Automated Reasoning and ACDCs
Secure Decentralized Reputation Algorithms

Leveraging Property Graphs in ACDC
to
reason with uncertainty …
securely

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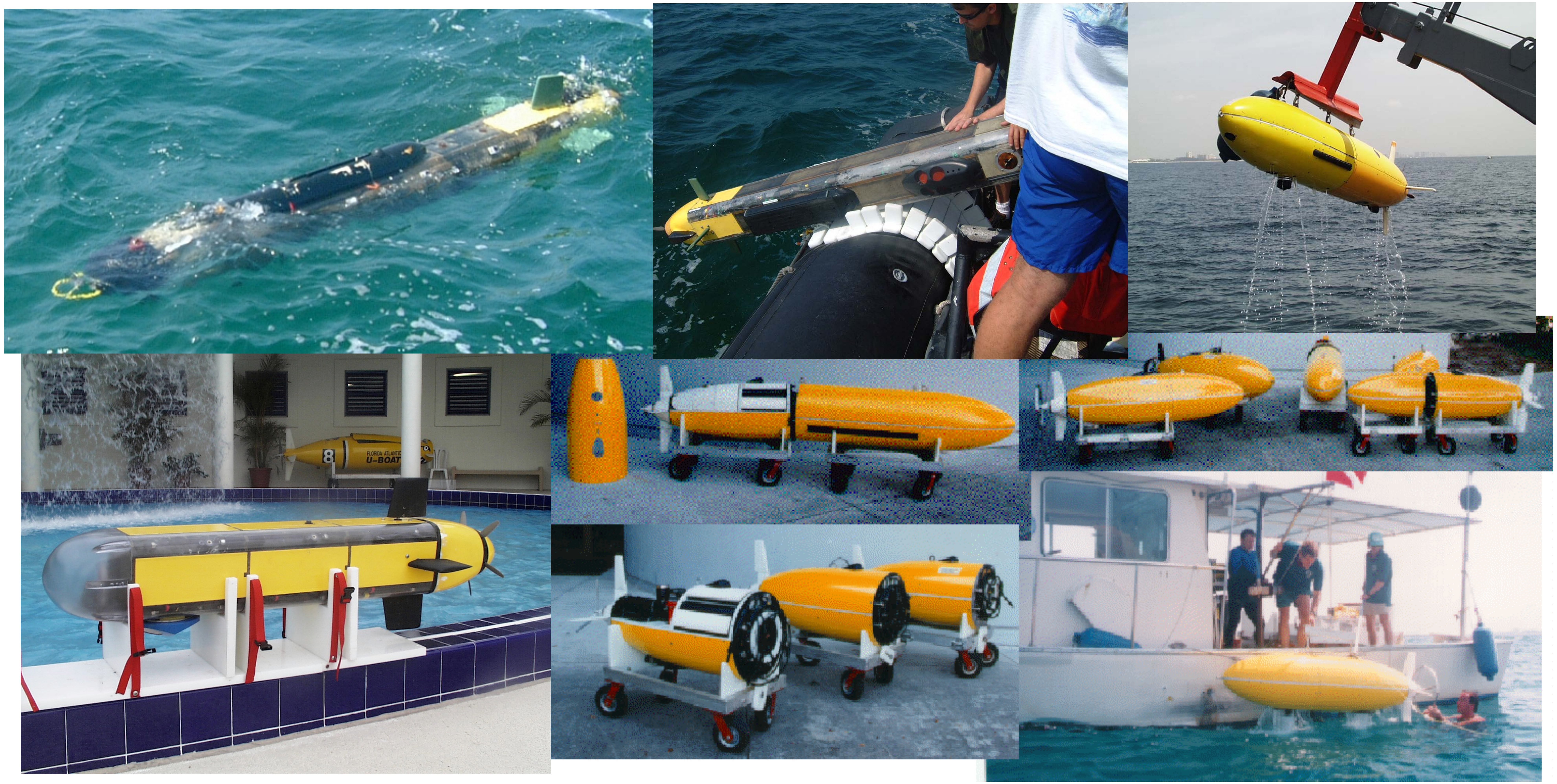
REPUTATION AI

Symmetric Multiple Elastic Constraint networks with Reinforcement-Learning

Works with sparse data

But can be tuned and optimized as more data is collected

Autonomous Underwater Vehicles



Uncertainty

Imprecision (Possibility Measures and operators)

Randomness (Probability Measures and operators)

Ambiguity (Similarity Measures and operators)

Hybrid (mixtures of imprecision, randomness, and ambiguity)

PROCESSING ISSUES

Measurement

Scoring, Rating and Ranking

Static vs Dynamic

Feedback effects

Data Rate

Data Provenance

MEASUREMENT THEORY

Scales

- Nominal (Labeled but not ordered)
  - aggregation operations: none
- Ordinal (Labeled and Ordered)
  - aggregation operations: median, mode
- Interval (Ordered with Distance)
  - aggregation operations: median, mode, mean and moments about mean, std)
- Ratio (Distance with True Zero)
  - aggregation operations: all

REPUTATION

noun:

The estimation in which a person or thing is held, especially by the community or the public generally.

root:

Latin word reputāre, which is equivalent to re + putāre, that is, to re-think or re-consider.

usage:

A considered evaluation (measure) of past behavior used to predict future behavior.

qualification:

Confidence improves with contextual similarity.

https://github.com/SmithSamuelM/Papers/blob/master/whitepapers/open-reputation-low-level-whitepaper.pdf

WHAT IS REPUTATION?
WHAT IS REPUTATION AI?

Contextual predictor of future behavior to enable a transaction

Closed-loop automated reasoning, not just open-loop pattern recognition

Means to filter and modulate transactions

Curator, recommender, decision aid, IA

Contextual predictors are more powerful

Behavior based predictors are more credible

Transitive predictors are more portable

COMPUTATIONAL REPUTATION

Computational generation of a reputation is to aggregate relevant instances of behavior.

Instances of behavior = reputational events or reputes for short

Reputation measures are inferred indirectly from reputes associated with an entity

Contrasting Example:

* Entities provide direct ratings of promptness of another entity

* Collect instances of behavior of entity in context from which promptness can be inferred.

Reputation from reputed behavior allows for re-scoping, re-weighting, re-combination, and re-evaluation of collected reputes (not so for ratings)

Enables arbitrary levels of nesting, precision, and granularity in the data aggregation process (not so for ratings)

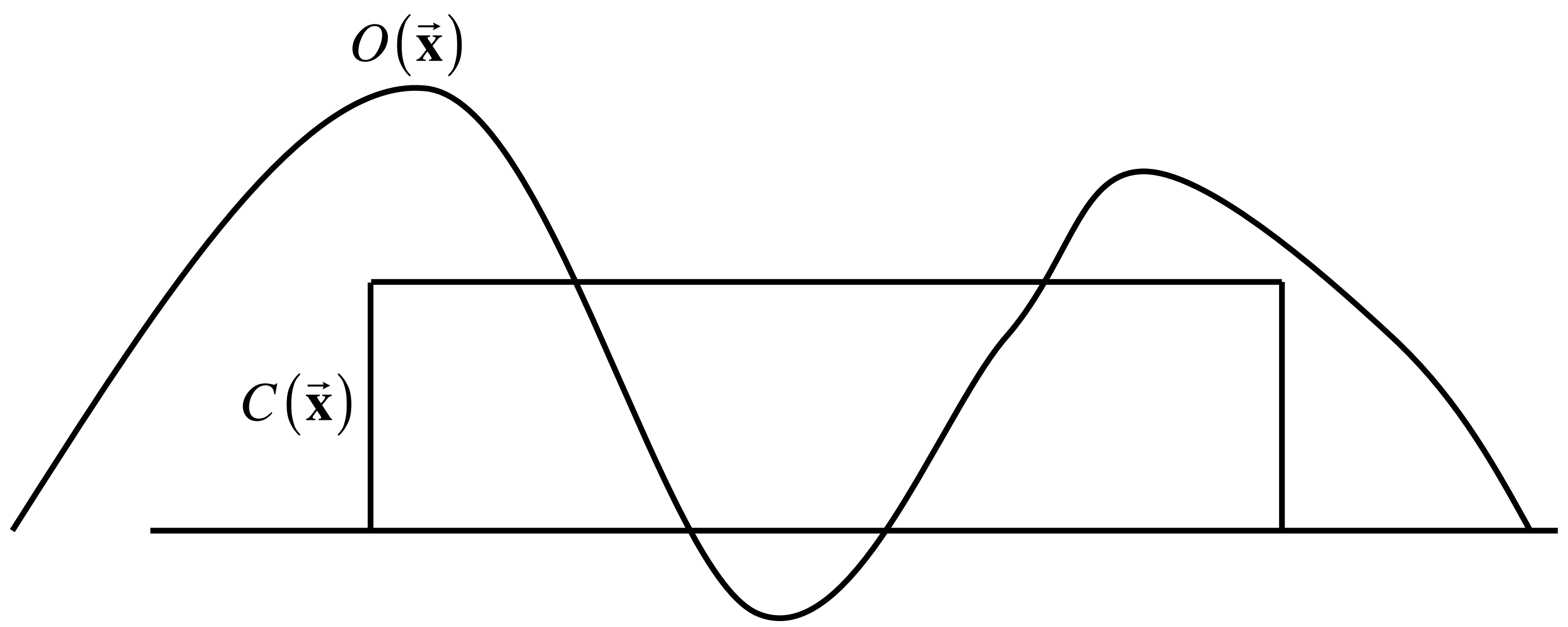
https://github.com/SmithSamuelM/Papers/blob/master/whitepapers/open-reputation-low-level-whitepaper.pdf

Symmetric Multiple Elastic Constraints Type of MCDM (Multiple-Criteria Decision Making)

Conventional

Crisp constraints (intervals) plus objective function(s).

Maximize objective function(s) in area allowed by crisp constraints



$$O(\vec{\mathbf{x}}) = f(x_1,\ldots,x_n)$$
$$C(\vec{\mathbf{x}}) = \{x_{1low} \le x_1 \le x_{1high},\ldots,x_{nlow} \le x_n \le x_{nhigh}\}$$
$$\max\big|_{C(\vec{\mathbf{x}})} O(\vec{\mathbf{x}})$$

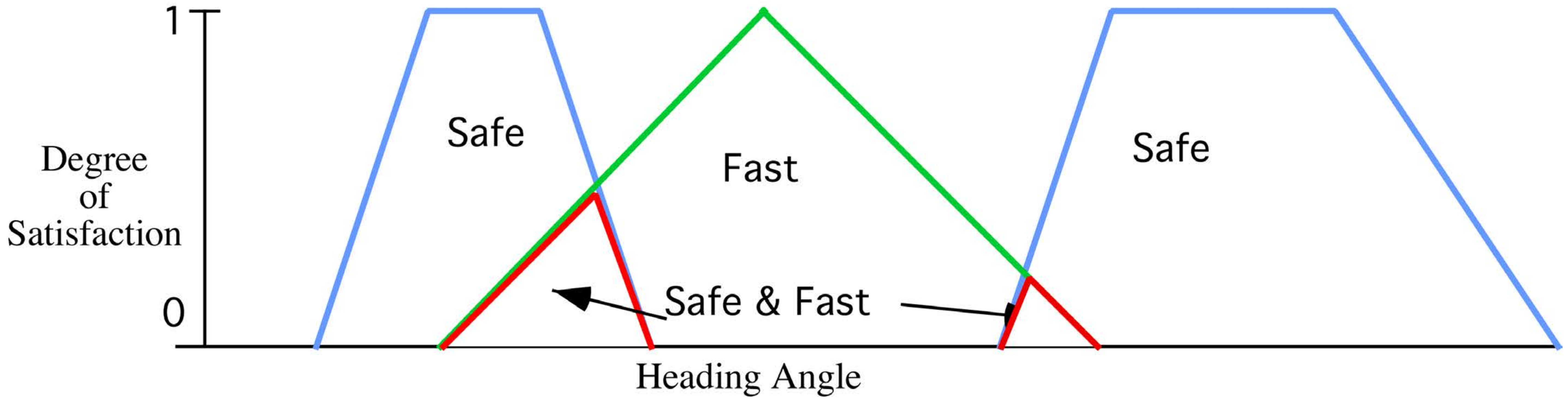
Symmetric

Both goals and constraints are expressed with elastic constraints.

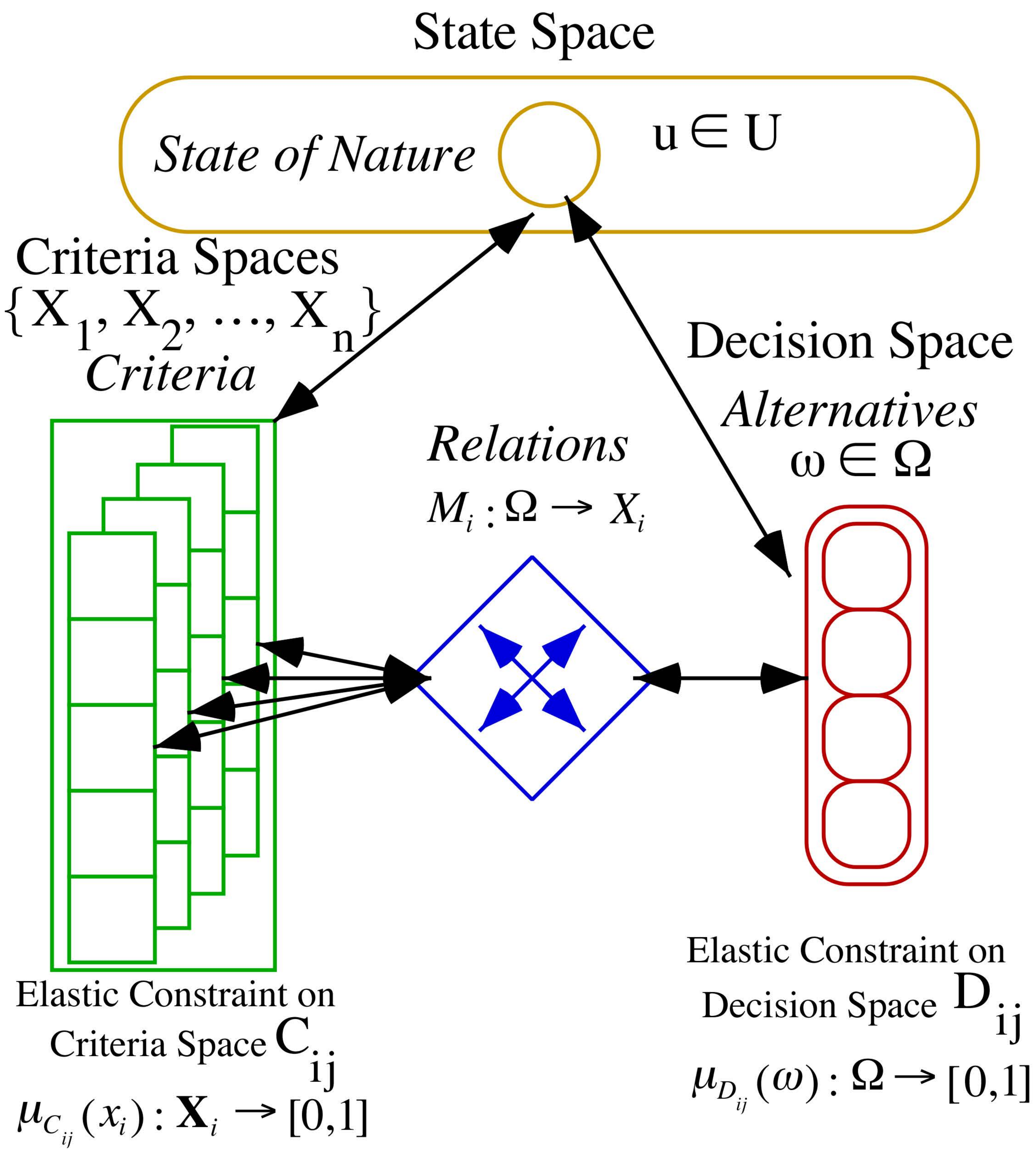
Decision-making consists of finding the confluence of goals and constraints by aggregating the respective membership functions.

Objective: get there fast and safe

Constraints: obstacles dead ahead and to sides, slower paths on bigger turns



SMEC



state of nature $u \in \mathbf{U}$ state space

decision alternative $\omega \in \Omega$ decison space

set of criteria $\mathbf{C}$ defined on $\mathbf{X} = \{X_1, \ldots, X_m\}$ criteria spaces

elastic constraint $C_{ij} = j^{th}$ constraint on i^{th} criteria space

membership function $\mu_{C_{ij}}(x_i) : \mathbf{X}_i \rightarrow [0,1]$

$M_i : \Omega \rightarrow X_i$ relation between decision space and i^{th} criteria space

C_{ij} induces a constraint D_{ij} on Ω through M

If $M_i \equiv m_i(\omega) \quad s.t. \quad x_i = m_i(\omega)$ Then

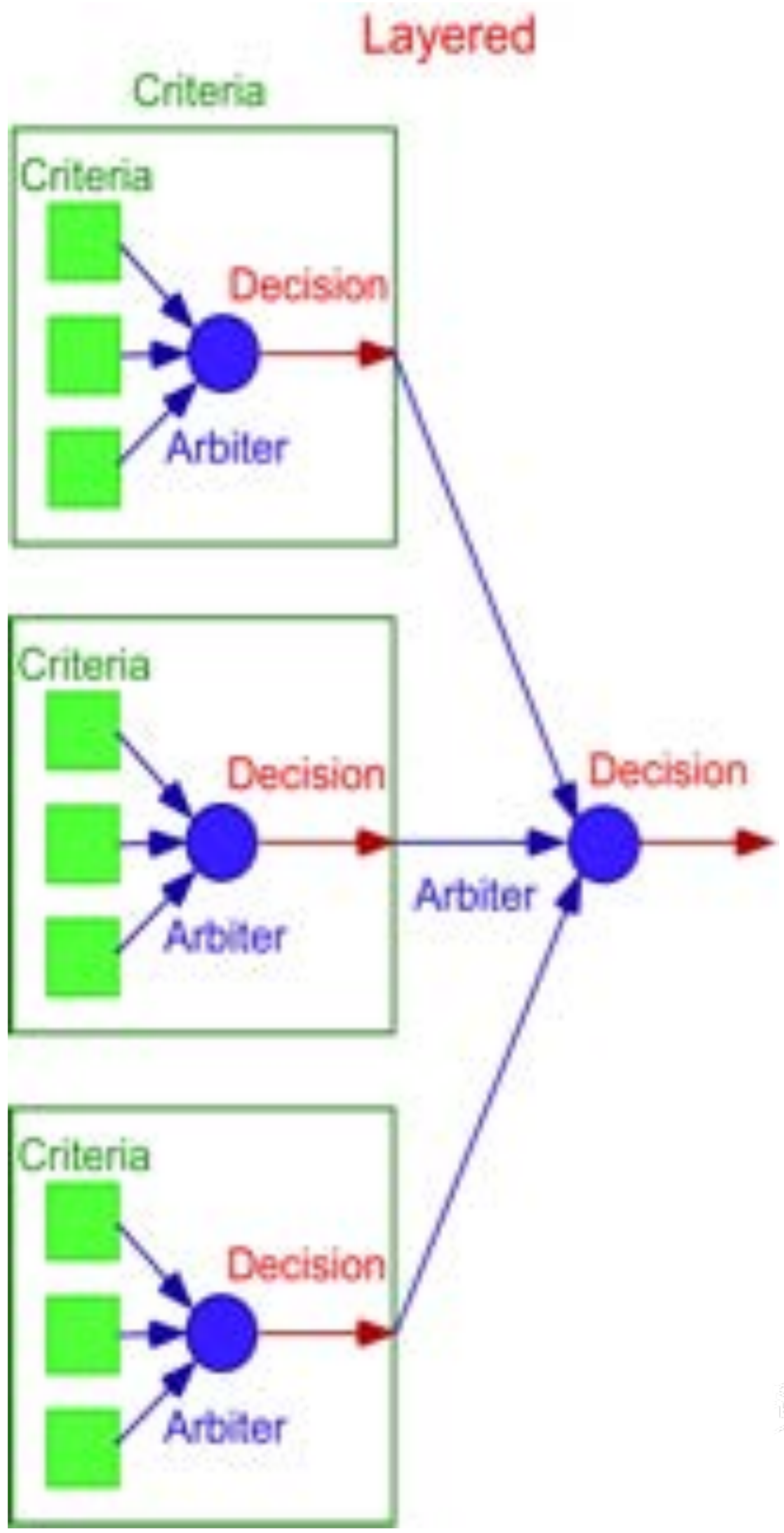
$$\mu_{D_{ij}}(\omega) = \mu_{C_{ij}}(x_i) = \mu_{C_{ij}}(m_i(\omega)) \quad \forall \omega \in \Omega$$

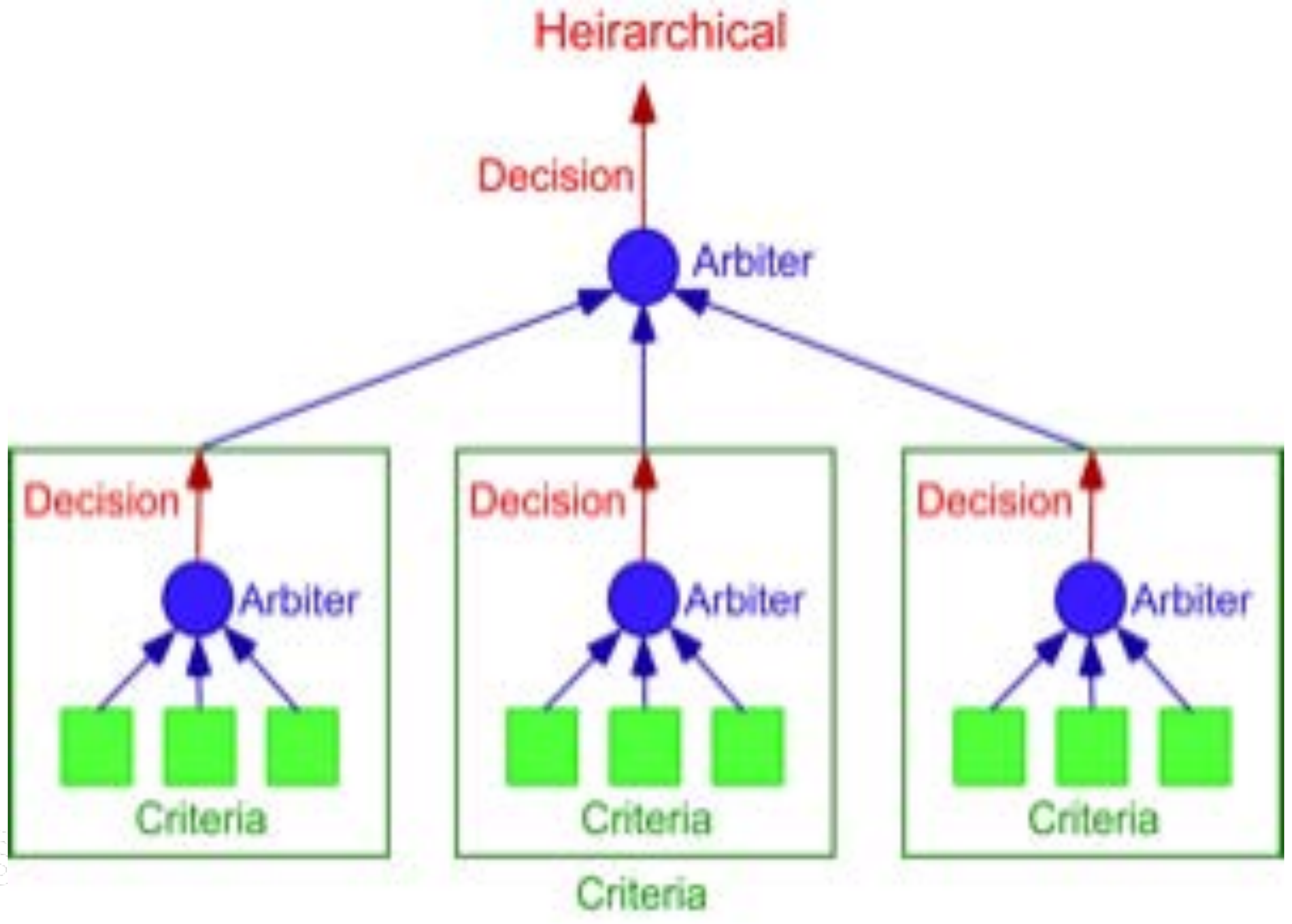
$$\mu_{D_{ij}}(\omega) : \Omega \rightarrow [0,1] \quad \mu_{C_{ij}}(x_i) : \mathbf{X}_i \rightarrow [0,1]$$

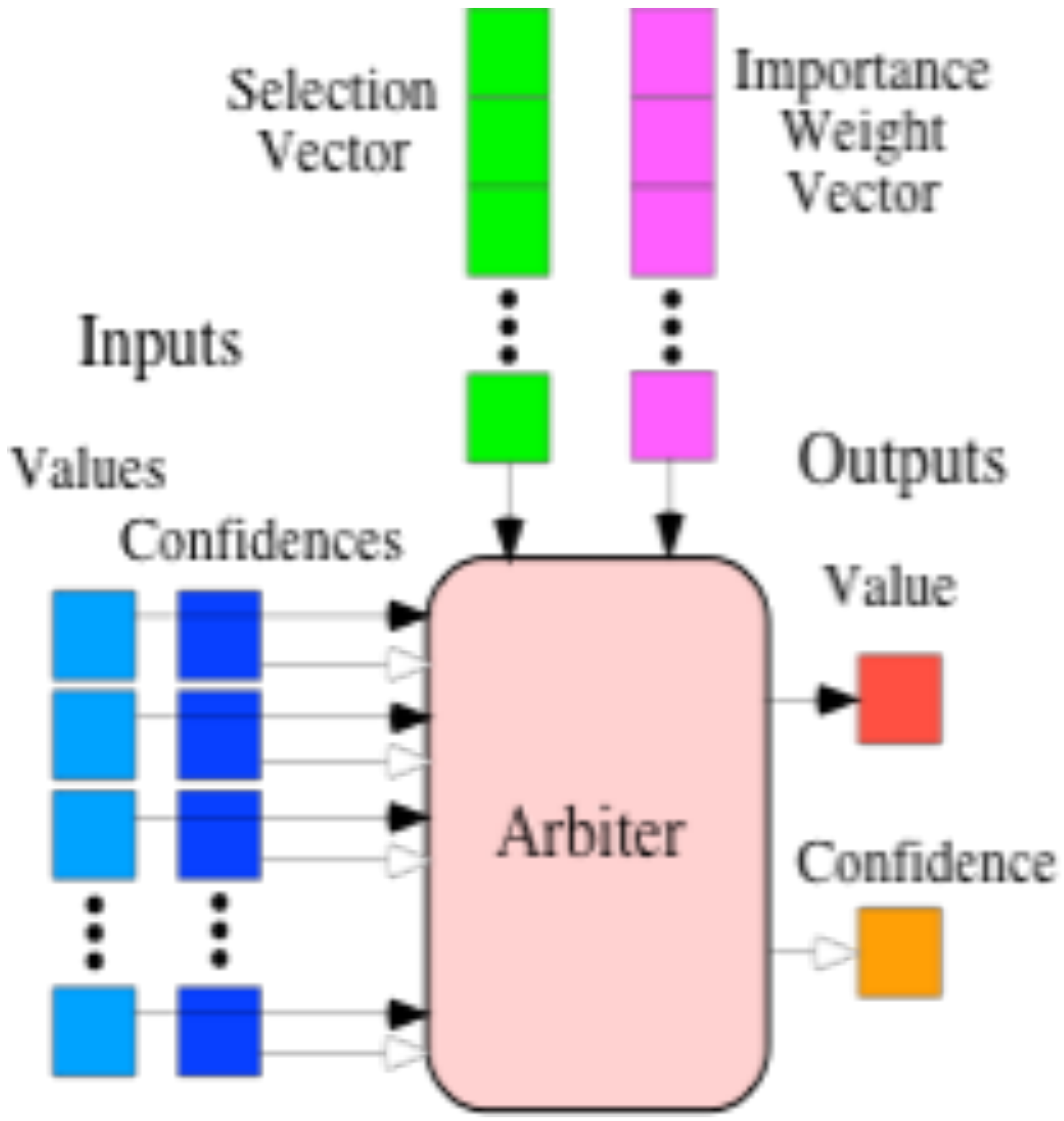
Final decision by aggregating constraints

$$\mu_D(\omega) = Agg(\mu_{D_{11}}(\omega), \mu_{D_{12}}(\omega), \ldots, \mu_{D_{21}}(\omega), \ldots, \mu_{D_{mn}}(\omega))$$

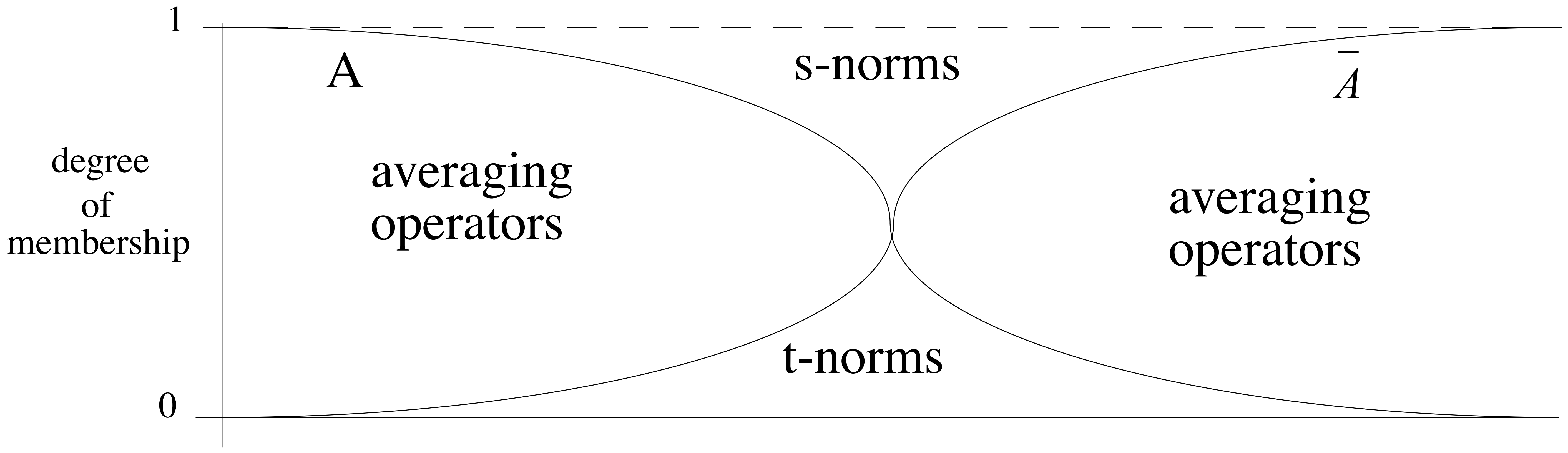
Elastic Constraint Network Building Blocks







Aggregation Operators



t-norms and s-norms,

weighted t-norms and s-norms

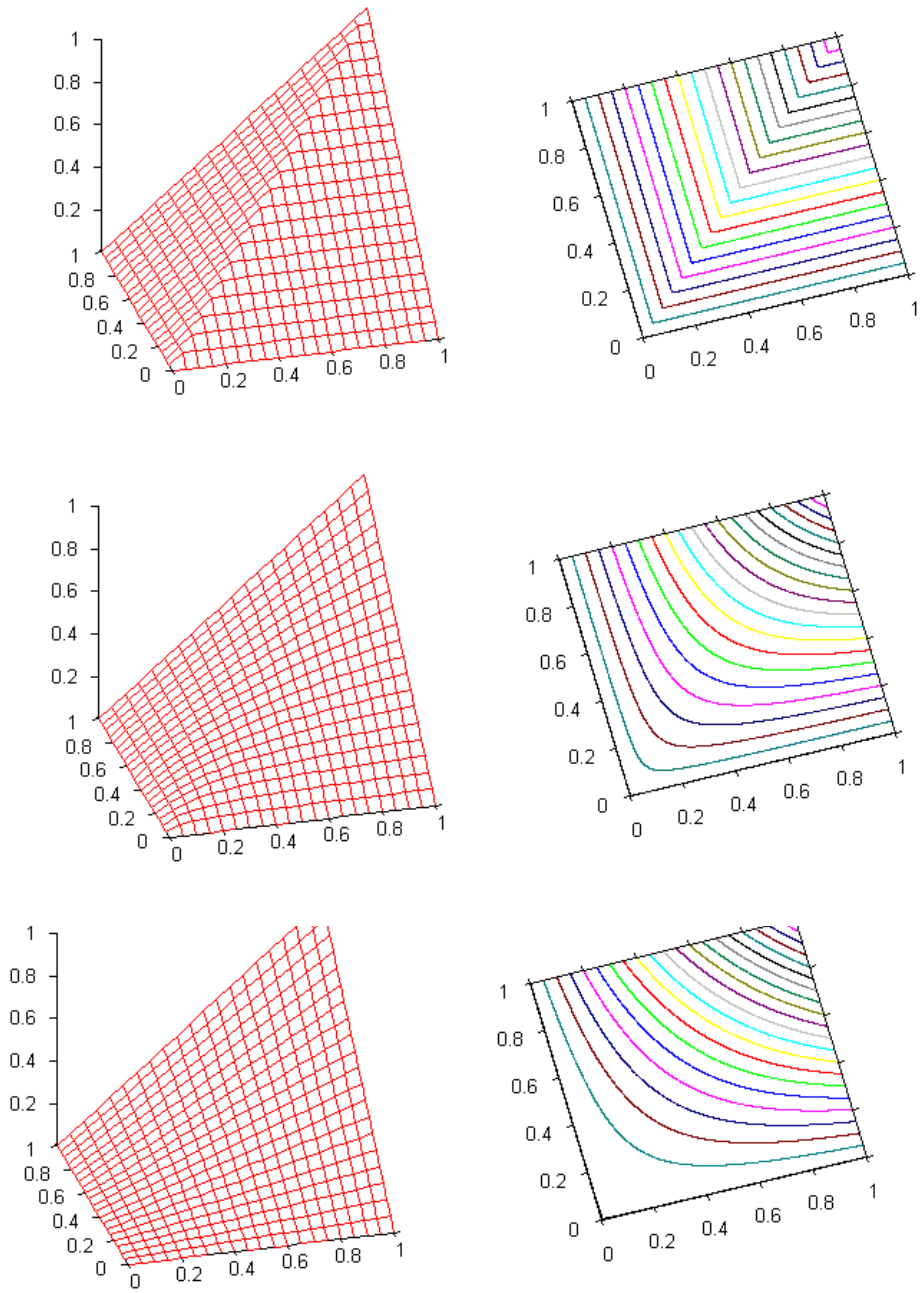
averaging operators

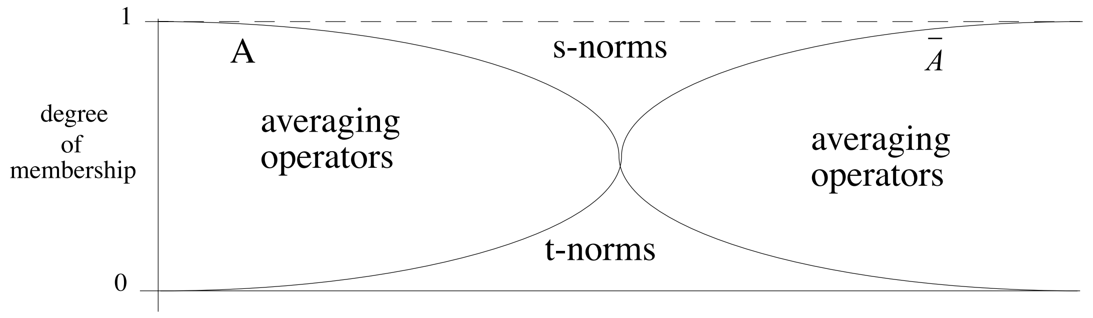
weighted aver- aging operators

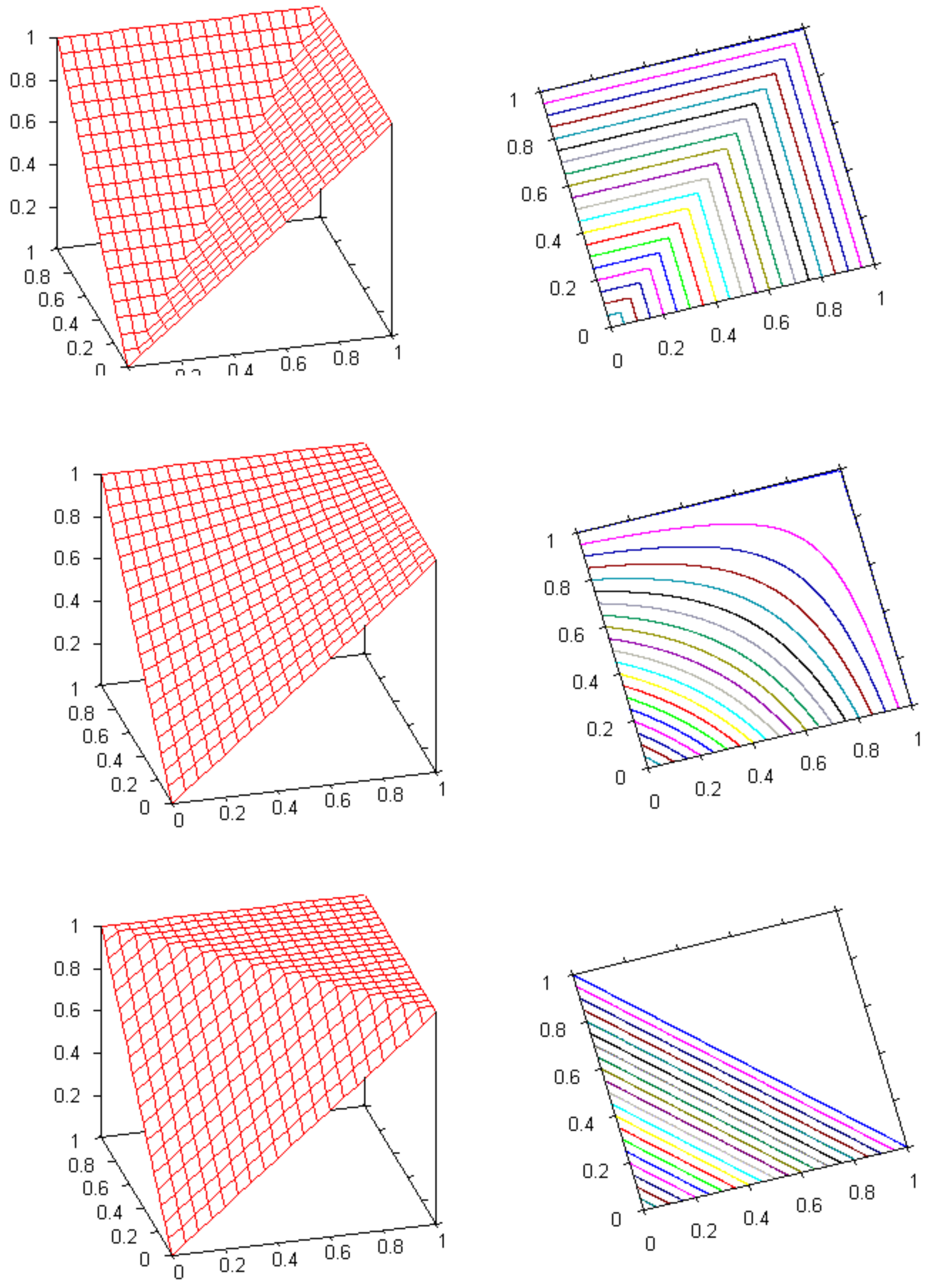
ordered weighted averaging operators (OWA)

hybrid operators.

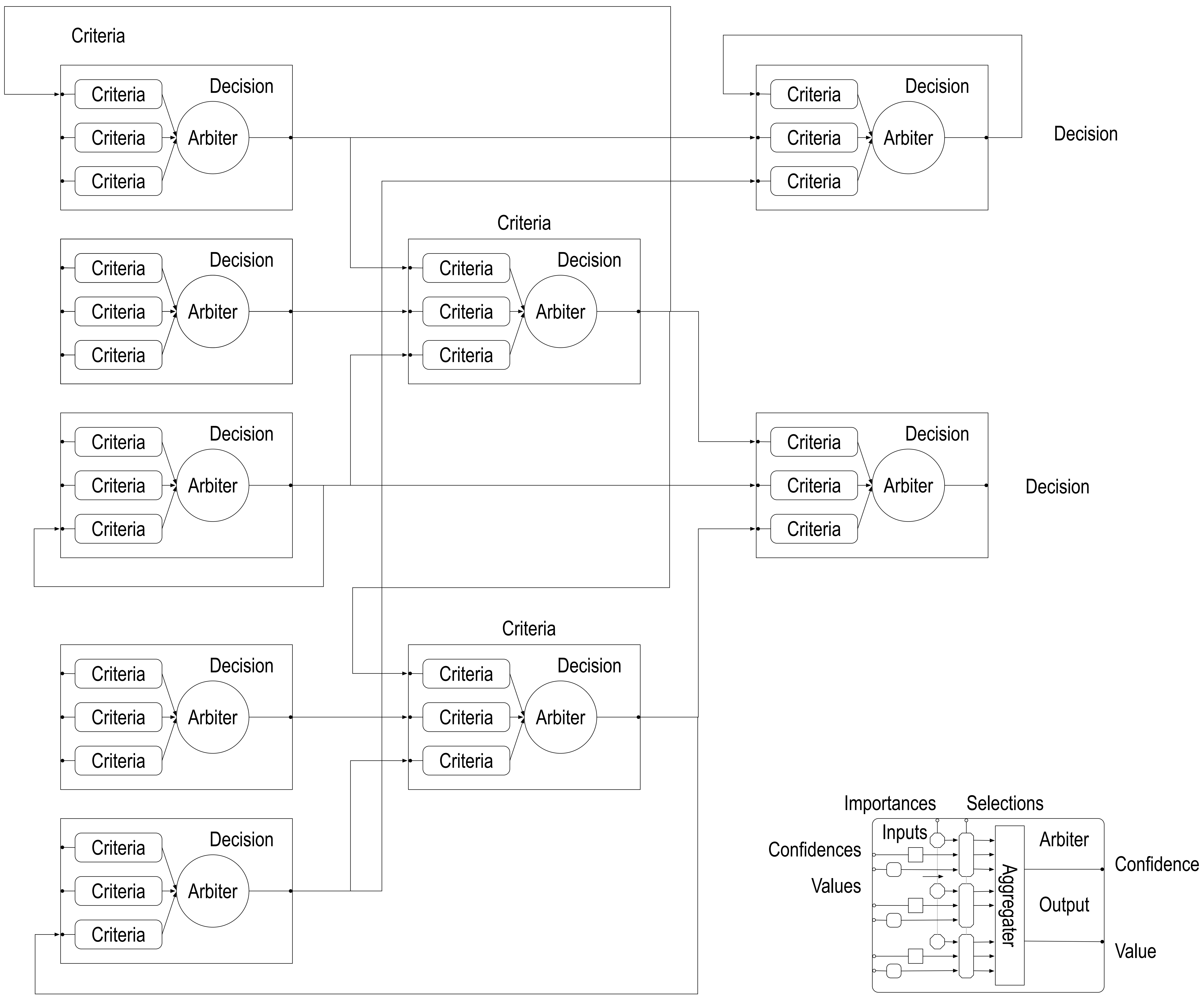
Aggregation Operators







Symmetry Enables Networks of Elastic Constraints



SMEC Features

Works well with sparse data. Bootstrap using default logic. Tune-up with more data. Refine with reinforcement learning.

Flat and wide constraint space most robust.

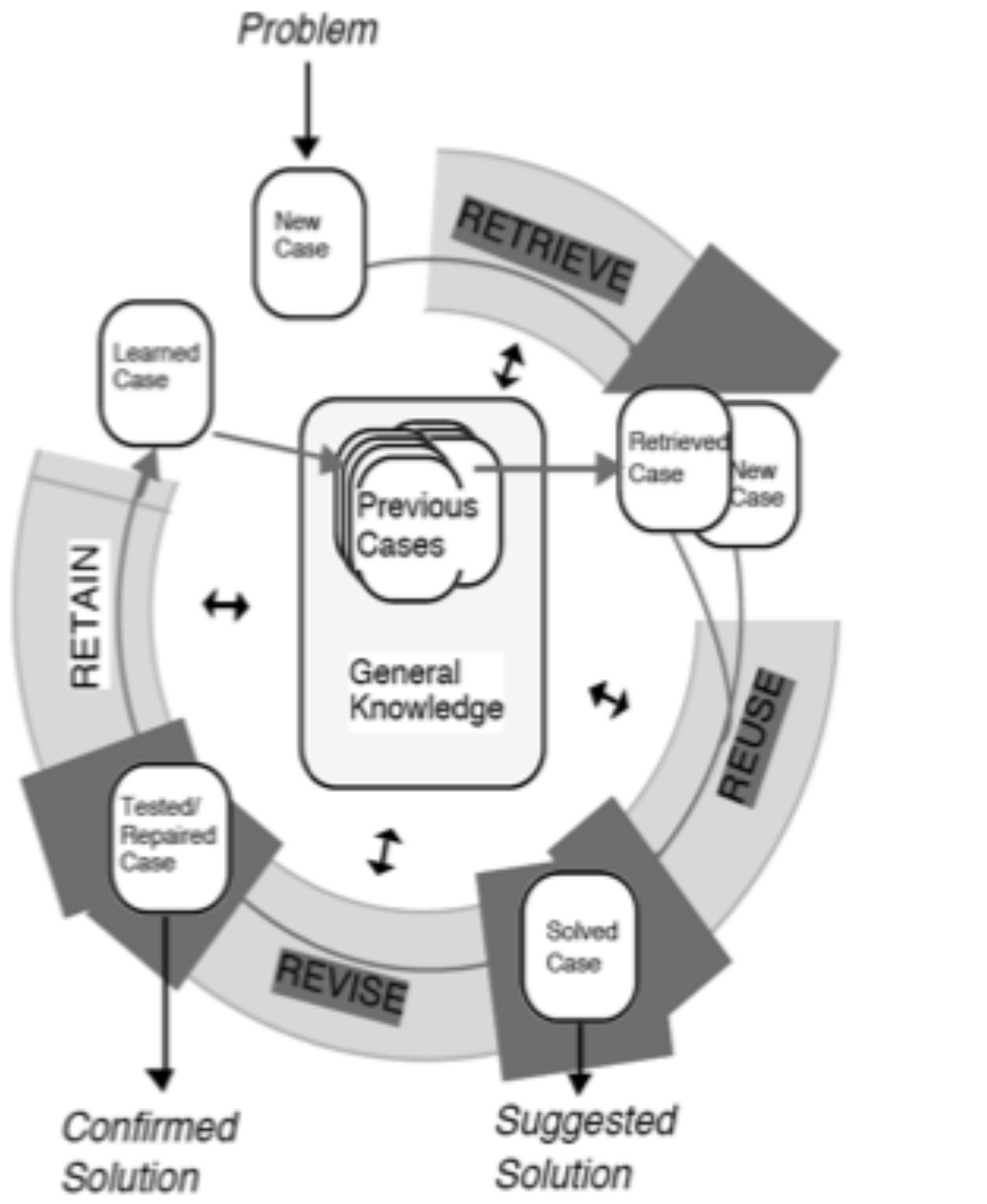
Modular, composeable, contextualizable without re-training.

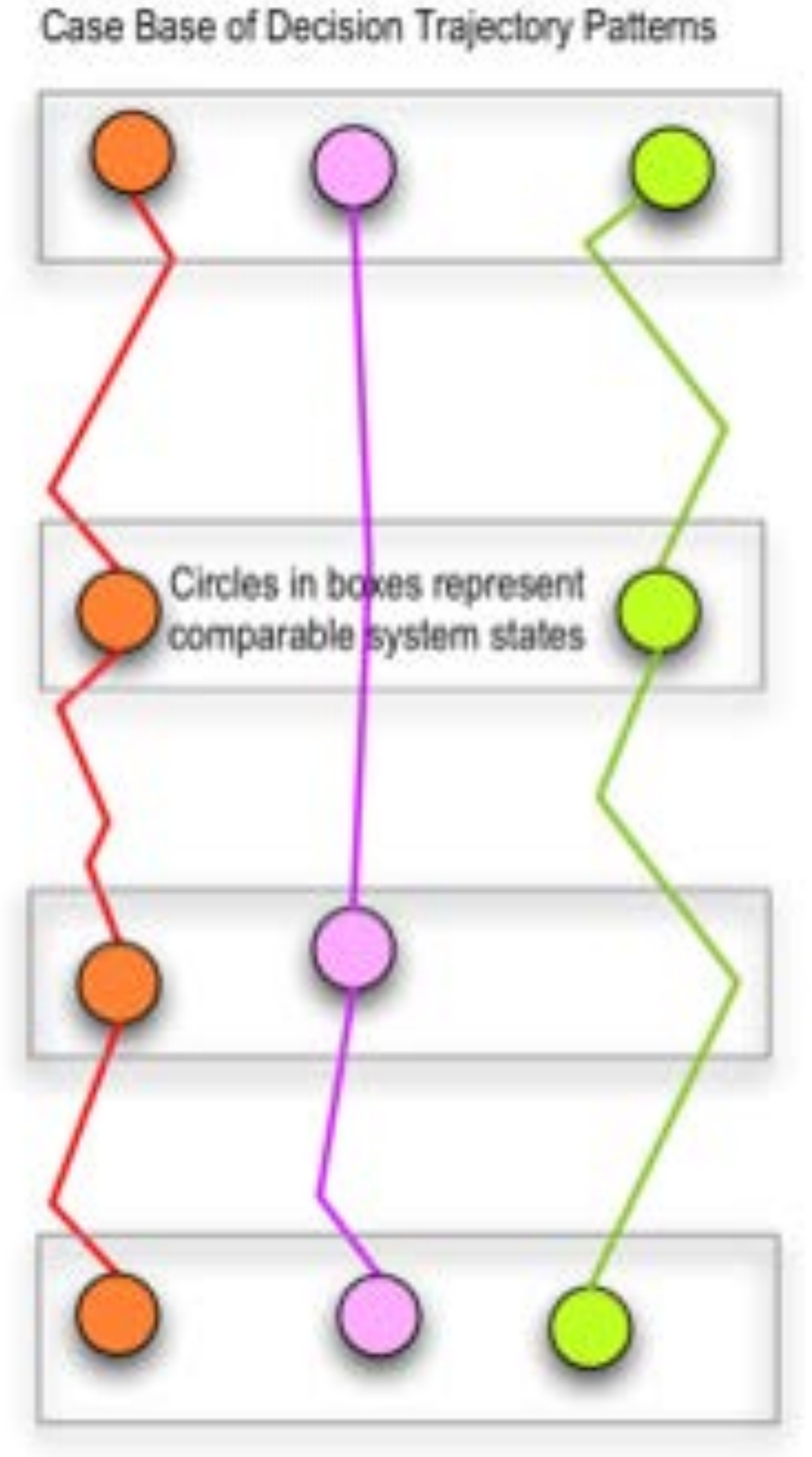
Elastic constraint network is explicable. GDPR compliant.

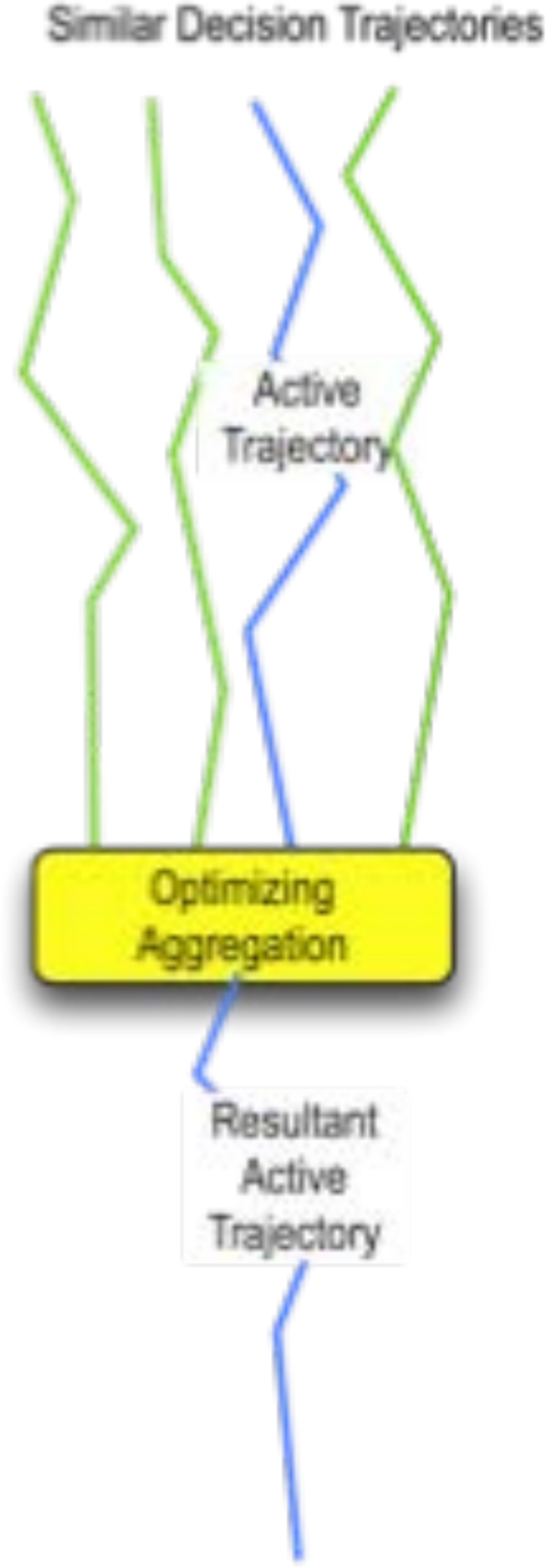
Can be modeled for prediction, recommendation, optimization, anti-gamification.

Decision Trajectory Based Optimization
Pattern Centric Reasoning

Predictive discrete event simulation with reinforcement learning to encode high level reasoning, strategy and tactics.







PORTABLE IDENTITY

Security, Privacy, Agency

(Trustworthy, Private Preserving, Self-Sovereign)

Portable Identifiers & Attributes

Decentralized (not in a silo)

PORTABLE REPUTATION

Security, Privacy, Agency

Portable Data & Algorithms

Reputation system that spans verticals and applications

Benefits from data network effects

OPEN & PORTABLE & PROPRIETARY

Open Data Formats

Open Frameworks

Open Algorithms

Open Governance

Proprietary Contextualization, Parametrization, Tuning & Data

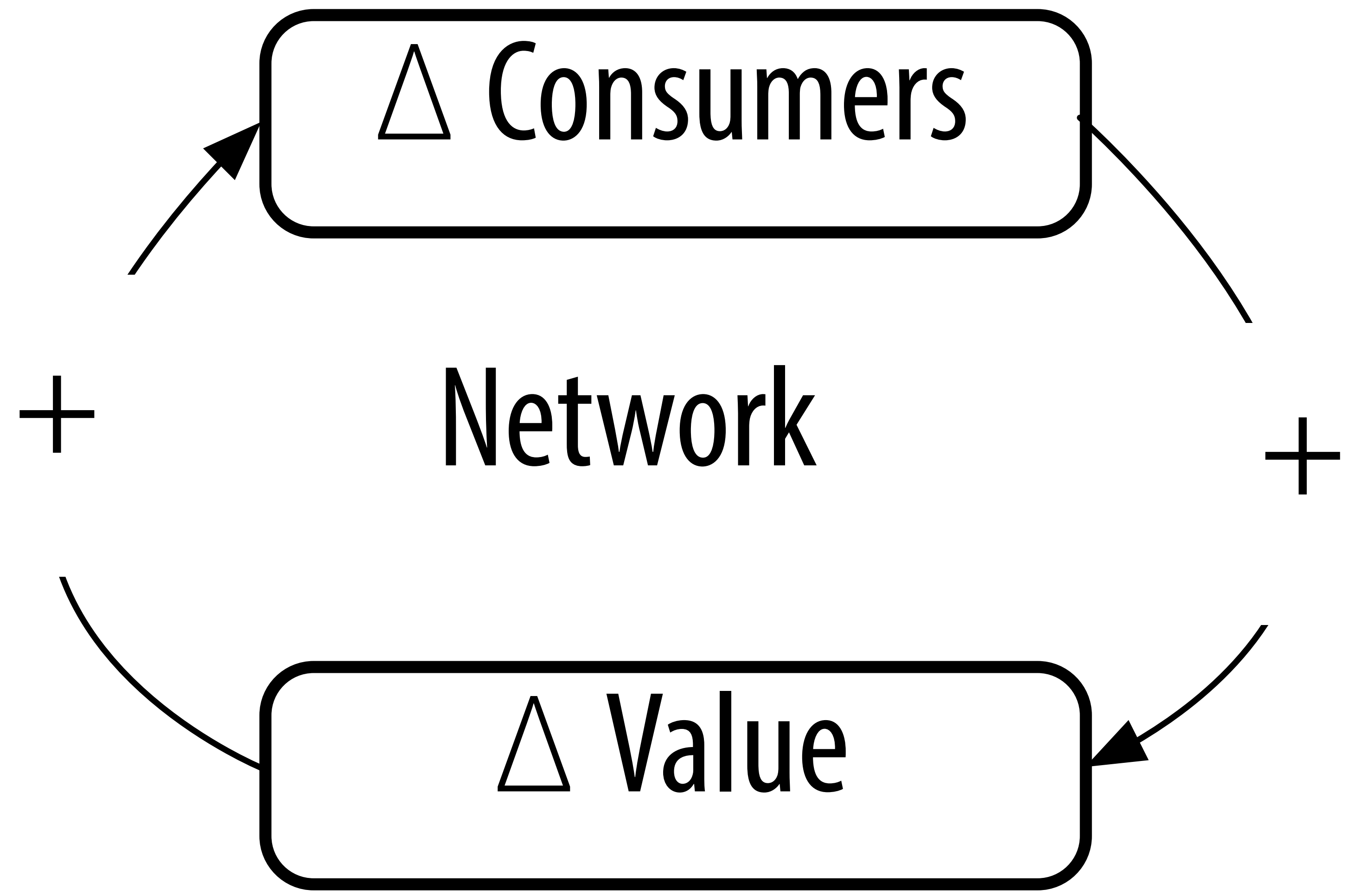
META-PLATFORM

Two Sided Network Effects

Curation, Filtering, Modulation

Optimal Control

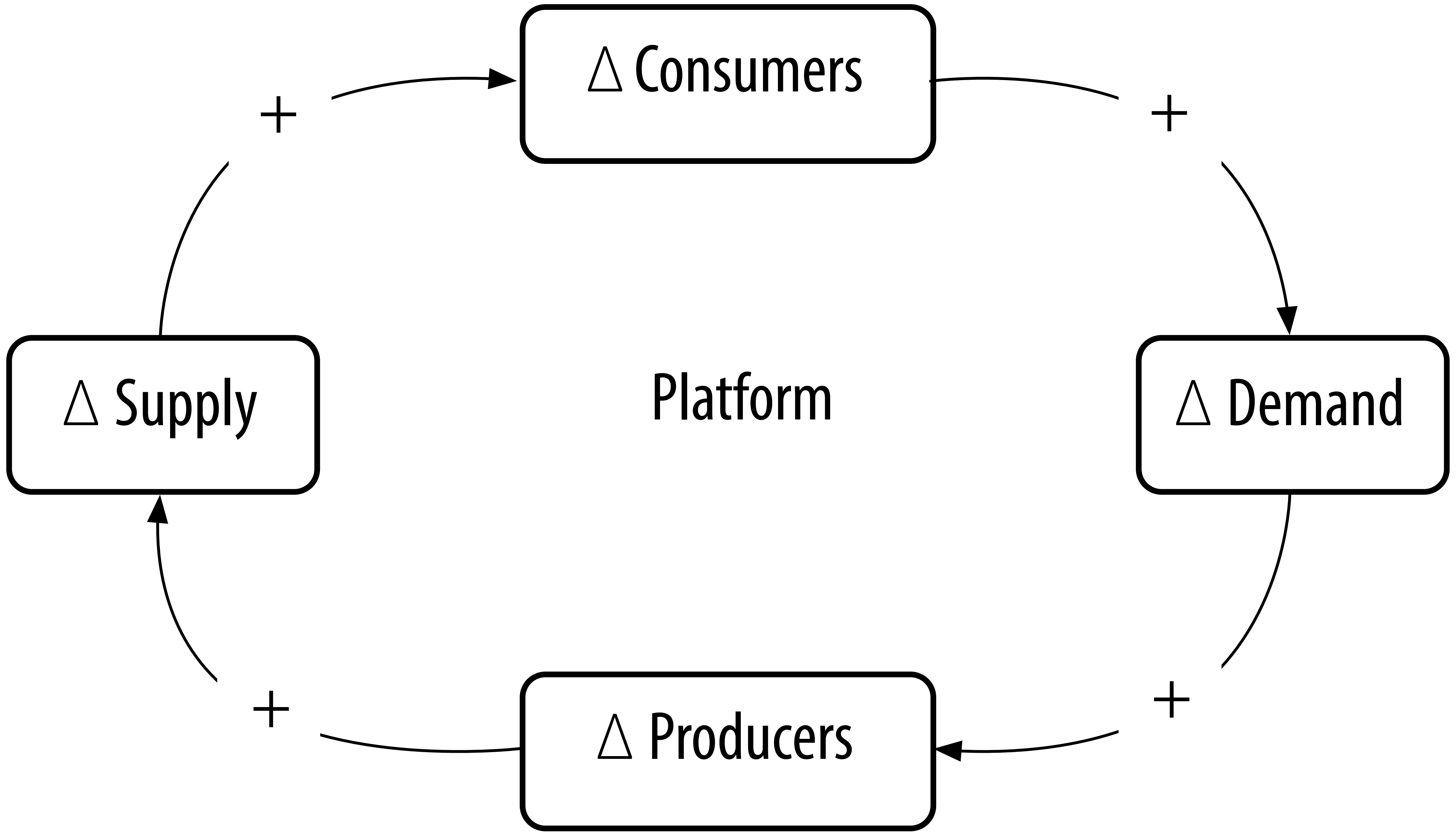
SINGLE-SIDED NETWORK EFFECT



More consumers increases value which attracts more consumers

Demand side driven

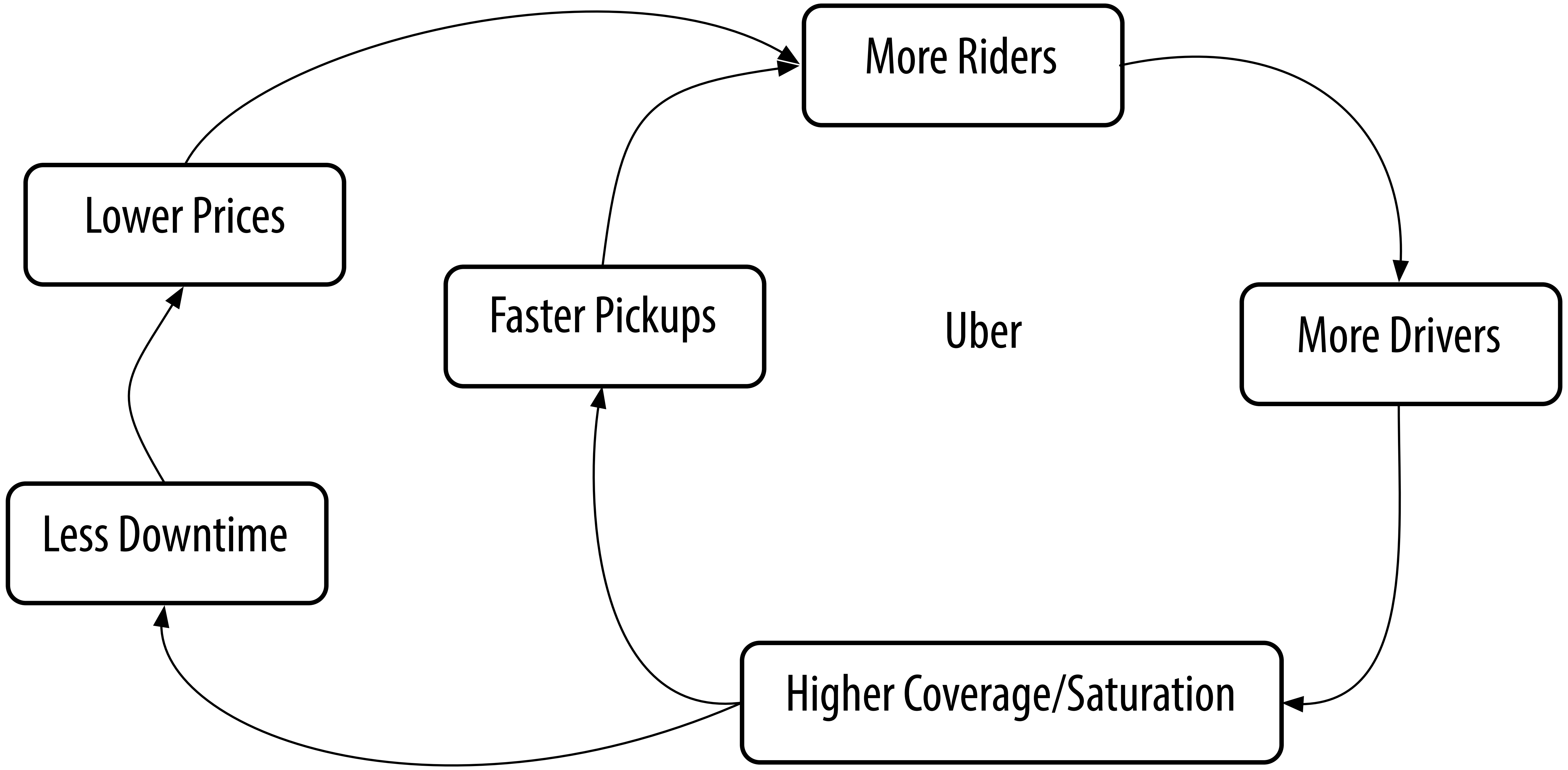
TWO-SIDED NETWORK



more consumers drive demand which attracts more producers

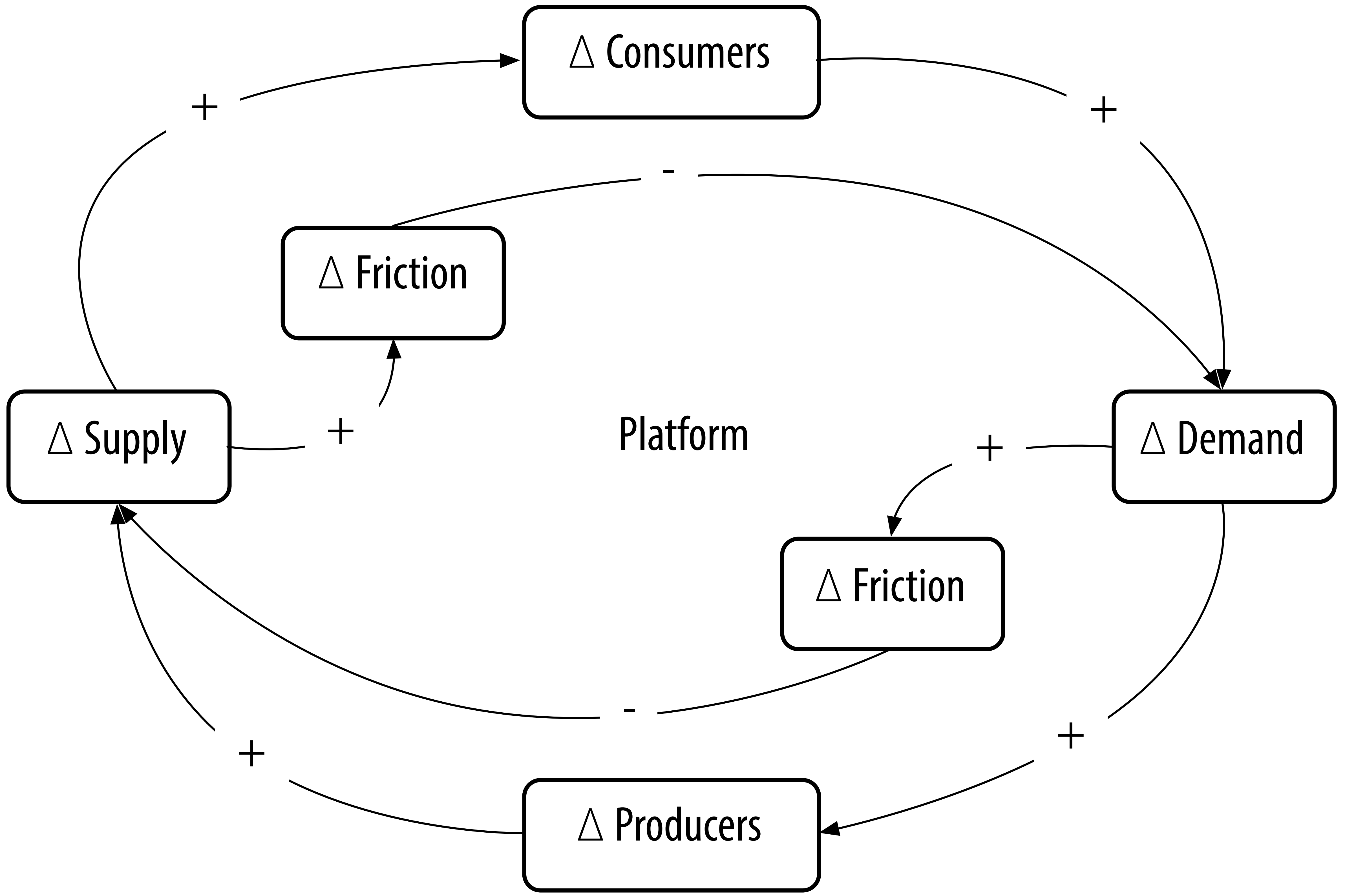
more producers drive supply which attracts more consumers

EXAMPLE



More Riders
Lower Prices
Faster Pickups
Uber
More Drivers
Less Downtime
Higher Coverage/Saturation

NEGATIVE CROSS-SIDE NETWORK EFFECTS



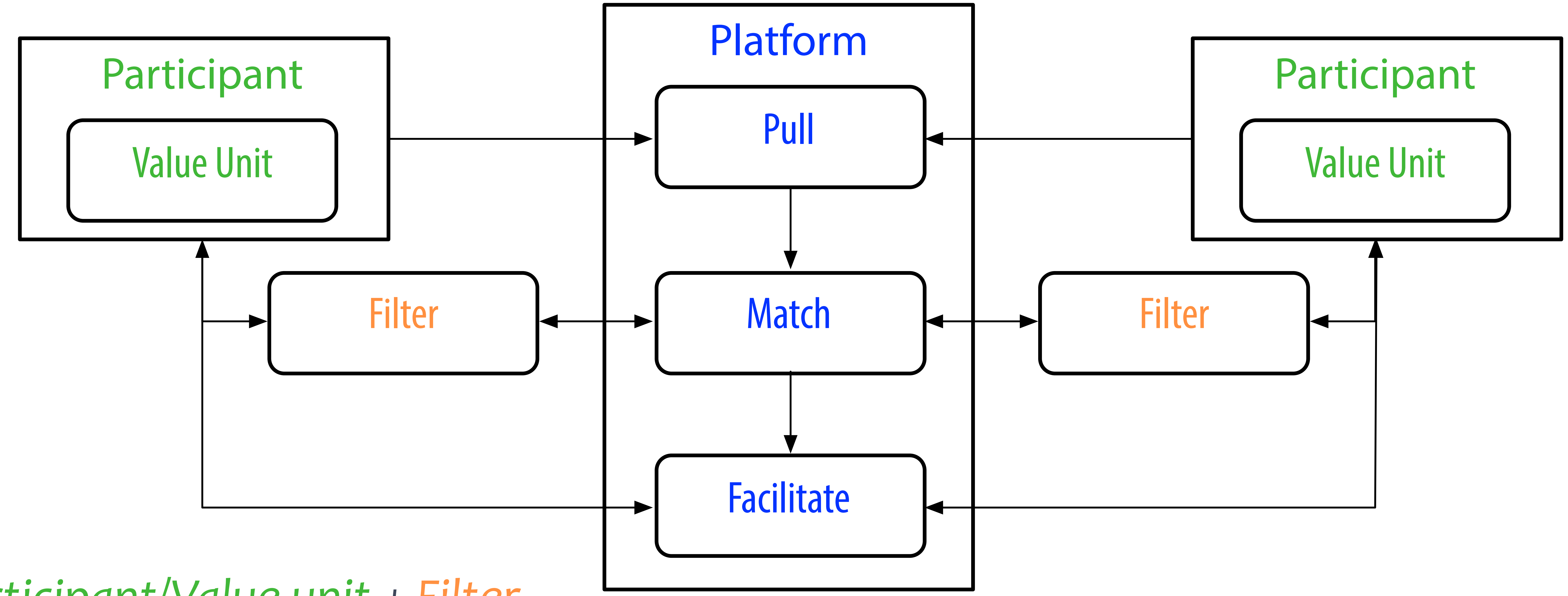
More supply choice increases friction e.g. customer confusion in producer selection thereby decreasing demand

More demand choice increases friction e.g. producer failure in customer satisfaction thereby decreasing supply

PLATFORM BUSINESS MODEL

Supply economies of scale (production efficiency)
replaced with
Demand economies of scale (network effect multipliers of value)

Two-sided network effects



Core Interaction = *Participant/Value unit* + *Filter*

Platform = *Pull* + *Match* + *Facilitate*

CURATION

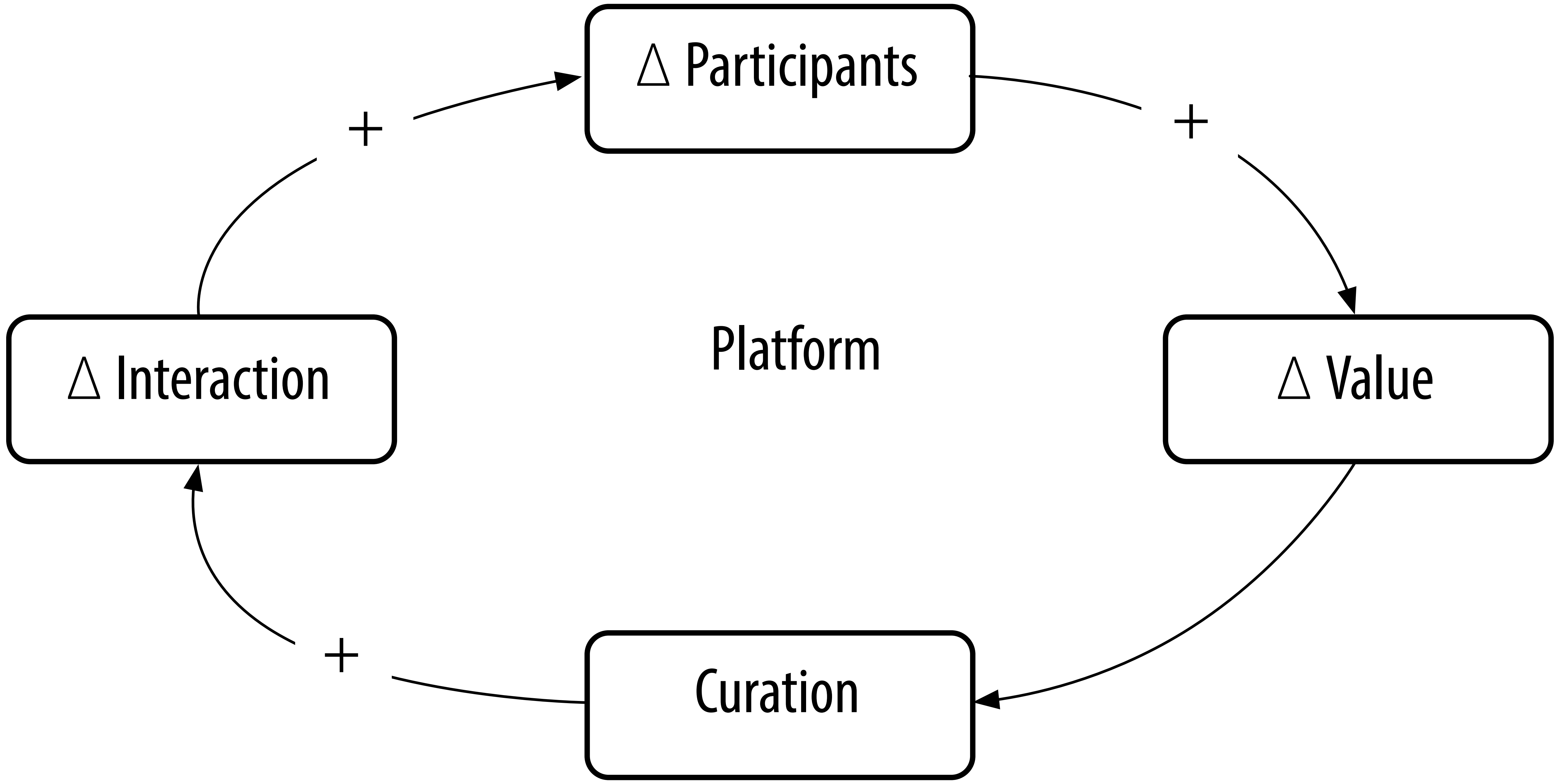
Match + Filter = Curation

Reduces negative cross-side network effects

Enhances positive cross-side network effects

Essential enabling capability for any platform

Curation is applied reputation



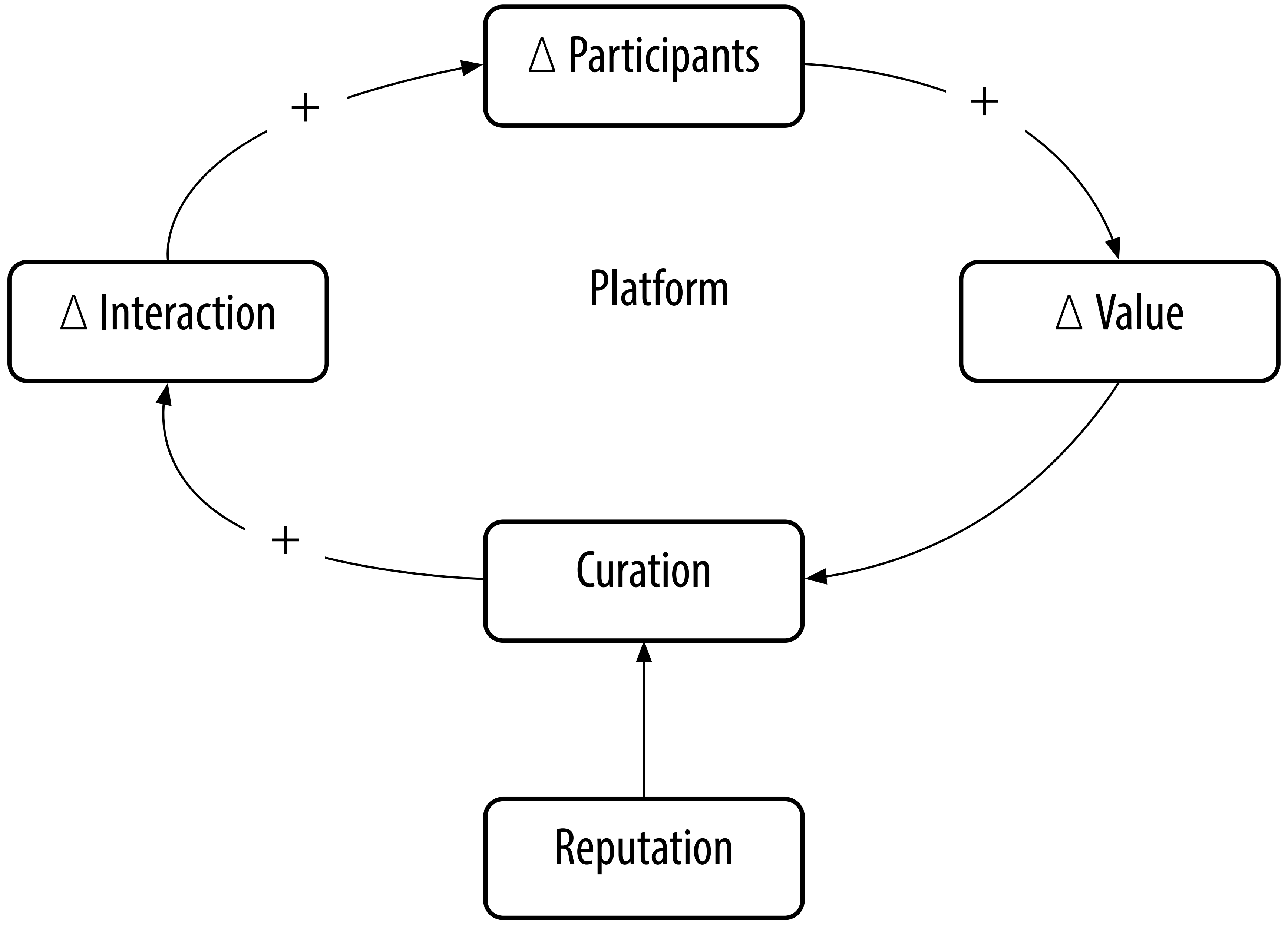
META-PLATFORM

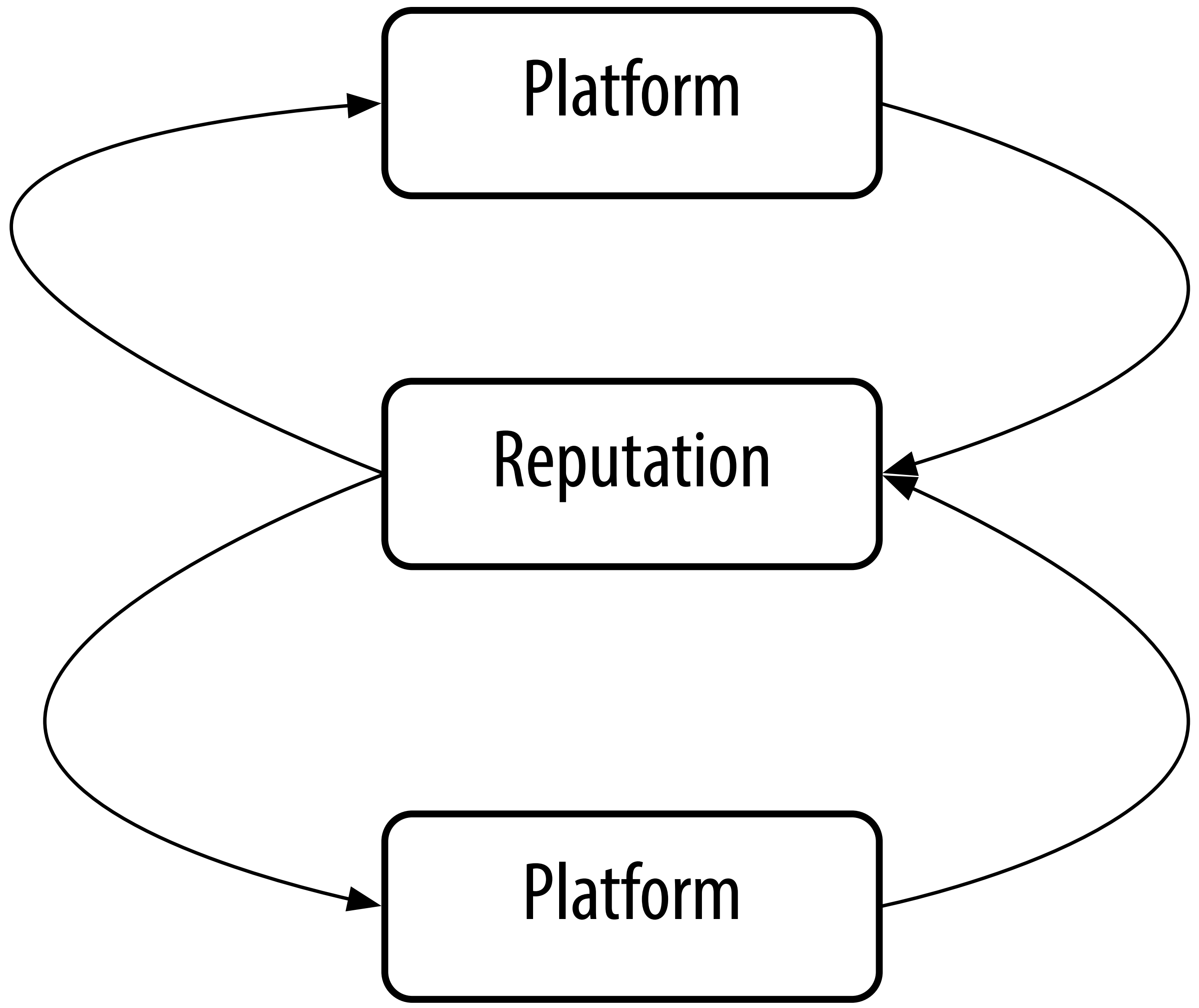
Platform that facilitates two-sided network effects across and amongst other platforms

Portable Reputation is a potential meta-platform

Contextual

Transitive



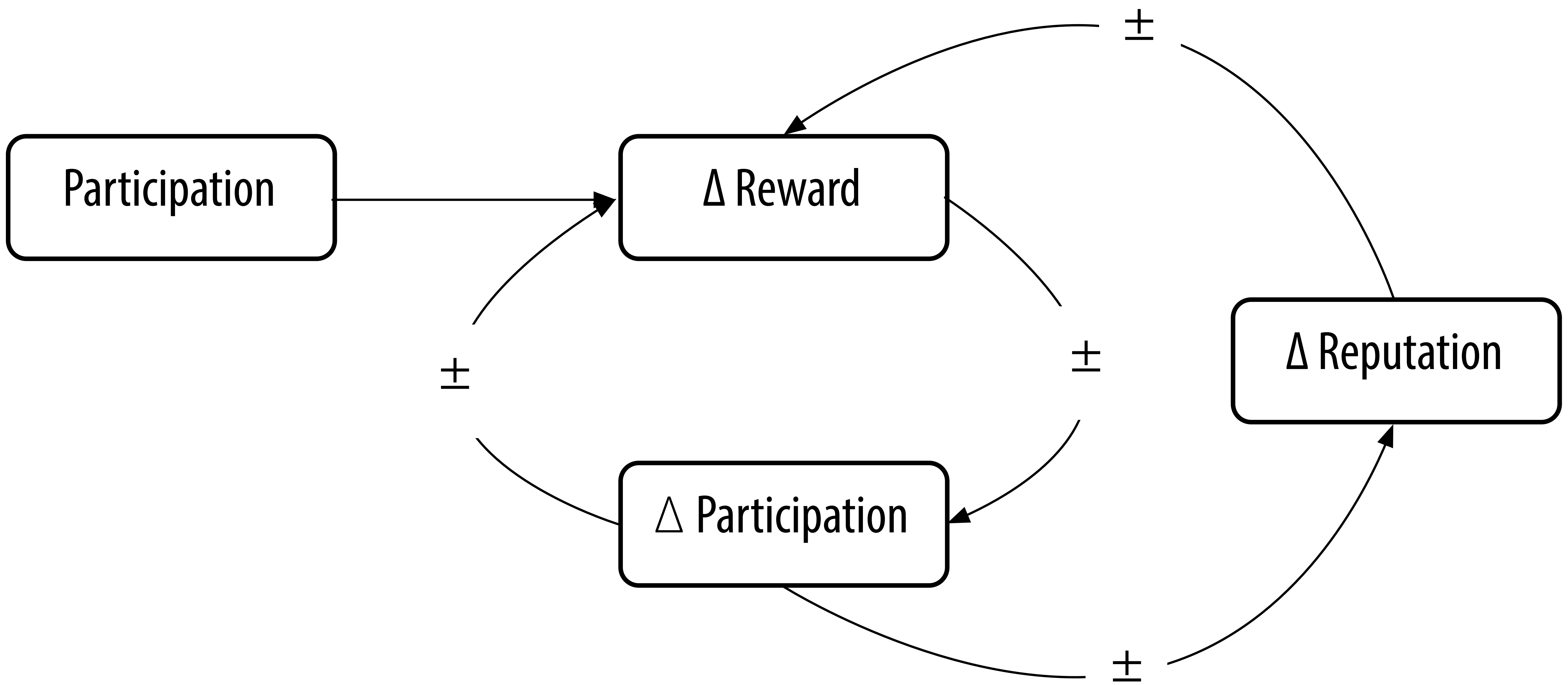


Meta-platform may be a system of network intelligence

Network effects on network effects

REPUTATION DRIVEN INTERACTION

Graduated Participation Interfaces



NETWORK EFFECTS

1-Sided *Direct*:
 - Physical: Phone Company
 - Protocol: Ethernet, HTTP
 - Personal: Influencers
 - Market: (N-Sided)

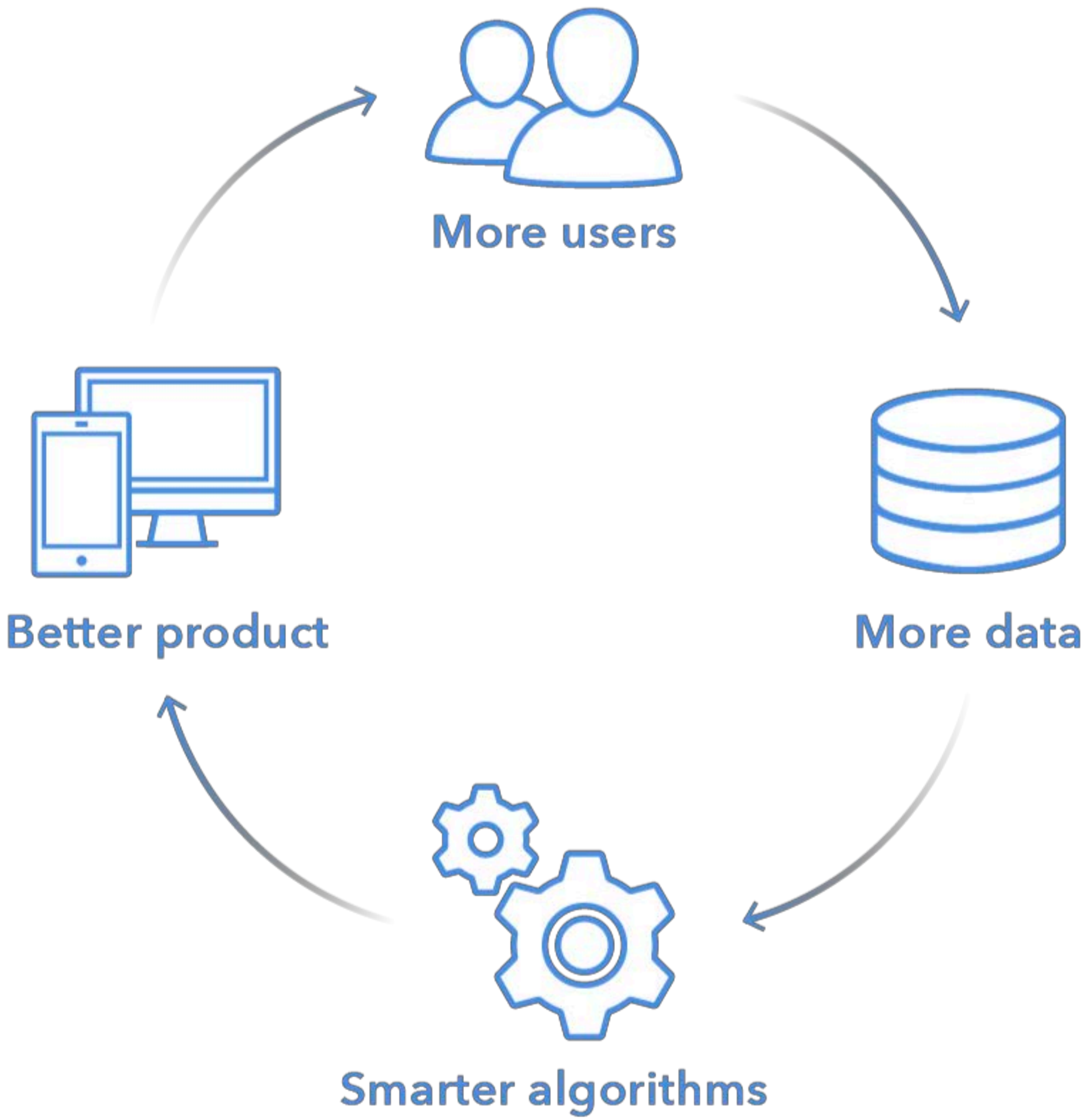
2-Sided *Indirect*: (Demand and Supply Sides)
 - Marketplace: Craigslist, AirBnB
 - Platform: (unique supply) iOS App Store
 - Asymptotic Marketplace: 2-Sided: Uber, Lyft

Data: (Product value increases with more data driving more users)

Technology Performance: (More users increases product value)

Social: (Interaction between users produces value)
 - Belief
 - Language
 - Bandwagon

DATA NETWORK EFFECTS



Graph Based Self Identity/Reputation

Identity = *Identifiers* + *Attributes*

Identifiers = *globally unique decentralized cryptonyms* + *aliases*

Attributes = *user data, proofs*

Facilitate attribute exchange between entities sufficient to enable transaction to proceed

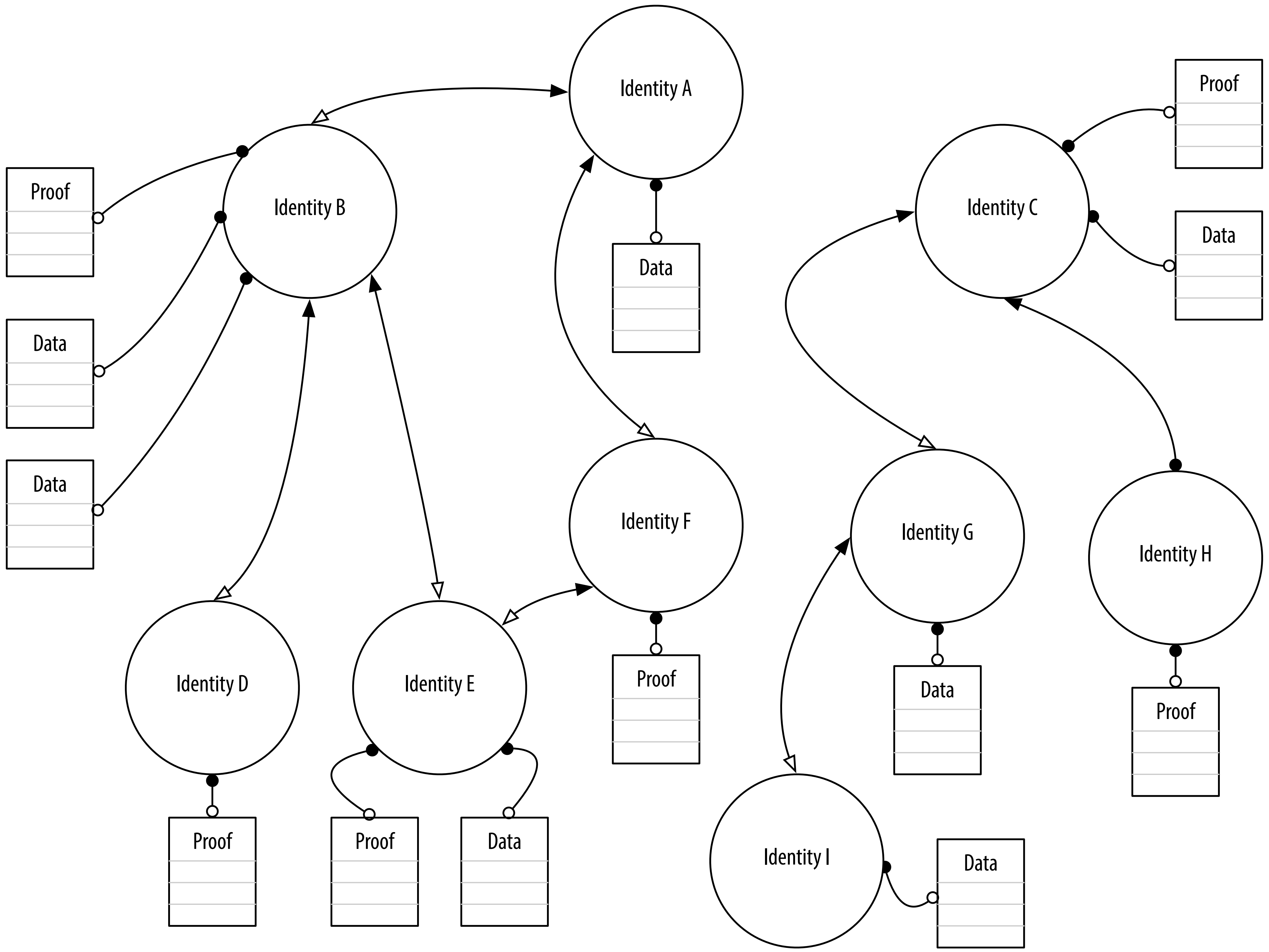
Identity System Features:

- Agency (own your own identity)
- Security (impervious to fraud)
- Privacy (least disclosure)

Agency = portable identifiers + user controlled

Security = distributed consensus + modern crypto

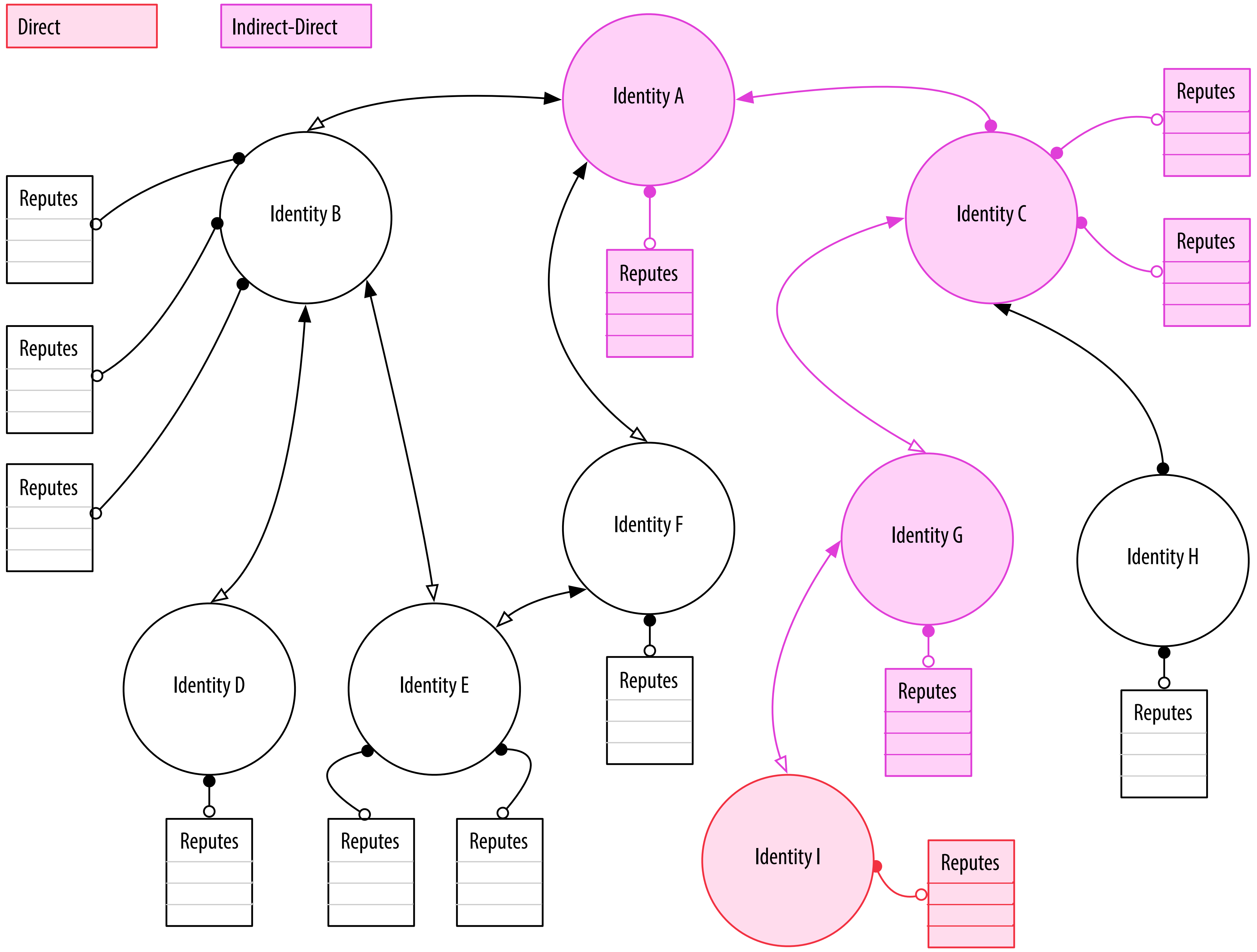
Privacy = granular graph based identities + layered disclosures + zero knowledge disclosures + group identities



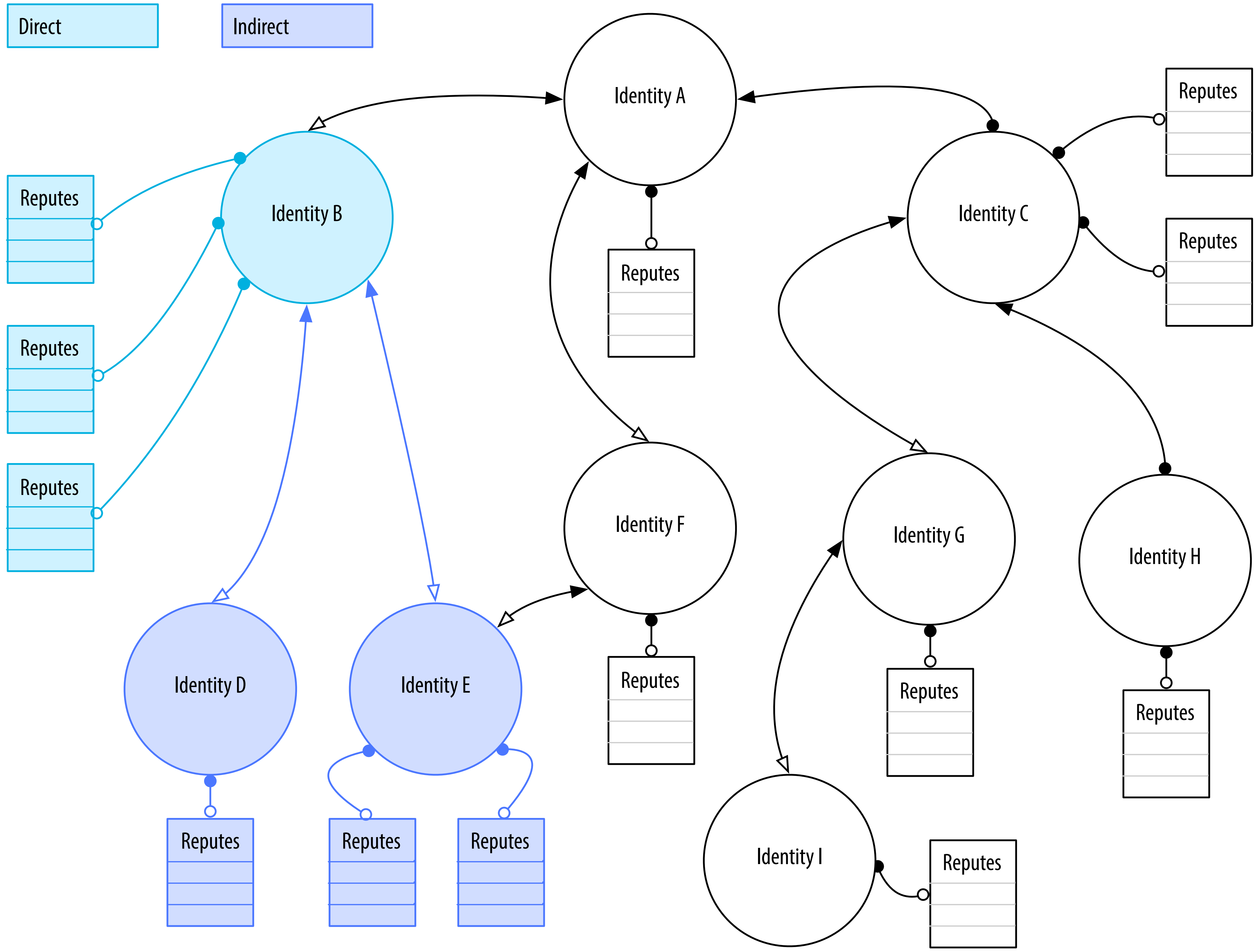
https://github.com/SmithSamuelM/Papers/blob/master/whitepapers/Identity-System-Essentials.pdf

Graph Based Other Identity/Reputation

Repute Down

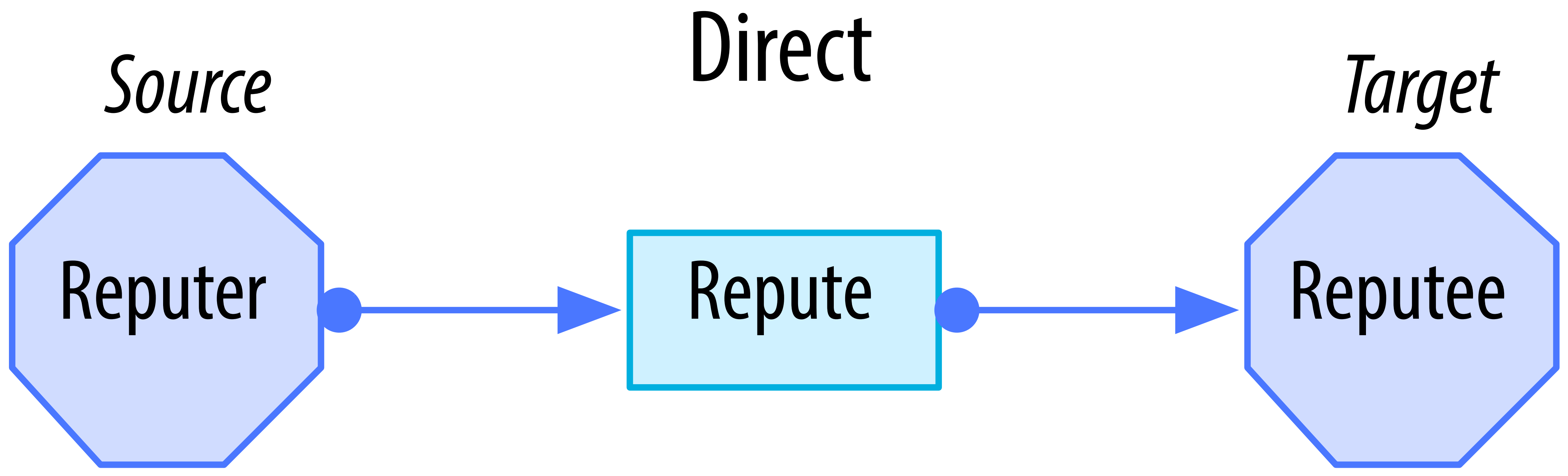


Repute Up



https://github.com/SmithSamuelM/Papers/blob/master/whitepapers/Identity-System-Essentials.pdf

REPUTING LEXICON



Repute = *Reputational Event (Data)*

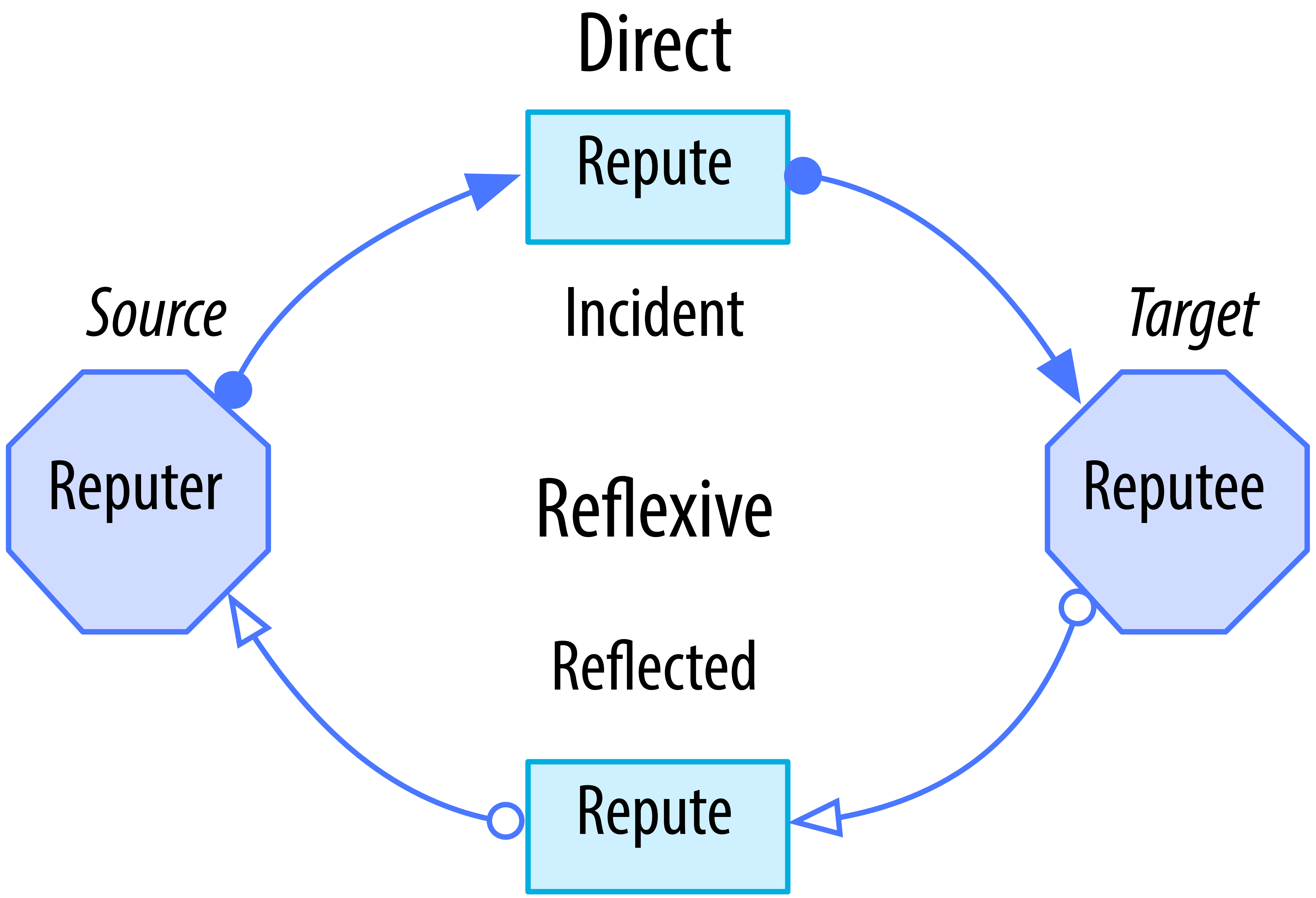
Reputee = *Reputational Entity, (Identity)*

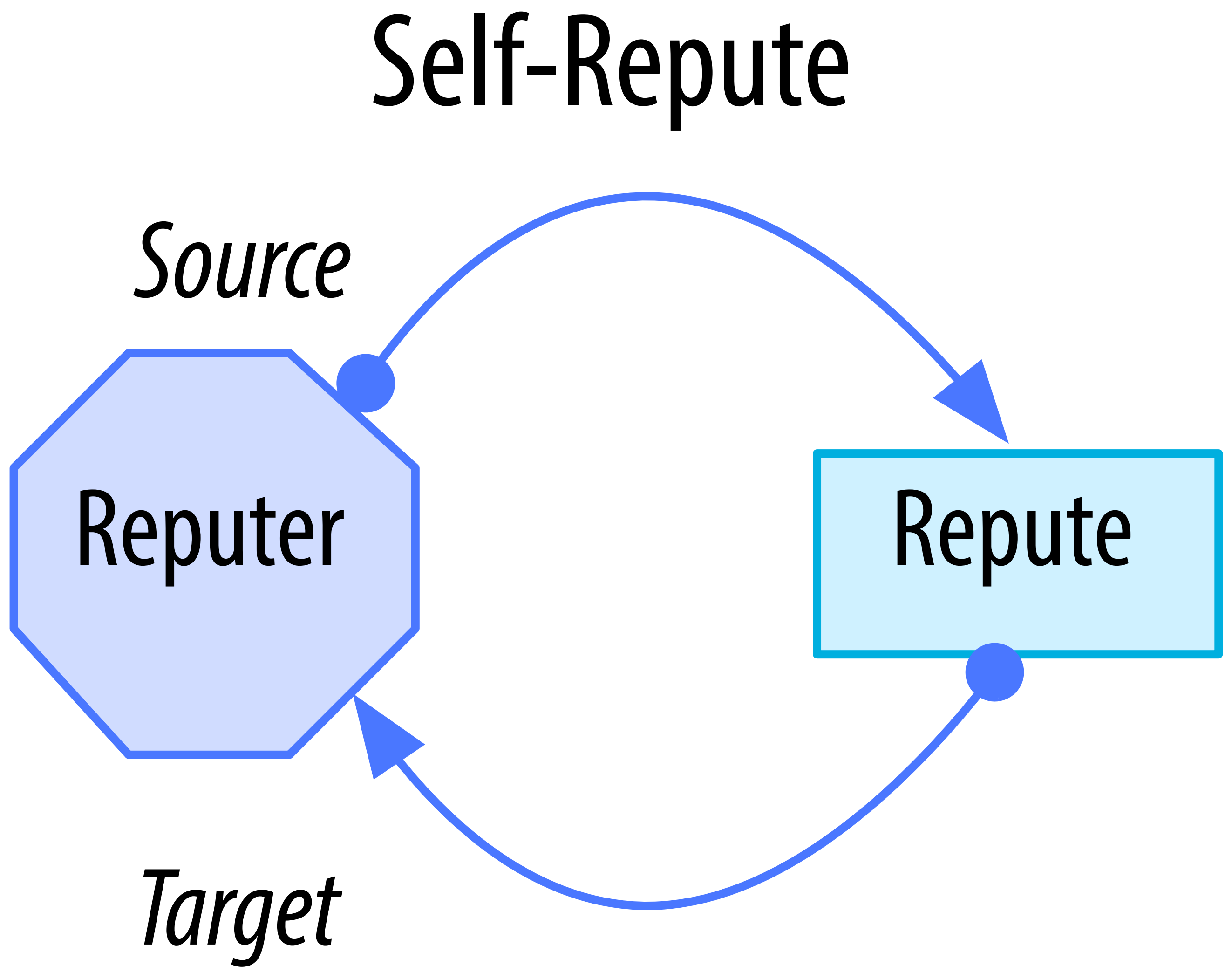
Target of Repute

Reputer = *Source of Repute*

https://github.com/SmithSamuelM/Papers/blob/master/whitepapers/open-reputation-low-level-whitepaper.pdf

REFLEXIVITY





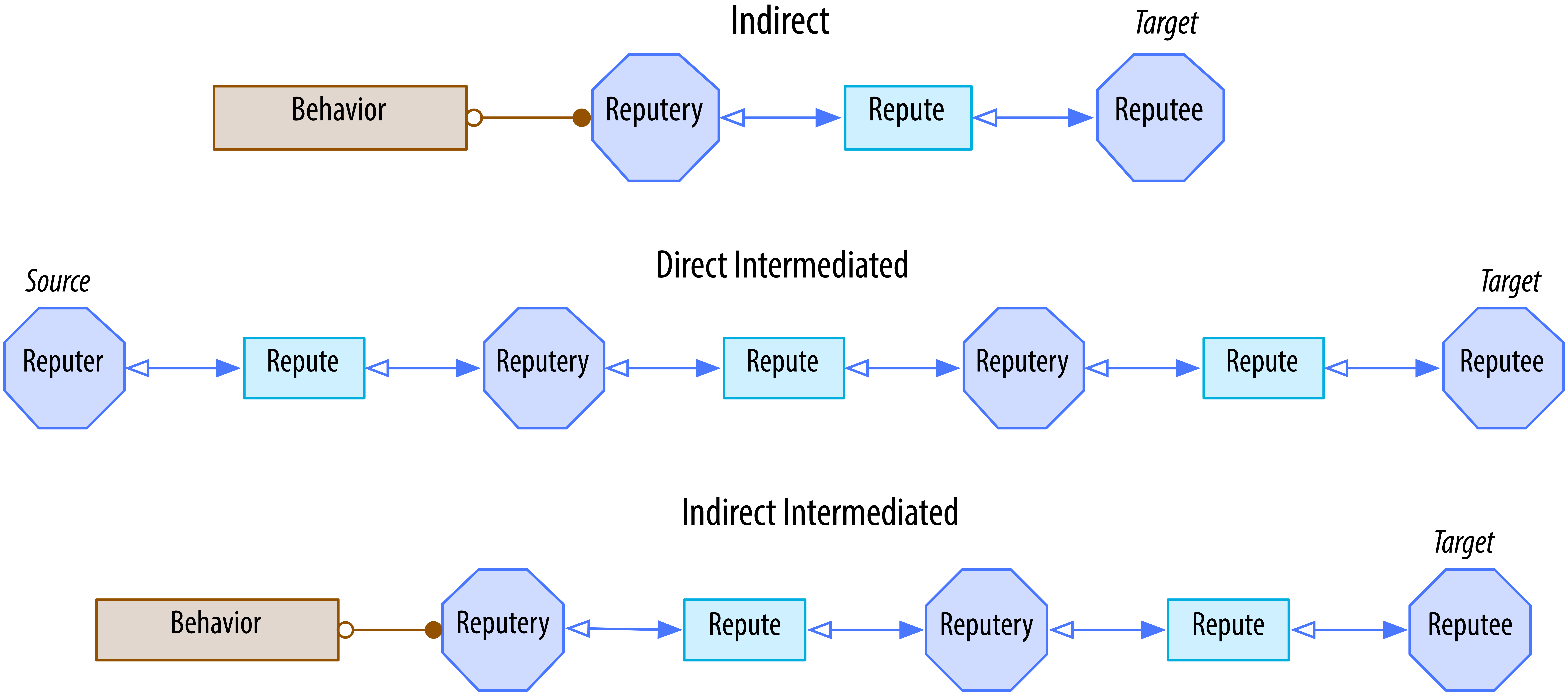
Reputation is Reflexive:

Reputer is simultaneously both a Source and a Target = Reputee

https://github.com/SmithSamuelM/Papers/blob/master/whitepapers/open-reputation-low-level-whitepaper.pdf

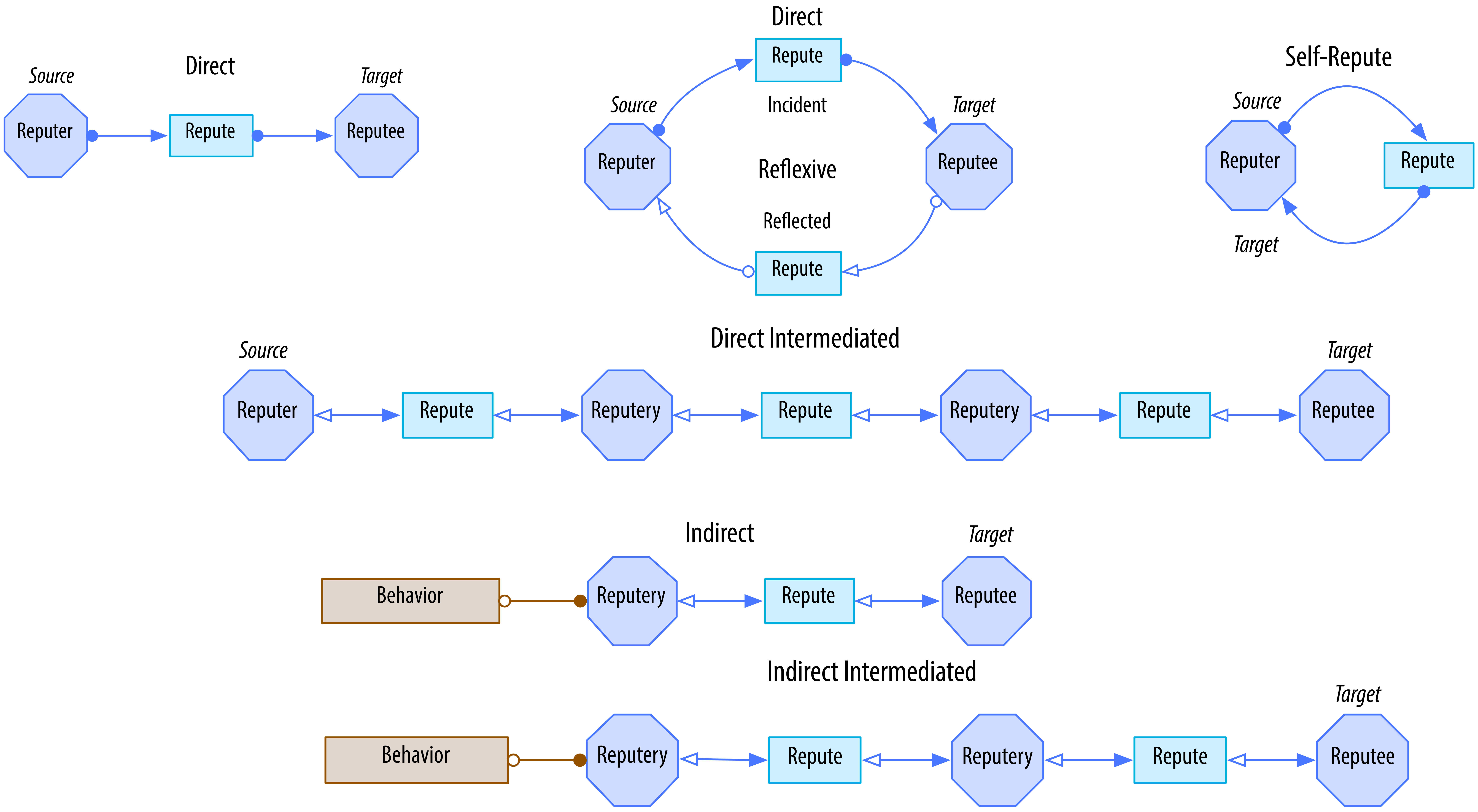
INDIRECT AND INTERMEDIATED REPUTING

Reputery = Indirect Source (Implied Reputer) or Intermediate Source



https://github.com/SmithSamuelM/Papers/blob/master/whitepapers/open-reputation-low-level-whitepaper.pdf

Reputing



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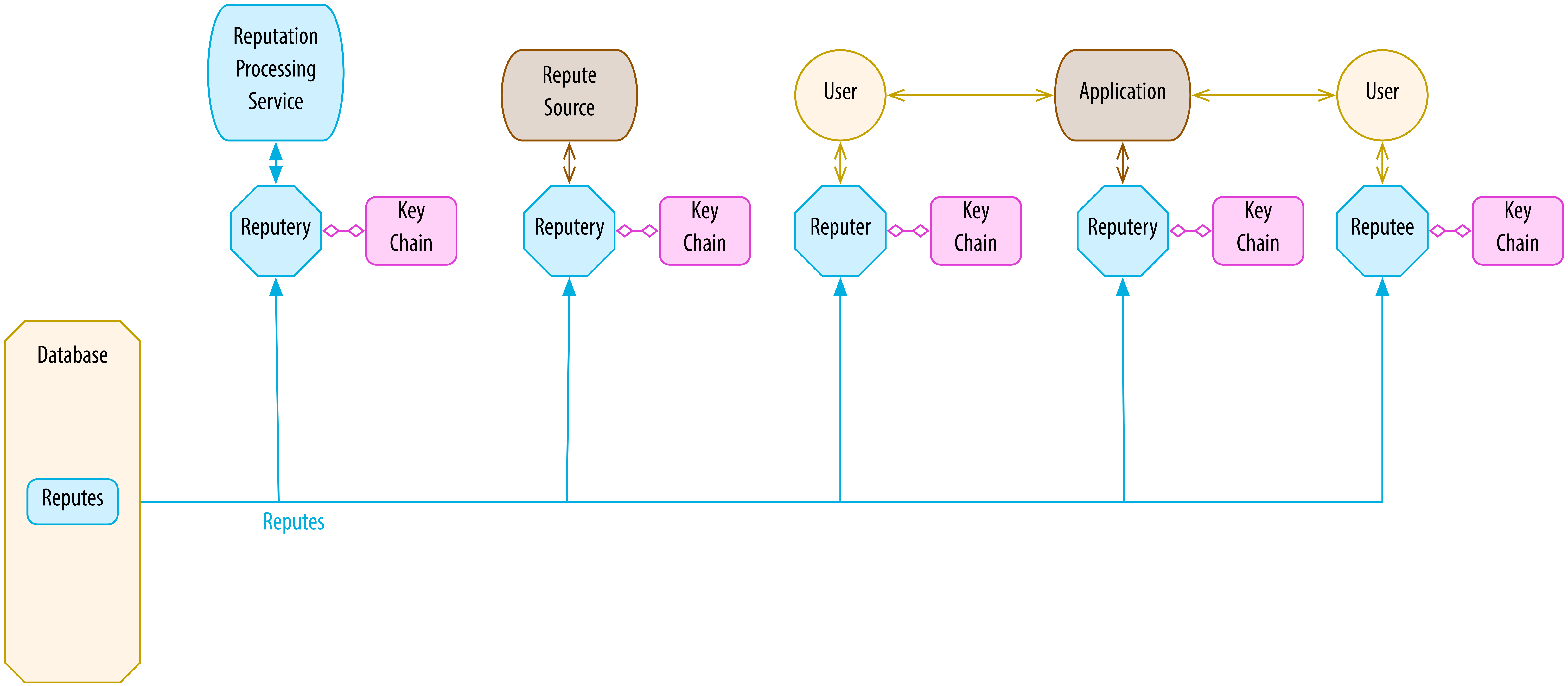
Basic Reputation



REPUTAGE

Reputage: *reputational event ancilliary data. Optional or infrequently used information associated with a repute separated from core repute for performance reasons.*

https://github.com/SmithSamuelM/Papers/blob/master/whitepapers/open-reputation-low-level-whitepaper.pdf

REPUTET

Reputet: reputational event transaction. A cryptographically signed and validated transaction of reputes between reputees or reputeries.

Initiator = first party.

Copartent = counter party.

Arbiter = trusted third party (notary).

https://github.com/SmithSamuelM/Papers/blob/master/whitepapers/open-reputation-low-level-whitepaper.pdf

REPUTE

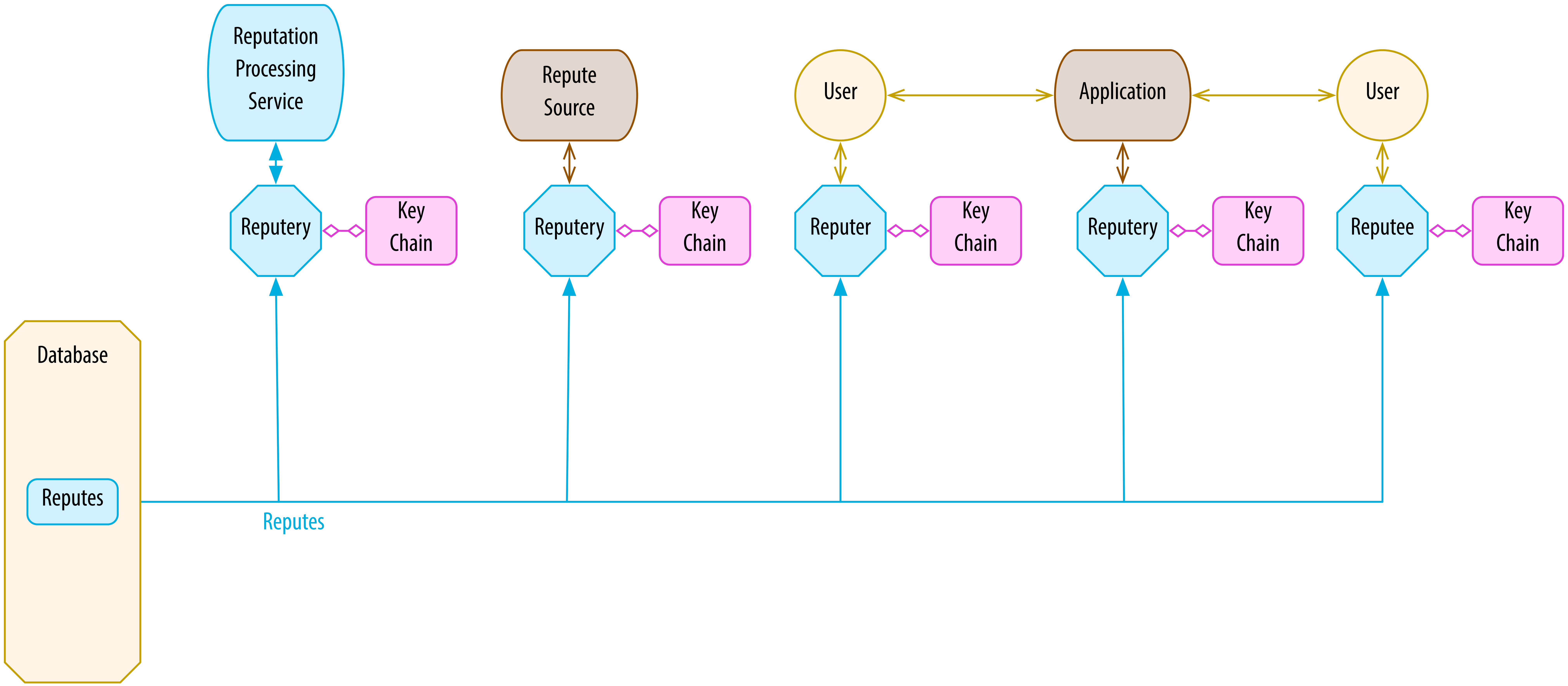

```
{
  "ruid": "bcd456",
  "stamp": "2015-03-19T10:30:45Z",
  "reputee": "z4def6",
  "reputer": "5efa75",
  "curator": "2bcd4",
  "signer": "2bcd4#0",
  "detail":
  {
    "rating":
    {
      "useful": 90,
      "fair": 80,
    },
    "url": "http://myblog.com/article19/"
  }
  "tags": {},
  "reputage": null,
}
/r/n/r/n
"abcdef987654321"
```



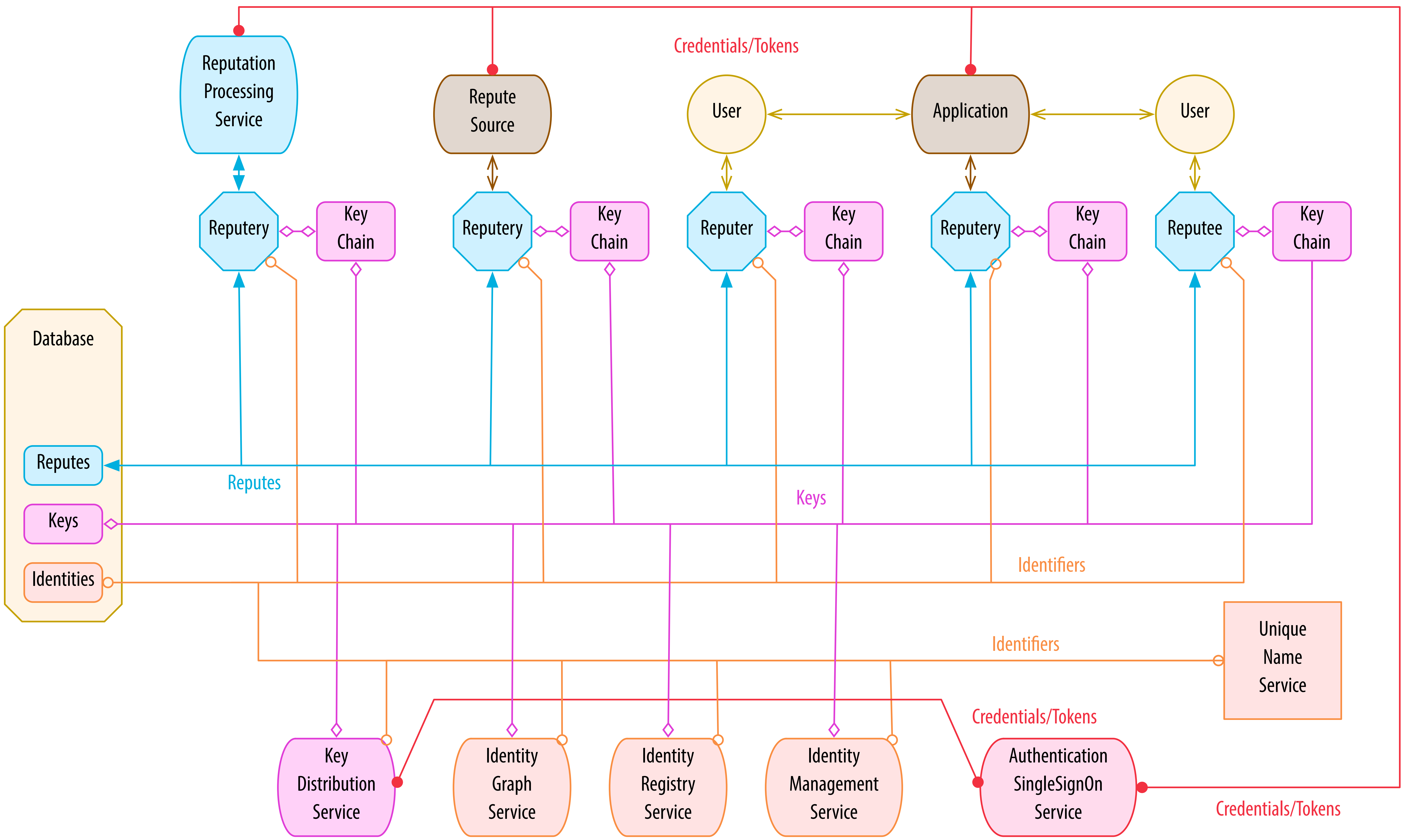
```
{
"puid": "abcefg",
"ruid": "bcd456",
"stamp": "2015-03-19T10:30:45Z",
"comment":
{
  "cuid": "1234abc",
  "url": "http://myblog.com/article19/comment19",
  "contents": "You are so awesome."
}

}
/r/n/r/n
"abcdef9871234567"
}
```

Background

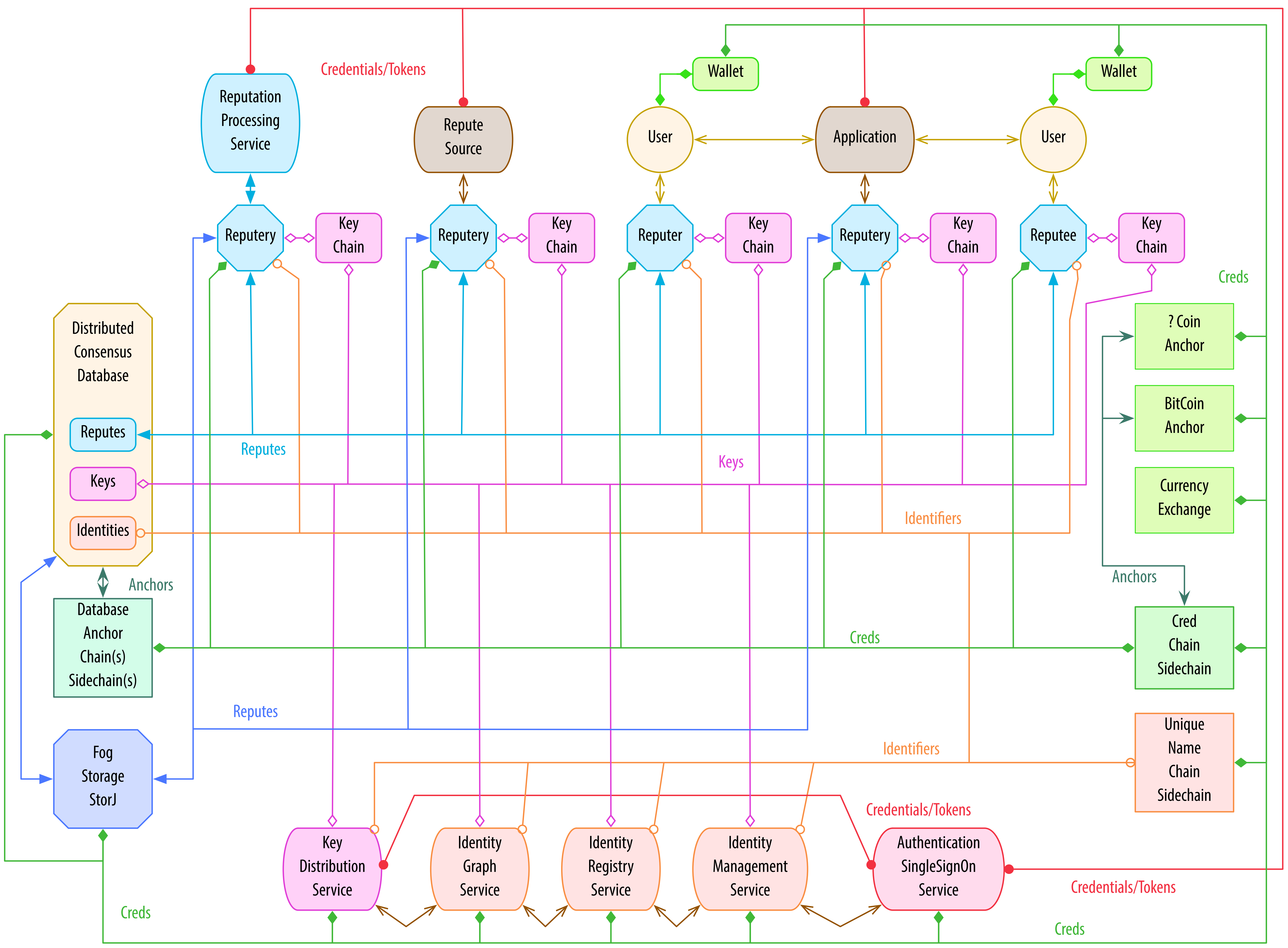
BASIC REPUTATION



Reputation & Identity



Decentralized Reputation System



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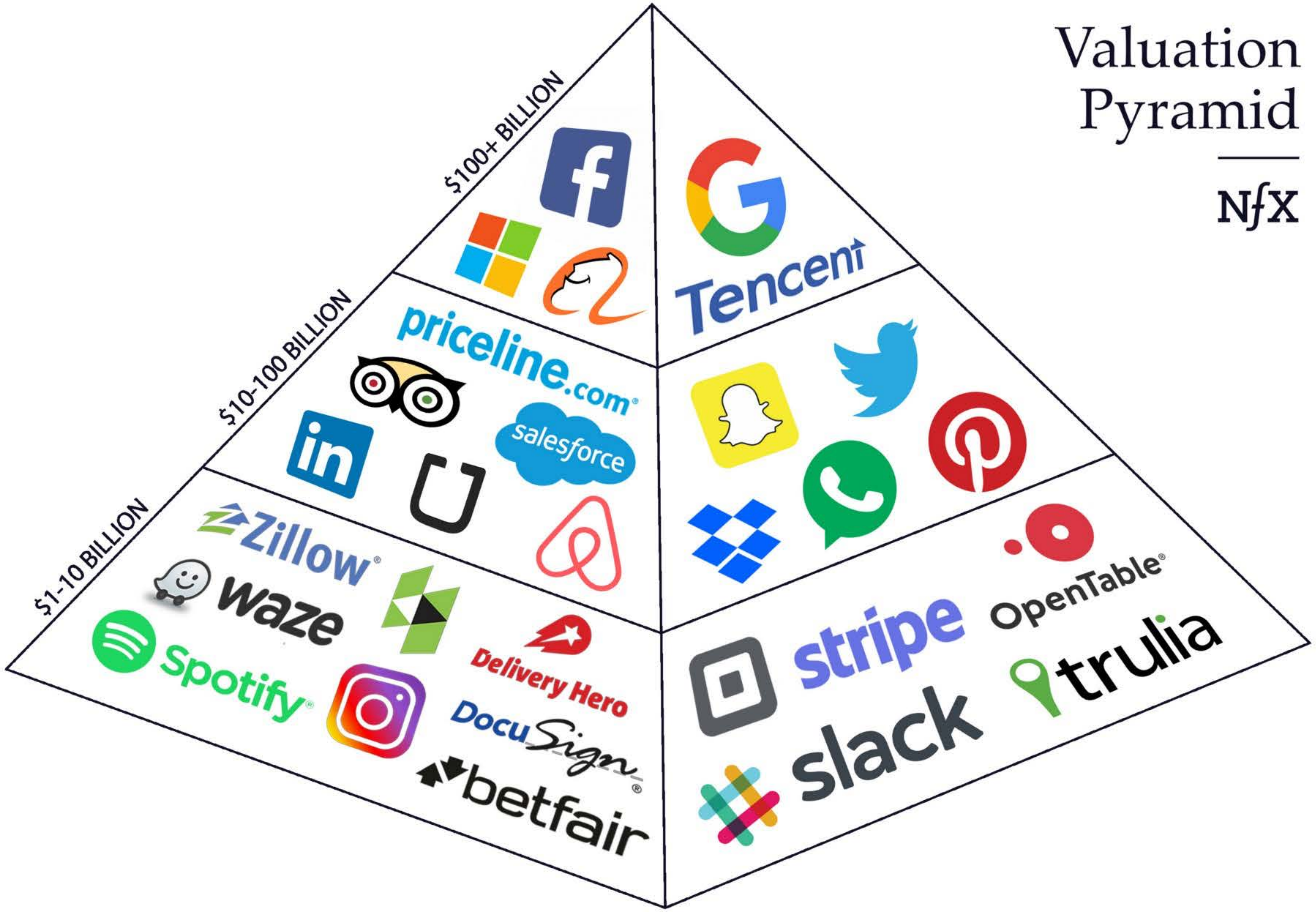
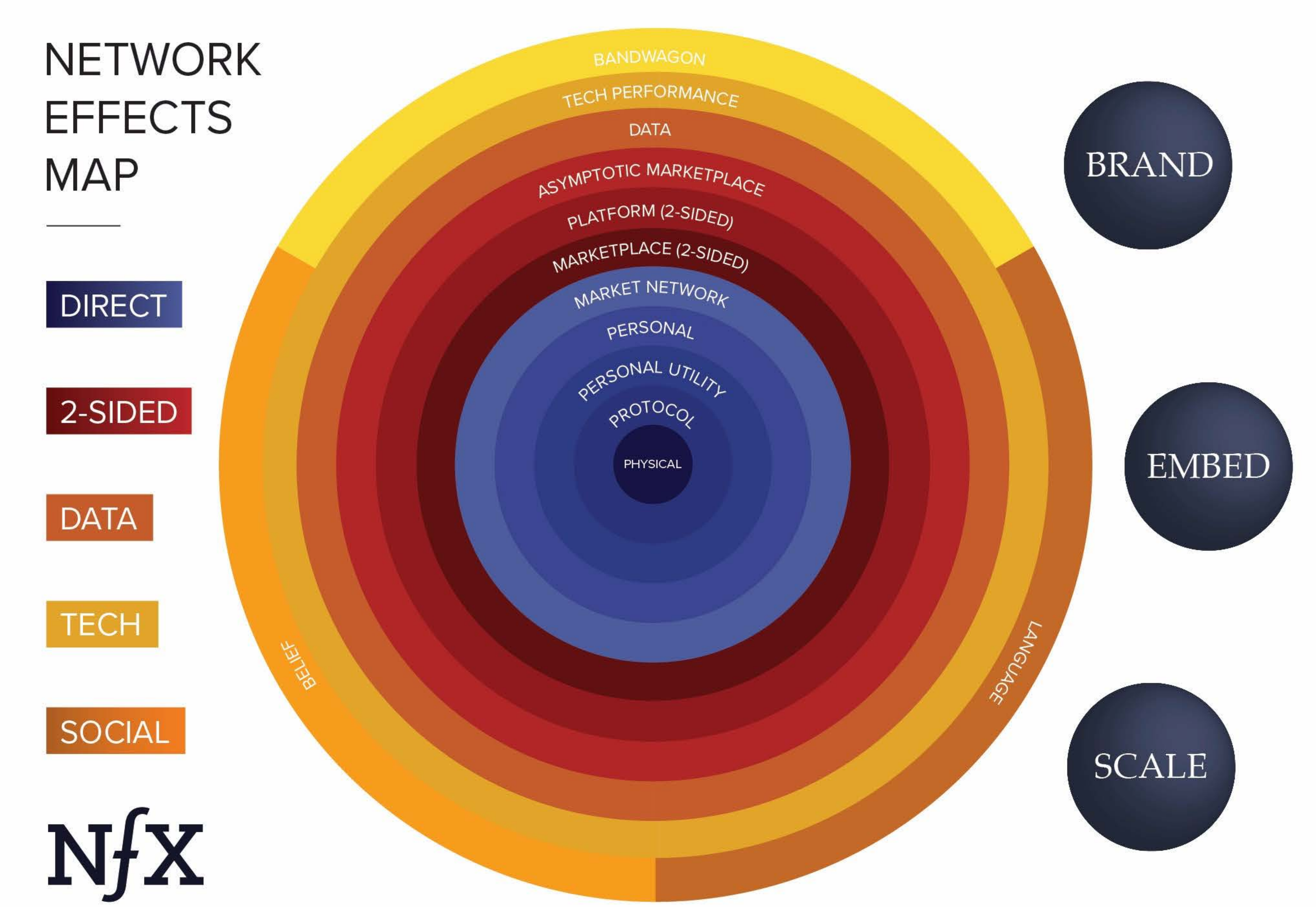
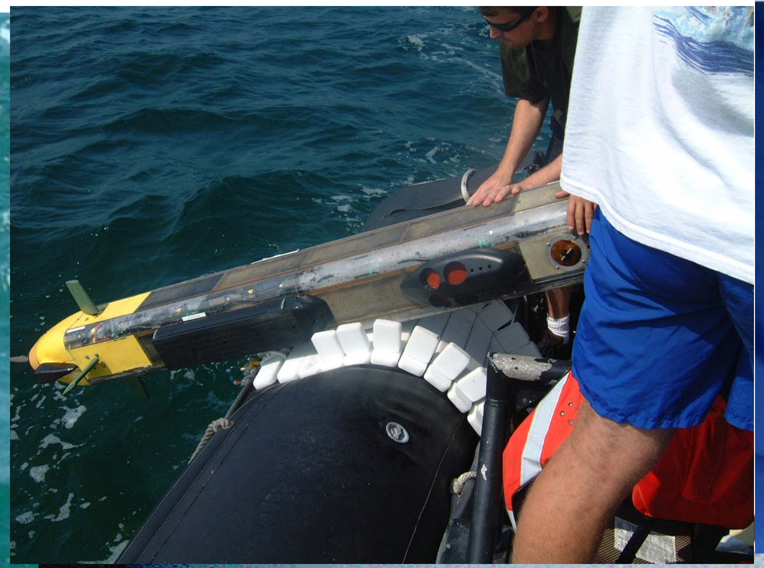
NETWORK EFFECTS

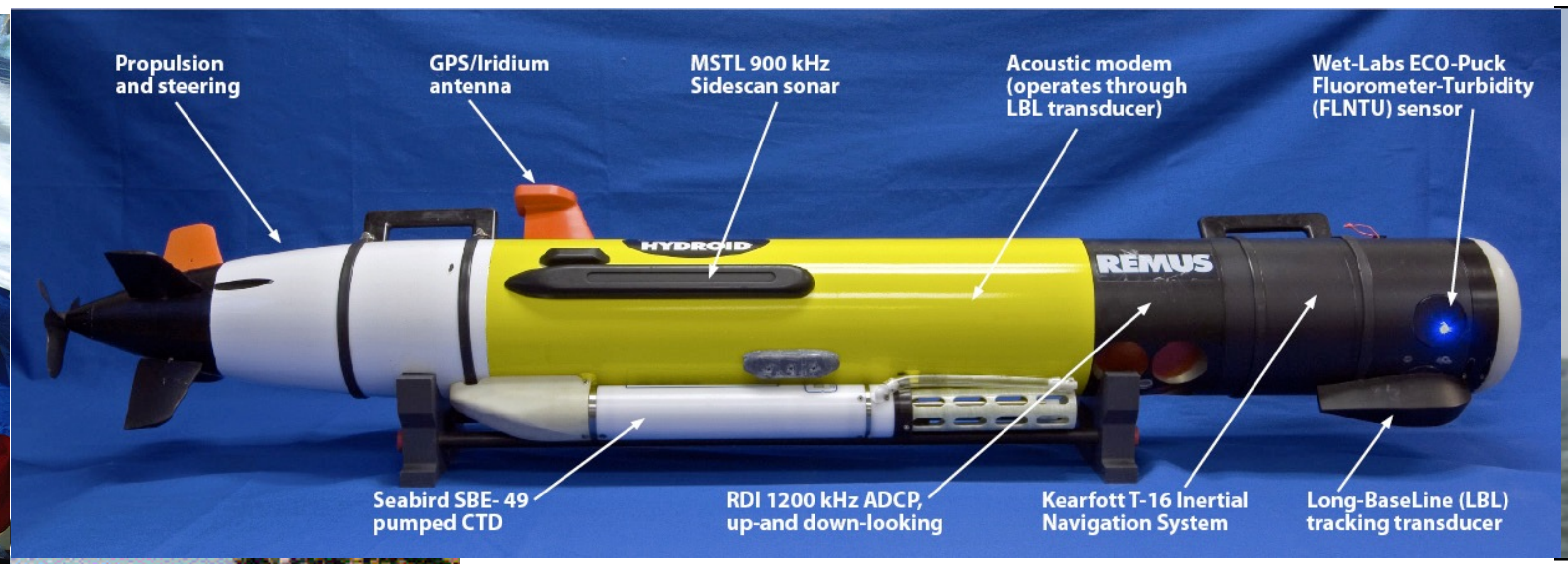


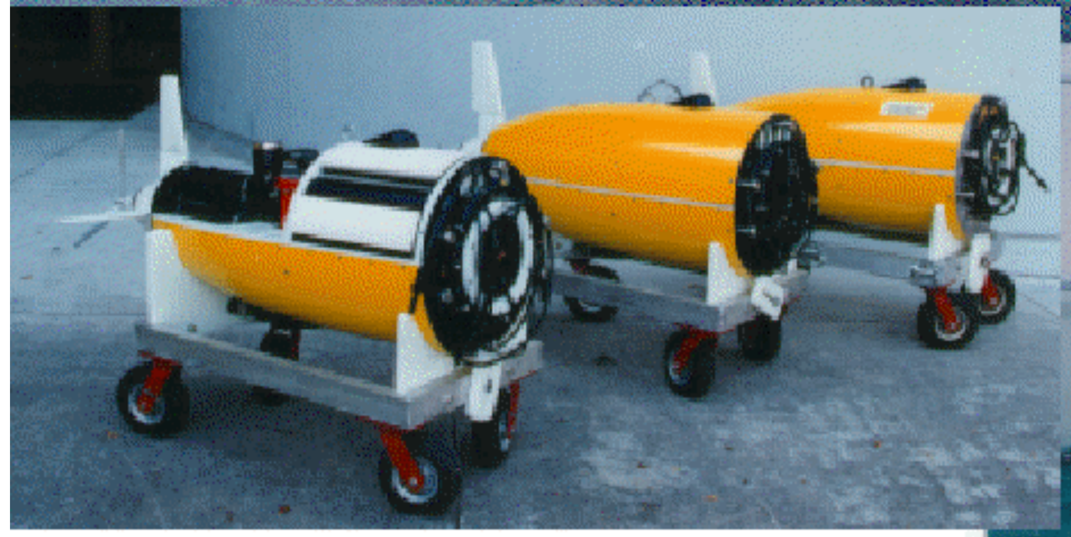
NETWORK EFFECTS MAP

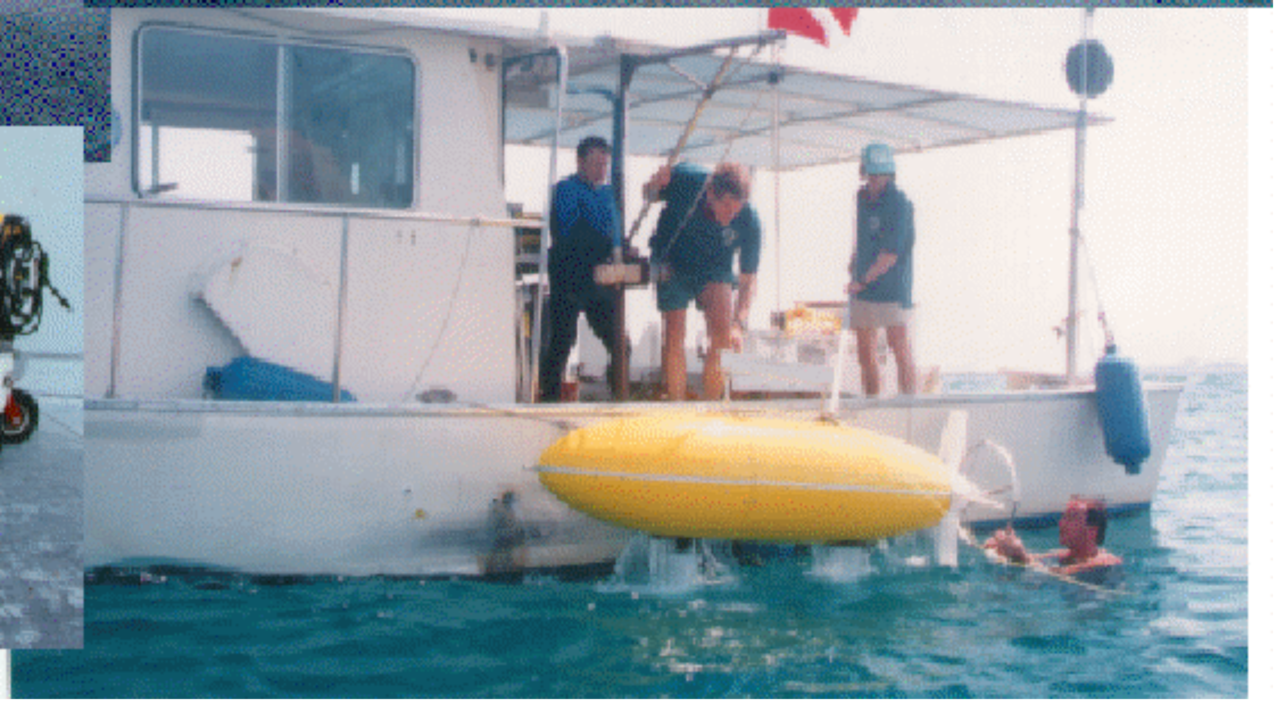


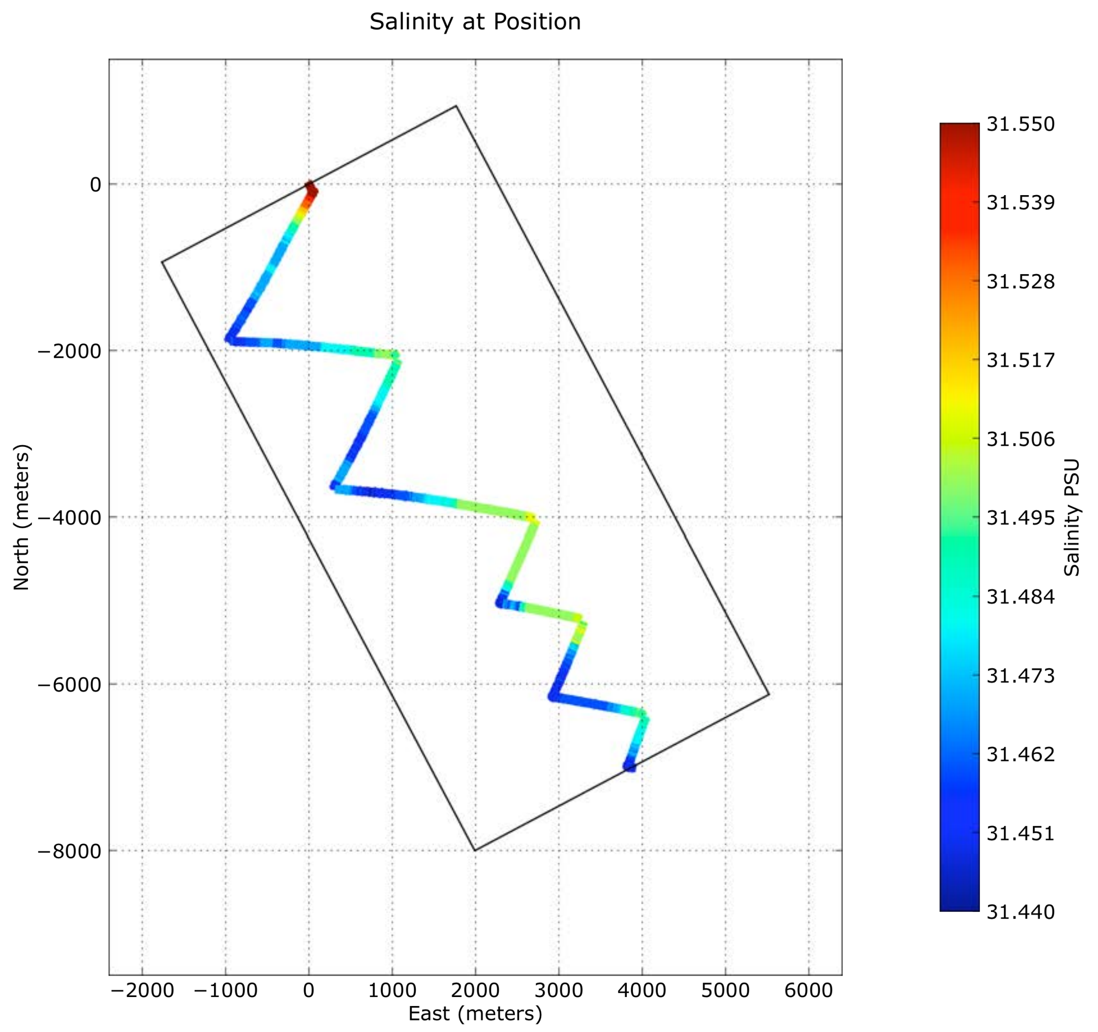
Technical Background:
Autonomous Autonomic Automated



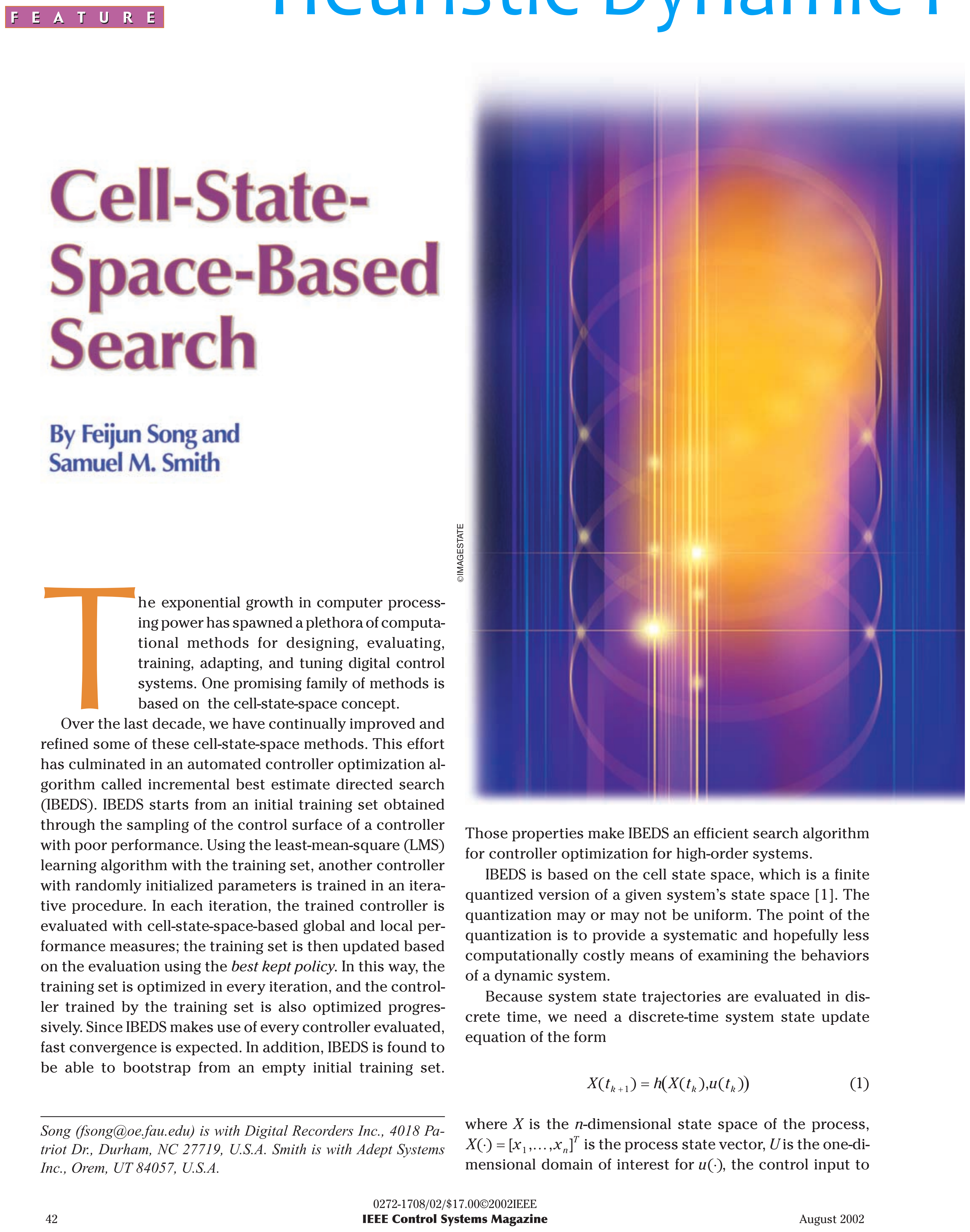








Reinforcement Learning:
Heuristic Dynamic Programming Computational Search



FEATURE

Cell-State-Space-Based Search

By Feijun Song and Samuel M. Smith

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The exponential growth in computer processing power has spawned a plethora of computational methods for designing, evaluating, training, adapting, and tuning digital control systems. One promising family of methods is based on the cell-state-space concept.

Over the last decade, we have continually improved and refined some of these cell-state-space methods. This effort has culminated in an automated controller optimization algorithm called incremental best estimate directed search (IBEDS). IBEDS starts from an initial training set obtained through the sampling of the control surface of a controller with poor performance. Using the least-mean-square (LMS) learning algorithm with the training set, another controller with randomly initialized parameters is trained in an iterative procedure. In each iteration, the trained controller is evaluated with cell-state-space-based global and local performance measures; the training set is then updated based on the evaluation using the *best kept policy*. In this way, the training set is optimized in every iteration, and the controller trained by the training set is also optimized progressively. Since IBEDS makes use of every controller evaluated, fast convergence is expected. In addition, IBEDS is found to be able to bootstrap from an empty initial training set. Those properties make IBEDS an efficient search algorithm for controller optimization for high-order systems.

IBEDS is based on the cell state space, which is a finite quantized version of a given system's state space [1]. The quantization may or may not be uniform. The point of the quantization is to provide a systematic and hopefully less computationally costly means of examining the behaviors of a dynamic system.

Because system state trajectories are evaluated in discrete time, we need a discrete-time system state update equation of the form

$$X(t_{k+1}) = h(X(t_k), u(t_k)) \quad (1)$$

where X is the n-dimensional state space of the process, $X(\cdot) = [x_1,\ldots,x_n]^T$ is the process state vector, U is the one-dimensional domain of interest for $u(\cdot)$, the control input to

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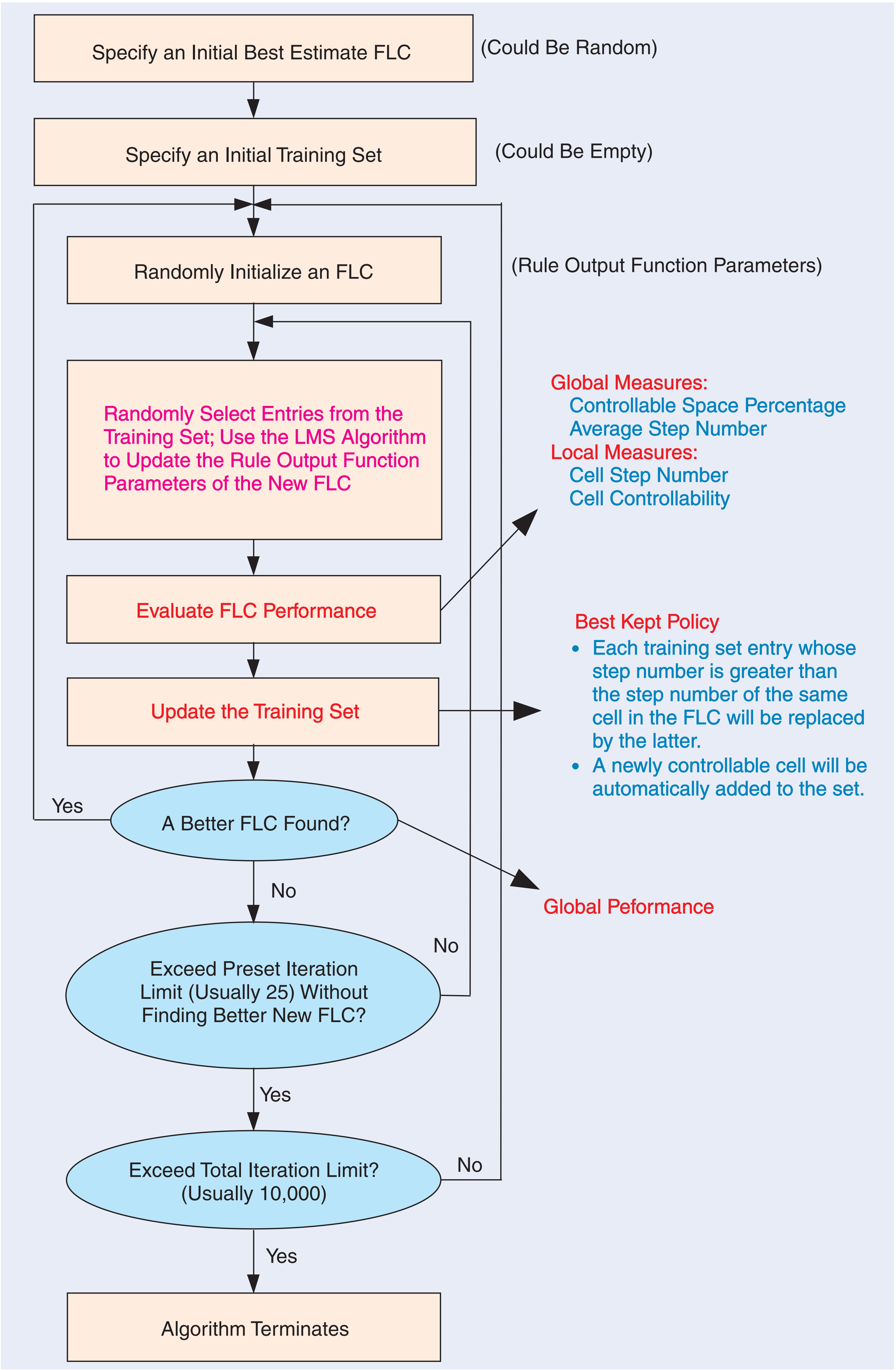

Reputation Business Models

Reputation as a Service (RAAS)

Distributed Autonomic Service (DAS)

Service using autonomic computing algorithms on scalable decentralized computing infrastructure managed by distributed consensus.

distributed AI

RAAS on a DAS

autonomic = self-managing, self-configuring, self-healing, self-optimizing, self-securing