A Liquid Democracy System for Human-Computer Societies

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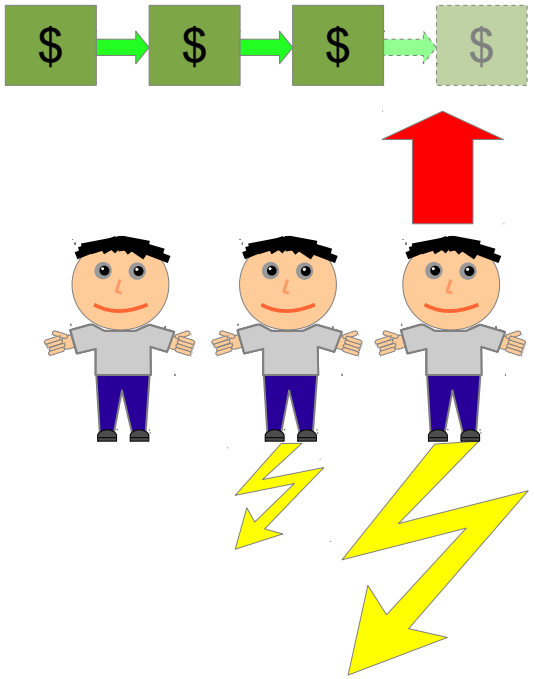
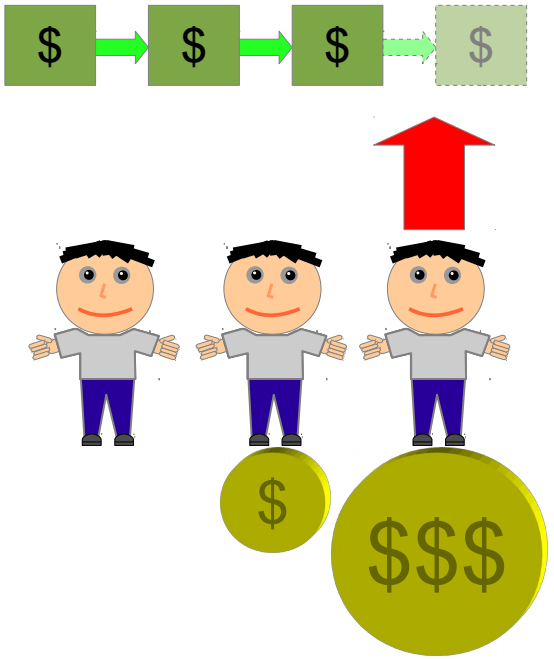
Liquid Reputation Consensus – to govern distributed multi-agent systems (blockchains and societies), to resist takeover and scam

Proof-Of-Work



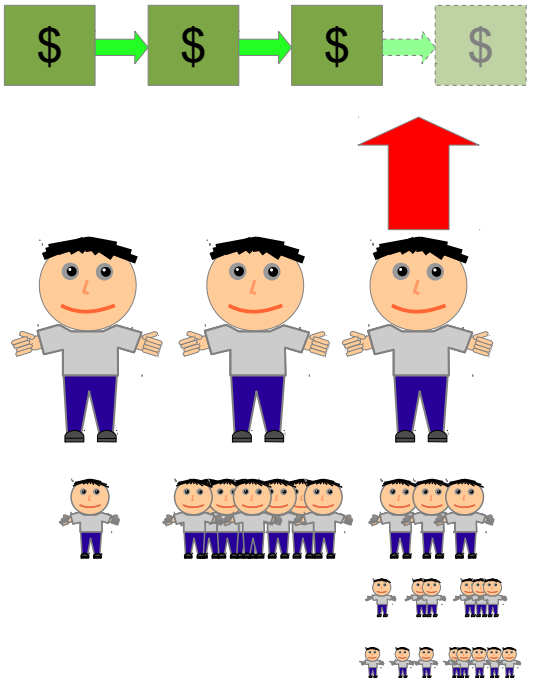
Force is Power:
Those who own more computing resources govern the network.

Proof-Of-Stake



Money is Power:
Those who have more money govern the network.

Proof-Of-Reputation



$$R_i = \sum_t \sum_j (R_j * V_{ijt})$$

Reputation is Power:
Those who earn a better reputation and a greater long-term audience base govern the network.

Liquid Reputation – Solving Problems

Marketplaces	Unfair competition, gaming ratings
News filtering	Fake news, information wars
Social Networking	Spam, abuse, harassment
Psychological security	Broken relationships
Financial security	Scam
Blockchain consensuses	Consensus takeover
Liquid Democracy	State instability

Reputation Systems Ingredients

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Weighted Liquid Rank

Algorithm 1 Weighted Liquid Rank (simplified version)

Inputs:
1) Volume of rated transactions each with financial value of the purchased product or service and rating value evaluating quality of the product/service, covering specified period of time;
2) Reputation ranks for every participant at the end of the previous time period.

Parameters: List of parmeters, affecting computations - default value, logarithmic ratings, conservatism, decayed value, etc.

Outputs: Reputation ranks for every participant at the end of the previous time period.

1: **foreach of** *transactions* **do**
2: **let** *rater_value* be rank of the rater at the end of previous period of default value
3: **let** *rating_value* be rating supplied by trasaction rater (consumer) to ratee (supplier)
4: **let** *rating_weight* be financial value of the transaction of its logarithm, if logarithmic ratings parameter is set to true
5: **sum** *rater_value*rating_value*rating_weight* for every ratee
6: **end foreach**
7: **do** normalization of the sum of the muliplications per ratee to range *0.0-1.0*, get *differential_ranks*
8: **do** blending of the old_ranks known at the end of previous peiod with differential_ranks based on parameter of conservatism, so that *new_ranks = (old_ranks*conservatism+N*(1-differential_ranks))*, using decayed value if no rating are given to ratee during the period
9: **do** normalization of *new_ranks* to range *0.0-1.0*
10: **return** *new_ranks*

- R_d - default initial reputation rank;
- R_c - decayed reputation in range to be approached by inactive agents eventually;
- *C* - conservatism as a blending "alpha" factor between the previous reputation rank recorded at the beginning of the observed period and the differential one obtained during the observation period;
- *FullNorm* – when this boolean option is set to *True* the reputation system performs a full-scale normalization of incremental ratings;
- *LogRatings* - when this boolean option is set to *True* the reputation system applies *log10(1+value)* to financial values used for weighting explicit ratings;
- *Aggregation* - when this boolean option is set to *True* the reputation system aggregates all explicit ratings between each unique combination of two agents with computes a weighted average of ratings across the observation period;
- *Downrating* - when this boolean option is set to *True* the reputation system translates original explicit rating values in range *0.0-0.25* to negative values in range *-1.0* to *0.0* and original values in range *0.25-1.0* to the interval *0.0-1.0*.
- *UpdatePeriod* – the number of days to update reputation state, considered as observation period for computing incremental reputations.

Reputation System for Marketplaces – Identifying Scam

Using Reputation System for protection from scam identifying dishonest suppliers.

Ranks of Suppliers, dishonest Supplier (including alias) in red and honest suppliers in blue

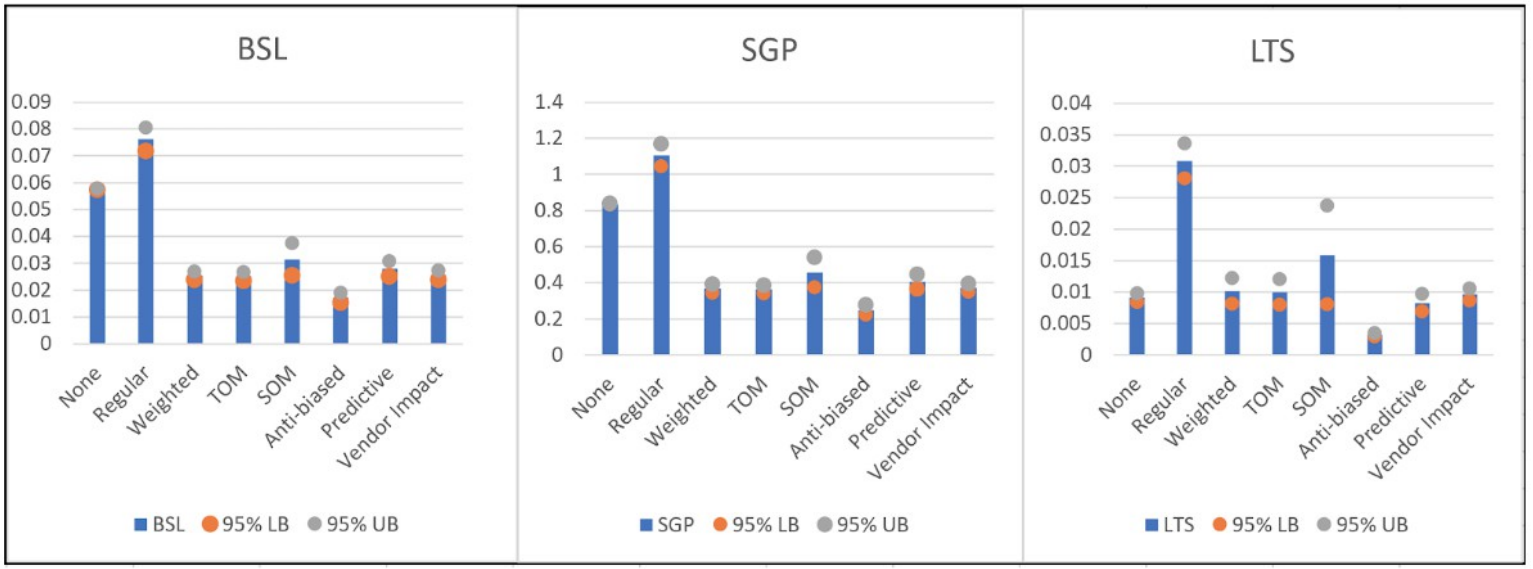
Reputation System for Marketplaces - Time/Spendings-based

Scam Period	Reputation System	Loss to Scam (LTS)	Profit from Scam (PFS)	LTS Relative Decrease	PFS Relative Decrease
182	No	2.4%	44%		
182	Regular	2.7%	49%	-13%	-13%
182	Weighted	2.3%	42%	2%	3%
182	TOM-based	1.4%	30%	41%	31%
182	SOM-based	2.2%	40%	8%	7%
92	No	3.0%	54%		
92	Regular	3.5%	65%	-19%	-20%
92	Weighted	2.8%	52%	5%	4%
92	TOM-based	1.7%	36%	43%	33%
92	SOM-based	2.6%	47%	13%	12%
30	No	3.9%	73%		
30	Regular	4.7%	86%	-19%	-18%
30	Weighted	3.3%	59%	17%	19%
30	TOM-based	1.5%	31%	63%	58%
30	SOM-based	1.5%	27%	63%	63%
10	No	4.4%	81%		
10	Regular	4.7%	88%	-7%	-8%
10	Weighted	3.0%	54%	33%	33%
10	TOM-based	0.2%	3%	**96%**	**96%**
10	SOM-based	0.3%	6%	**93%**	**93%**

- No reputation system: participants are making decisions relying only on their own memories and not referring to any reputation system.
- Regular reputation system: standard version of reputation system. Does not take into account any factors other than values of ratings that consumers make to suppliers.
- Weighted reputation system: When considering ratings as regular reputation system does, accounts to financial values of transactions between participants so that rating values are weighted by costs of transactions that are rated.
- TOM-based reputation system: In addition to weighting ratings with financial values per-transaction, weights the ratings based on the rater's time on the market (TOM) as a "proof-of-time". That is, the raters (buyers) are implicitly rated based on how long have they been on the market. So, rating by buyer with a longer history influences reputation of a seller more than the one made by rater with shorter history.
- SOM-based reputation system: In addition to weighting ratings with financial values per-transaction, weights the ratings based on rater's spendings on the market (SOM) as a "proof-of-burn" value. That is, the raters (buyers) are implicitly rated based on how much they spend on this market. So, rating by buyer with a lot of spendings influences reputation more than the one made by rater with smaller spendings.

Reputation System for Marketplaces against Reputation Gaming

Reputation System Type	OMU	LTS	BSL	SGP
None	0.99	0.01	0.06	0.83
Regular	0.97	0.03	0.08	1.11
Weighted	0.99	0.01	0.03	0.37
TOM	0.99	0.01	0.03	0.36
SOM	0.99	0.02	0.03	0.46
Anti-biased	1.00	0.00	0.02	0.25
Predictive	0.99	0.01	0.03	0.40
Vendor Impact	0.99	0.01	0.03	0.37



- Table and charts presenting performance of financial metrics for different reputation systems using adaptive simulation. The charts show a 95% confidence interval for the highest and lowest the true values could be (had we repeated the simulations indefinitely).
- Compared results between “Regular” and “Weighted” reputation system, TOM/SOM (time/spendings on the market) based ones, “Anti-biased”, “Predictive” and “Vendor Impact” reputation system. The optimisation was targeting to make OMU (Organic Market Utility) higher and making the other metrics such as LTS (Loss to Scam), BSL (Buyers Satisfaction Loss), SGP (Seller Gaming Profit) lower.
- Use of “Regular” reputation system makes all financial metrics instantly worse than in the case when no reputation system is used at all - just because of the reputation gaming redirecting the market to the dishonest providers increasing their profits (SGP), decreasing the volume of honest market (OMU) and causing losses for buyers (LTS and BSL). We can also see than most ot the reputation system configurations, such as “Anti-biased”, Weighted, TOM, “Predictive”, and “Vendor Impact” improve the financial metrics. The LTS column shows that the best “Anti-biased” reputation system configuration reduced the total market volume spent on scams to zero making the OMU approached 1.00, rounding to the first two decimal places.