\pi_{i,t} < a_{i,t})(-\alpha)$$

$$\text{Simplified: } \alpha(2\Pr(\pi_{i,t} \geq a_{i,t}) - 1)$$

\therefore expected change in propensity is... 0

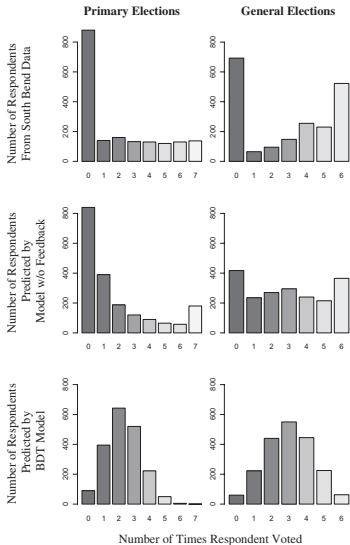
Comparing Models

TABLE 2 The Effect of Cost on Aggregate Turnout

C	<i>Average Turnout (t = 1,000)</i>			
	Model without Feedback		BDT Model	
	Democrats	Republicans	Democrats	Republicans
.05	.471	.471	.498	.498
.25	.259	.261	.481	.483
.80	.058	.056	.416	.415

Simulation run for 1000 periods

In the BDT model up to 1/3 of individuals continue to vote even when the benefits of voting exceed the costs



R

- What is R
- Benefits of R
- How to get- www.r-project.org
- RStudio
- Packages
- Additional Resources
 - Stack Overflow

The Variables

nPeriods- number of elections

nSims- number of simulations

nDems- number of democrats

nReps- number of republicans

winPayoffD- Dem payoff for winning

winPayoffR- Rep payoff for winning

losePayoffD- Dem payoff for losing

losePayoffR- Rep payoff for losing

costD- cost to democrats

costR- cost to republicans

iasperationD- initial aspiration Dems

iasperationR- initial aspiration Reps

iturnoutpropensityD- initial propensity to turnout Dems

iturnoutpropensityR- initial propensity to turnout Reps

The Variables

nPeriods- 1000

nSims- 1000

nDems- 5000

nReps- 5000

winPayoffD- 1.0

winPayoffR- 1.0

losePayoffD- 0

losePayoffR- 0

costD- 0.25

costR- 0.25

iasperationD- 0.5

iasperationR- 0.5

iturnoutpropensityD- 0.5

iturnoutpropensityR- 0.5

Auxiliary Variables

tau- if 1, use Bush-Mosteller Rule. If 0, no moderating feedback

alpha- propensity update weight for success

beta- propensity update weight for failure

lambda (λ)- weight of aspiration update

inert- proportion of voters will not update propensity or aspiration

support (ω)- support of random payoff shock

Auxiliary Variables

tau- 0

alpha- 0.1

beta- 0.1

lambda (λ)- 0.95

inert- 0.01

support (ω)- 0.2

Voter Structure

Vectors of preferences and costs

- `preferences <- c(rep(0,nDems),rep(1,nReps))`
- `costs <- c(rep(costD,nDems),rep(costR,nReps))`

Each element in the vector represents an individual voter

Programming Note

In R, an operation can be applied to an entire vector

For example,

```
x <- c(1:10)
```

```
x
```

```
1 2 3 4 5 6 7 8 9 10
```

```
y <- x + 4
```

```
y
```

```
5 6 7 8 9 10 11 12 13 14
```

The Functions

```
payoff<-function(winner,preference,cost,action)  
preference*(winner*winPayoffR+(1-winner)*losePayoffR)+  
(1-preference)*(winner*losePayoffD+(1-winner)*winPayoffD)-  
action*cost+round(runif(length(action),-support/2,support/2),3)
```

- preference- either 0 or 1 depending on Democrat or Republican
- winner- either 0 or 1 depending on Democrat or Republican
- action- either TRUE (1) or FALSE (0)
- round to 3 digits
- runif- random uniform distribution
- length(action)- 1 or 0 accordingly
- -support/2- lower bound
- support/2- upper bound

The Functions

$$a_{i,t+1} = \lambda a_{i,t} + (1 - \lambda)\pi_{i,t}, \text{ where } \lambda \in [0, 1]$$

```
aspirationf<-function(aspiration,payoff)
((aspiration>payoff)*floor(1000*(lambda*aspiration+(1-lambda)*payoff))+
(aspiration<payoff)*ceiling(1000*(lambda*aspiration+(1-lambda)*payoff)))/1000+
(aspiration==payoff)*aspiration
```

TRUE = 1

FALSE = 0

The Functions

```
aspirationf<-function(aspiration,payoff)
((1)*floor(1000*(lambda*aspiration+(1-lambda)*payoff))+
(0)*ceiling(1000*(lambda*aspiration+(1-lambda)*payoff)))/1000+
(0)*aspiration
```

Or

```
aspirationf<-function(aspiration,payoff)
((0)*floor(1000*(lambda*aspiration+(1-lambda)*payoff))+
(1)*ceiling(1000*(lambda*aspiration+(1-lambda)*payoff)))/1000+
(0)*aspiration
```

Or

```
aspirationf<-function(aspiration,payoff)
((0)*floor(1000*(lambda*aspiration+(1-lambda)*payoff))+
(0)*ceiling(1000*(lambda*aspiration+(1-lambda)*payoff)))/1000+
(1)*aspiration
```

The Functions

```

propensity<-function(propensity,aspiration,action,payoff)
pmin(1,pmax(0,((action) *
((payoff>=aspiration)*ceiling(1000*(propensity+alpha*(1-tau*propensity)))+
(payoff<aspiration)*floor(1000*(propensity-beta*(1-tau*(1-propensity)))))+
(1-action) *
((payoff>=aspiration)*floor(1000*(propensity-alpha*(1-tau*(1-propensity))))+
(payoff<aspiration)*ceiling(1000*(propensity+beta*(1-tau*propensity)))))/1000))

```

Recall,

$$p_{i,t+1}(I) = \min(1, p_{i,t}(I) + \alpha)$$

$$p_{i,t+1}(I) = \max(0, p_{i,t}(I) - \alpha)$$

The Simulation

- Each voter starts out with the same characteristics
- Random shock affects payoff function
- Probability that voter updates propensity applied
- Probability that voter updates aspiration applied
- Every election, voter values updated, and recorded in a list
- Each simulation represents 1000 elections

Follow an individual voter's behavior...

The Simulation

- Each voter starts out with the same characteristics
- Random shock affects payoff function
- Probability that voter updates propensity applied
- Probability that voter updates aspiration applied
- Every election, voter values updated, and recorded in a list
- Each simulation represents 1000 elections

Follow an individual voter's behavior...

Democrat: preference = 0
Voted in election: action = 1
Democrat won: winner = 0

Payoff Function

- `payoff<-function(winner,preference,cost,action)`
`preference*(winner*winPayoffR+(1-winner)*losePayoffR)+`
`(1-preference)*(winner*losePayoffD+(1-winner)*winPayoffD)-`
`action*cost+round(runif(length(action),-support/2,support/2),3)`
- `payoff<-function(0,0,.25,1)`
`0*(0*winPayoffR+(1-0)*losePayoffR)+`
`(1-0)*(0*losePayoffD+(1-0)*winPayoffD)-`
`1*.25+round(runif(length(1),-.02/2,.02/2),3)`
- `payoff<-function(0,0,.25,1)`
`1 - 1*.25+round(runif(length(1),-.1,.1),3)`
- `payoff<-function(0,0,.25,1)`
`1 - 25 - .052 = .698`

Aspiration Function

- `aspirationf<-function(aspiration,payoff)`
`((aspiration>payoff)*floor(1000*(lambda*aspiration+(1-lambda)*payoff))+`
`(aspiration<payoff)*ceiling(1000*(lambda*aspiration+(1-lambda)*payoff)))/1000+`
`(aspiration==payoff)*aspiration`
- `aspirationf<-function(.5,.698)`
`((aspiration>payoff)*floor(1000*(lambda*aspiration+(1-lambda)*payoff))+`
`(aspiration<payoff)*ceiling(1000*(lambda*aspiration+(1-lambda)*payoff)))/1000+`
`(aspiration==payoff)*aspiration`

- `aspirationf<-function(aspiration,payoff)`

$$((0)*\text{floor}(1000*(\lambda*\text{aspiration}+(1-\lambda)*\text{payoff}))+$$

$$(1)*\text{ceiling}(1000*(\lambda*\text{aspiration}+(1-\lambda)*\text{payoff}))) / 1000 +$$

$$(0)*\text{aspiration}$$
- `aspirationf<-function(.5,.698)`

$$((0)*\text{floor}(1000*(.95*.5+(1-.95)*.698))+$$

$$(1)*\text{ceiling}(1000*(.95*.5+(1-.95)*.698))) / 1000 +$$

$$(0)*.5$$
- `aspirationf<-function(.5,.698)`

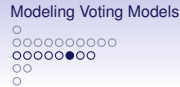
$$((1)*\text{ceiling}(1000*(.95*.5+(1-.95)*.698))) / 1000$$
- `aspirationf<-function(.5,.698)`

$$((1)*\text{ceiling}(1000*(.475+.05*.698))) / 1000$$
- `aspirationf<-function(.5,.698)`

$$((1)*\text{ceiling}(1000*(.475+.0349))) / 1000$$
- `aspirationf<-function(.5,.698)`

$$((1)*\text{ceiling}(1000*(.5099))) / 1000$$
- `aspirationf<-function(.5,.698)`

$$((1)*510) / 1000 = .51$$



- propensityf<-function(propensity,aspiration,action,payoff)
 pmin(1,pmax(0,((action) *
 ((payoff>=aspiration)*ceiling(1000*(propensity+alpha*(1-tau*propensity))))+
 (payoff<aspiration)*floor(1000*(propensity-beta*(1-tau*(1-propensity)))))+
 (1-action) *
 ((payoff>=aspiration)*floor(1000*(propensity-alpha*(1-tau*(1-propensity))))+
 (payoff<aspiration)*ceiling(1000*(propensity+beta*(1-tau*propensity))))/1000))
- propensityf<-function(.5,.5,1,.698)
 pmin(1,pmax(0,((action) * ((.698>=.5)*ceiling(1000*(.5+alpha*(1-tau*.5)))+
 (.698<.5)*floor(1000*(.5-beta*(1-tau*(1-.5)))))+ (1-action) *
 ((.698>=.5)*floor(1000*(.5-alpha*(1-tau*(1-.5))))+
 (.698<.5)*ceiling(1000*(.5+beta*(1-tau*.5))))/1000))
- propensityf<-function(.5,.5,1,.698)
 pmin(1,pmax(0,((1) * ((1)*ceiling(1000*(.5+alpha*(1-tau*.5)))+
 (0)*floor(1000*(.5-beta*(1-tau*(1-.5)))))+ (1-1) *
 ((1)*floor(1000*(.5-alpha*(1-tau*(1-.5))))+
 (0)*ceiling(1000*(.5+beta*(1-tau*.5))))/1000))

- `propensityf<-function(.5,.5,1,.698)`
`pmin(1,pmax(0,((1) * ((1)*ceiling(1000*(.5+alpha*(1-tau*.5))))/1000))`
- `propensityf<-function(.5,.5,1,.698)`
`pmin(1,pmax(0,((1) * ((1)*ceiling(1000*(.5+alpha*(1-tau*.5))))/1000))`
- `propensityf<-function(.5,.5,1,.698)`
`pmin(1,pmax(0,((1) * ((1)*ceiling(1000*(.5+.1*(1-0*.5))))/1000))`
- `propensityf<-function(.5,.5,1,.698)`
`pmin(1,pmax(0,((1) * ((1)*ceiling(1000*(.6))))/1000))`
- `propensityf<-function(.5,.5,1,.698)`
`pmin(1,pmax(0,.6))`
- `propensityf<-function(.5,.5,1,.698)`
`pmin(1,.6) = .6`

Simulation Results

- Run the simulation, and wait a while
- Extract the data of interest
- Evaluate the results
- Do the empirical results support theory?
- Let's have a look...

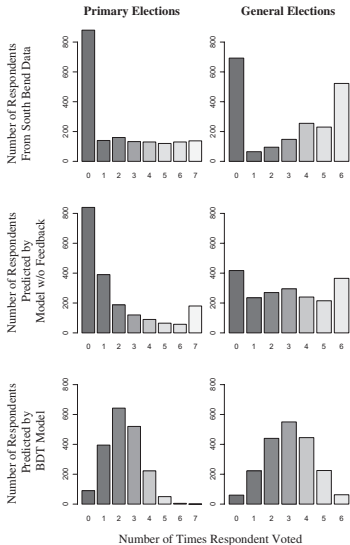
Shiny

`install.packages('shiny')`

In a folder, two files are needed for every Shiny application

- `server.r` - the R application and controls for interface
- `ui.r` - user interface and controls
- `global.r` (optional) - all functions and variables available in global environment

Application and interface run in a browser window



Overview
○○○

History
○○○○○
○○○○○
○○
○○○
○○
○
○○○
○○
○○

Bendor, Diermeier, Ting
○○
○○○○○
○○○○○

Fowler
○
○○
○○

Modeling Voting Models
○
○○○○○○○○○
○○○○○○○○○
○○
●

Thank you!

Jeremy Gilmore
jgilmore@usfca.edu

