Meme Stocks and Herd Behaviour - A Multi-Agent System examination

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Table of Contents

GameStop overview

- Bad performance after 2015
- Heavy competition from online (Amazon, Steam etc.)
- Believed by institutional investors to go bankrupt (i.e Sears)
- Individual investors organized online a massive short-squeeze
- In 3 months price skyrocket to almost $500 per share and then collapsed to less than $40

Gamestop Overview

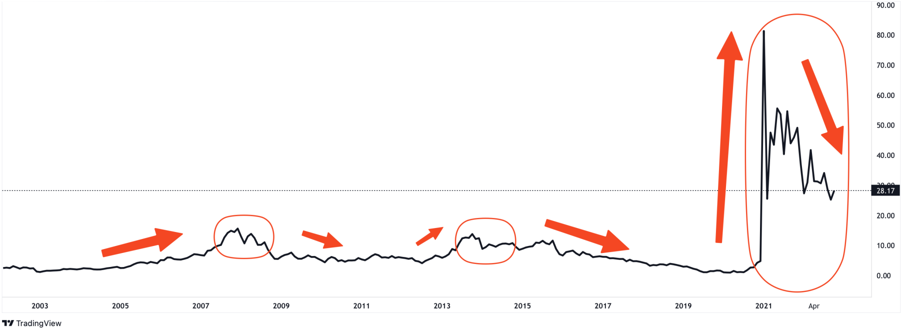
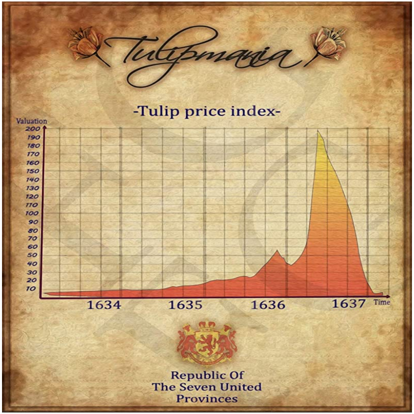


Figure: GameStop (GME) stock value over time

Market Bubbles



- Tulipmania - early 1600s in The Netherlands
- Investors started using leverage, derivatives and other financial instruments
- Tulips value exceeded U$1.000.000 in today's money
- Buyers weren't able to pay the prices they agreed
- Market eroded by the end of 1637

Stanley Druckenmiller's 3 billion loss

"I bought $6 billion worth of tech stocks, and in six weeks I had lost $3 billion in that one play. You asked me what I learned. I didn't learn anything. I already knew that I wasn't supposed to do that. I was just an emotional basketcase and I couldn't help myself. So maybe I learned not to do it again, but I already knew that."
(Druckenmiller, S.)

Market Bubbles - Summary

1. Investors lose track of rational expectations
2. Psychological factors (herd behaviour) lead to a massive spike in the price of the asset
3. A self-fulfilling prophecy happens. Investors create a positive-feedback loop that continues to inflate the prices
4. At some point investors realize they are holding assets with irrational values
5. Prices collapse due to massive sell-off (Market correction)
6. Many investors go bankrupt

Why Meme Stocks matter?

- New phenomenon
- Intense use of social networks (i.e Reddit)
- Thousands of individual investors organized a short squeeze
- More than just a "market play"
- "Stick it to the man" attitude
- Act of defiance against the system

Goals

1. An environment to study belief spread
2. A simulation of the market
3. Understanding the possible interaction

Model requirements

1. Market
2. Information exchange
3. Belief update

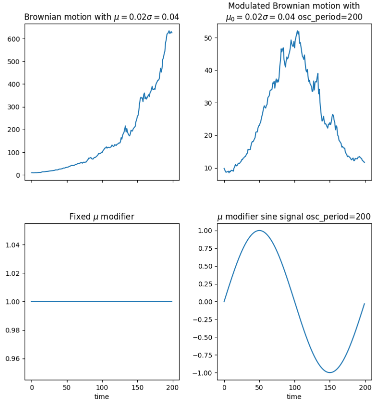
Market model

1. Simple abstraction: Brownian motion
2. Price observation: Model parameter π
3. ~~Market interaction~~: Agents observe the market but do not influence it

Price Generation (1)

Price is generated according to a Brownian motion based process (Wiener process).
A sequence of normally distributed ($\mu_{price}, \sigma_{price}$) percent changes from an initial price.
We apply a sine wave as modulation to μ_{price} to obtain a bubble.

Price Generation (2)



Agent Model

Agents are modeled as noisy estimators of the market trend.
They have a mechanism for autonomously updating their sentiment belief.

Agent State (belief)

- Market sentiment $s : [-1, 1], real$

Agent parameters (part 1 - self update)

- Self update probability $p_{update} : [0, 1], real$
- Learning rate $u_{\pi} : [0, +\infty], real$

Agents without communication

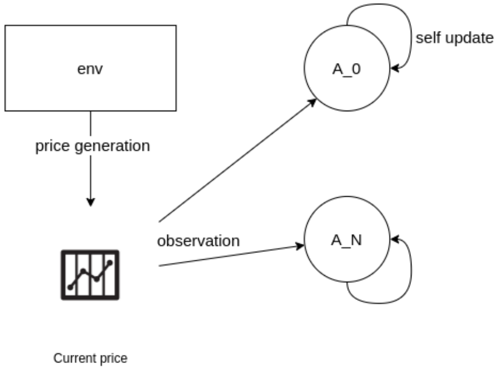


Figure: Agents as individual noisy estimators

Information model

1. Based on a model proposed in (Gleeson, O'Sullivan, Baños, & Moreno, 2016), (O'Brien, Dassios, & Gleeson, 2019)
2. Agents are connected in a (directed) network
3. Agents exchange memes in a subscriber/follower dynamic
4. Parameters dictate activity, innovation and information acceptance

Agent communication (meme sharing)

Simple communication protocol
Agents can share their sentiment
A second mechanism updates sentiment based on consumed memes

Agent parameters (part 2 - sharing behavior)

- Activity rate $\beta : [0, 1]$, *real*
- Innovation rate $\mu : [0, 1]$, *real*
- Meme acceptance rate $\lambda : [0, 1]$, *real*

Agent parameters (part 3 - interaction update)

- Confidence $\alpha : [0, 1]$, *real*

2 different network topologies random vs. preferential attachment

Belief update

1. The two mechanisms for updating agent sentiment s
   1. Updating based on the price change (sign of update) with probability p_{update}.
   $$s_{self}(t+1) = s_{self}(t) + u_{\pi} \cdot sign(\pi(t) - \pi(t-1)) \quad (1)$$
   2. Updating based on the received information.
   $$s_{self}(t+1) = \alpha \cdot s_{self}(t) + (1-\alpha) \cdot \bar{s_m}(t) \quad (2)$$
   where $\bar{s_m}(t)$ is the mean sentiment of consumed memes.

Agent desire

1. Based on their sentiment (s) agents pick a desire

$$\begin{cases} BUY & s \geq 0.5 \\ HOLD & -0.5 < s < 0.5 \\ SELL & s \leq -0.5 \end{cases}$$

Model overview

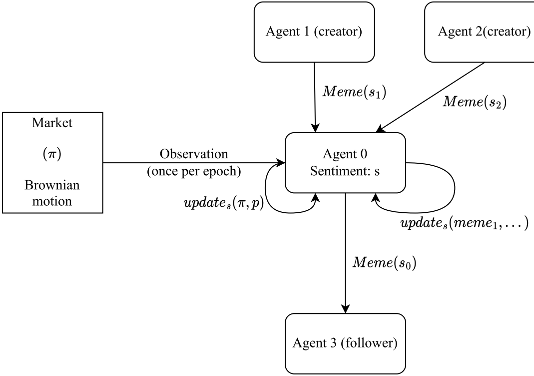


Figure: An overview of the model from the perspective of an agent

General Fixed Parameters

The following experiments share some fixed parameters:

- Initial price 10$
- Price osc. period 200
- Price $\mu_{price_{base}} = 0.02$,
- Price $\sigma_{price} = 0.04$,
- Price seed 42
- Population initial sentiment $N(0, 1)$
- # of agents 100

Each configuration is repeated 40 times.

Response variables

Response variables are measured at the peak of the modulation signal (maxima of the sine wave $t = \frac{1}{4}T = 200/4 = 50$). At this point the modulation signal has value 1

- *belief_mean*: the average market sentiment $\bar{s}$
  - 'Good' sentiment reflects the modulation signal so 1 is best at $t = 50$
- *belief_std*: the deviation of market sentiment.
- *desire_BUY*: the fraction of the population having a 'BUY' desire.

Self update Experiments (1)

We observe the system dynamics when agents are not connected.
Fix the learning rate and vary the probability of performing a self update.

update_lr	self_upd_p
0.1	0.0625
	0.125
	0.25
	0.5
	0.75
	1

Table: Parameters of interest self update experiment

Self update Experiments (2)

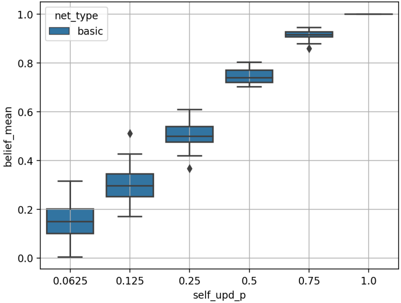


Figure: Boxplots for varying *self_upd_p*

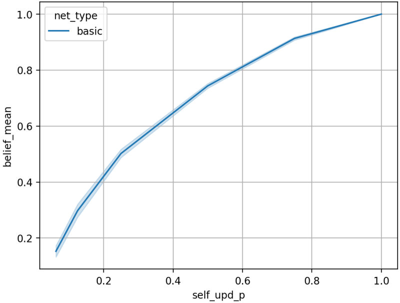


Figure: *belief_mean* as function of *self_upd_p*

Self update Experiments (3)

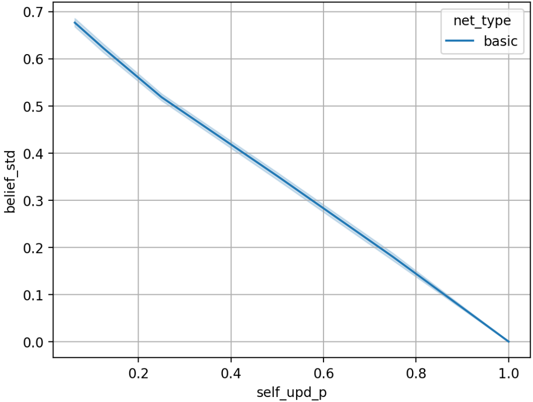


Figure: *belief_std as function of self_upd_p*

Erdos-Renyi network (1)

We introduce communication between agents, connected in a random directed graph (*basic*). We vary the connectivity parameter from sparse to dense networks.

update_lr	self_upd_p	net_beta	net_lambda	net_mu	net_type	net_param
0.1	0.5	1	0.5	0.1	basic	0.00625
						0.0125
						0.025
						0.05
						0.1
						0.2
						0.4
						0.8

Table: Parameters of the Erdos-Renyi network experiment

Erdos-Renyi network (2)

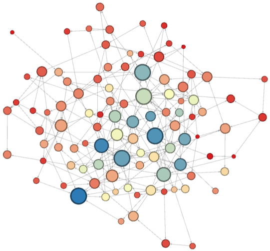


Figure: A sparse Erdos-Renyi network net_param = 0.025

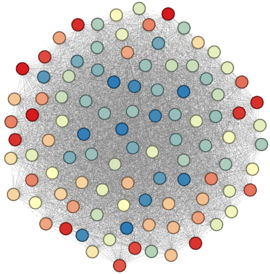


Figure: A dense Erdos-Renyi network net_param = 0.8

Erdos-Renyi network (3) Expectations

More frequent self updates $\longrightarrow$ more accurate sentiment (experiment 1)
Expected # of updates for a single agent in k epochs

$$k \cdot self\_upd\_p$$

Expected # of updates for a community of M agents in k epochs

$$M \cdot k \cdot self\_upd\_p$$

Consuming memes can compensate for skipped updated
Wisdom of the crowd?

Erdos-Renyi network (4)

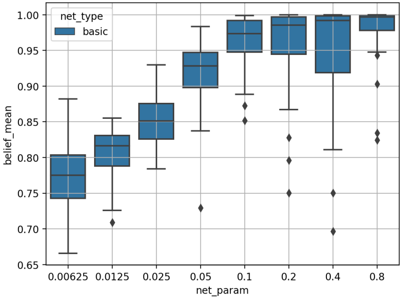


Figure: *belief_mean* boxplots for varying *net_param* (basic network)

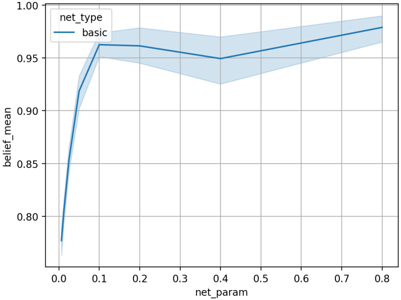


Figure: *belief_mean* as function of *net_param* (baisc network)

Erdos-Renyi network (5)

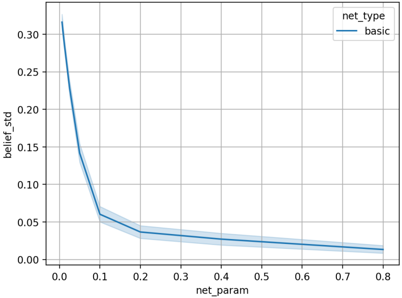


Figure: *belief_std* as function of *net_param* (baisc network)

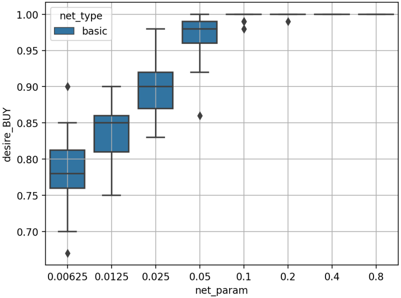


Figure: *desire_BUY* boxplots for varying *net_param* (basic network)

Erdos-Renyi networks are not realistic

Real world networks are almost never randomly connected

- Distribution of degree (# of connections) usually follows a power law **not** uniform
- Few nodes with many connections **hubs**
- Prefrential attachment principle

$$p_{ni} = \frac{k_i}{\sum_j k_j}$$

Prob that a new node n attaches to an existing node i proportional to i's degree.

Barabasi-Albert network (1)

We extend communication between agents, in a more realistic preferential attachment based directed graph (*barabsi*). We vary the connectivity parameter from sparse to dense networks.

update_lr	self_upd_p	net_beta	net_lambda	net_mu	net_type	net_param
0.1	0.5	1	0.5	0.1	basic	0.00625
					barabasi	0.0125
						0.025
						0.05
						0.1
						0.2
						0.4
						0.8

Table: Parameters of the Barabasi-Albert network experiment

Barabasi-Albert network (2)

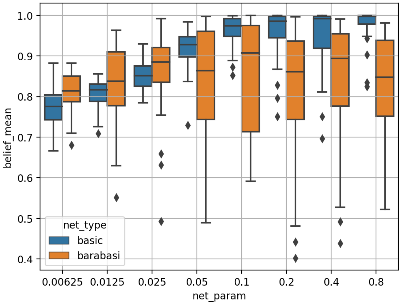


Figure: *belief_mean* boxplots for varying *net_param* (basic network)

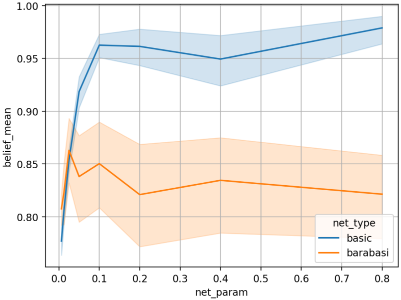


Figure: *belief_mean* as function of *net_param* (both networks)

Barabasi-Albert network (3)

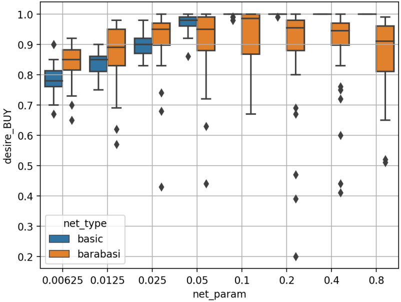


Figure: *desire_BUY* boxplots for varying *net_param* (both networks)

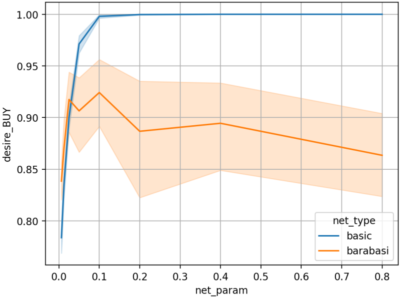


Figure: *desire_BUY* as function of *net_param* (both networks)

Barabasi-Albert network (4)

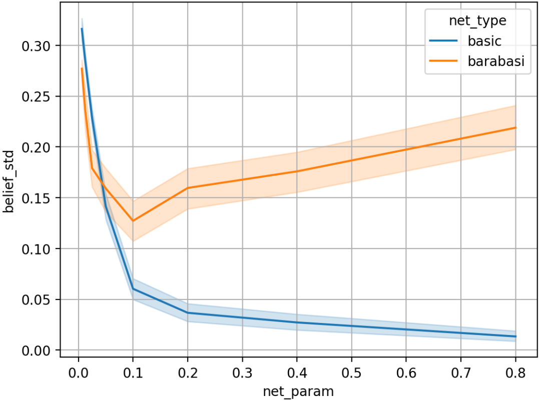


Figure: *belief_std as function of net_param (both networks)*

Comparing networks (Extremely low density)

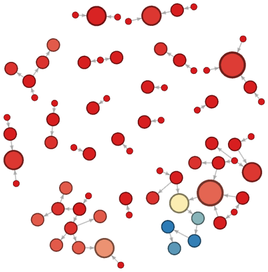


Figure: Erdos-Renyi net_param = 0.00625

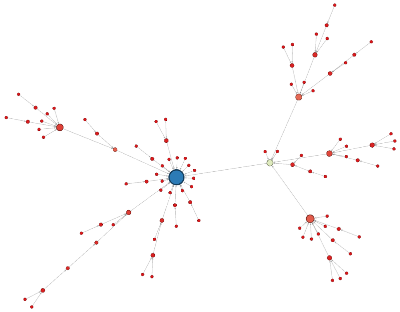


Figure: Barabasi-Albert net_param = 0.00625

Comparing networks (Medium density)

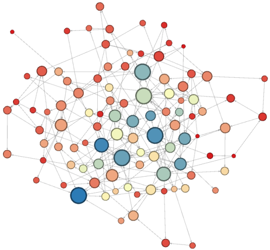


Figure: Erdos-Renyi net_param = 0.025

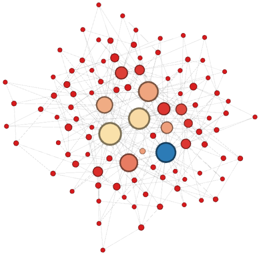


Figure: Barabasi-Albert net_param = 0.025

Comparing networks (High density)

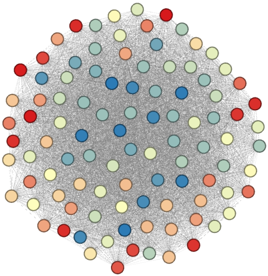


Figure: Erdos-Renyi net_param = 0.8

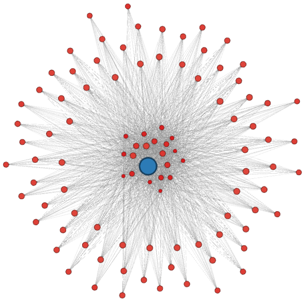


Figure: Barabasi-Albert net_param = 0.8

Conclusion

- Simple rules lead to agents behaving as noisy estimators of the market trend
- Herd behavior from connecting agents in communities can improve the estimation
- In preferentially attached networks there is a risk associated with centralization

Full agent specification

Variable Characteristics

1. Market sentiment $s : [-1, 1]$, *real*

Fixed Characteristics

2. Confidence $\alpha : [0, 1]$, *real*
3. Innovation rate $\mu : [0, 1]$, *real*
4. Activity rate $\beta : [0, 1]$, *real*
5. Meme acceptance rate $\lambda : [0, 1]$, *real*
6. Self update probability $p_{update} : [0, 1]$, *real*

Gleeson, J. P., O'Sullivan, K. P., Baños, R. A., & Moreno, Y. (2016, May). Effects of network structure, competition and memory time on social spreading phenomena. *Phys. Rev. X*, *6*, 021019. Retrieved from `https://link.aps.org/doi/10.1103/PhysRevX.6.021019` doi: 10.1103/PhysRevX.6.021019

O'Brien, J. D., Dassios, I. K., & Gleeson, J. P. (2019, feb). Spreading of memes on multiplex networks. *New Journal of Physics*, *21*(2), 025001. Retrieved from `https://doi.org/10.1088/1367-2630/ab05ef` doi: 10.1088/1367-2630/ab05ef