

# A shared understanding between humans and autonomous cyber collectives

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# Situational Awareness

- May have smart sensors, System-of-Systems(SoS).
  - May be distributed SoS over large areas.
  - May have thousands of smart entities (Battlespace).
  - May produce large volumes of data.
- Need to share information with humans.
  - Big Data problem = need to semantically integrate the voluminous data.
  - Aggregate data needs to be summarized to relevant details, in an actionable (i.e. short) timeframe.
- Need to create: sparse yet relevant data stream for shared “world model”.

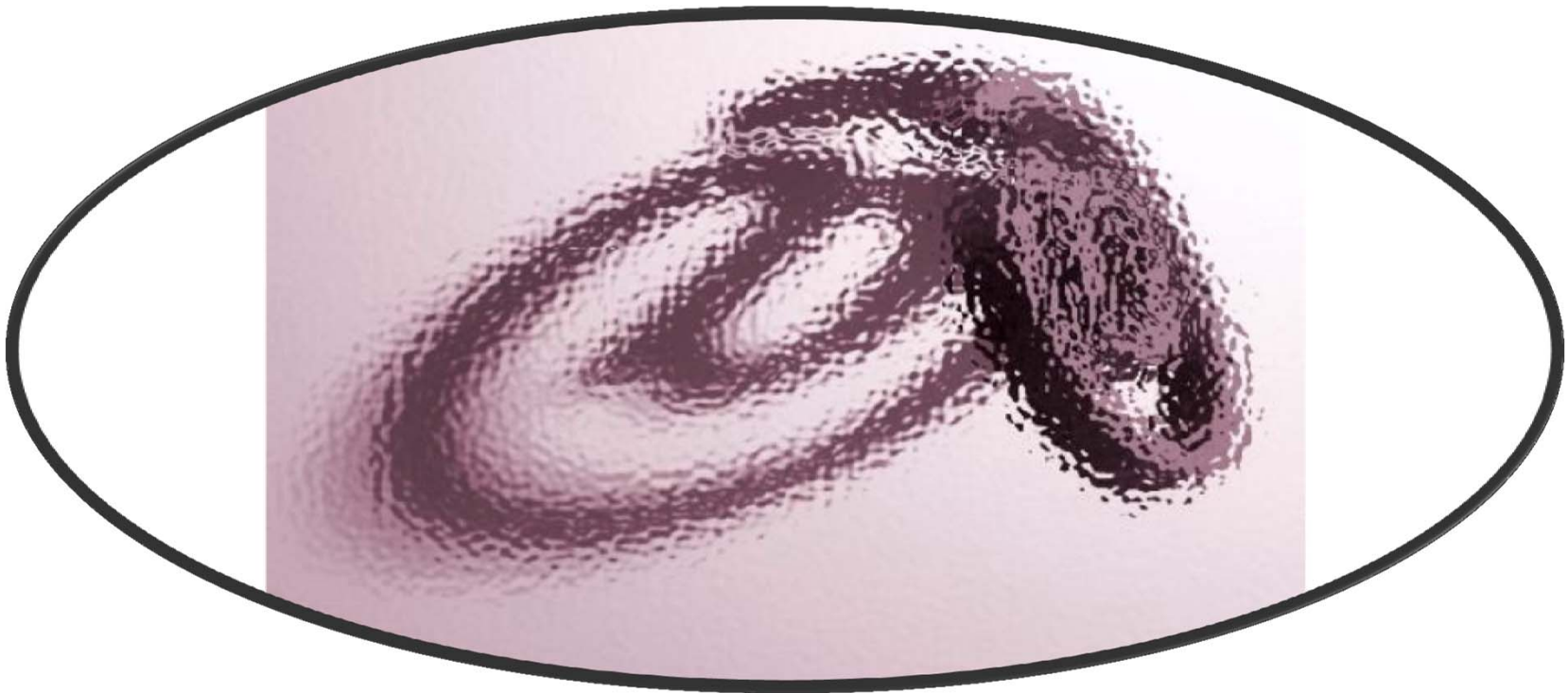
# Problems in Achieving Data Rendering

- Many methods are computationally intensive.
- Want to render Big Data to sparse data without losing relevant information.
  - Nature example: Stigmergy = collective behaviors.
  - How to do this in our synthetic autonomy?
- Leverage off topology for distributed systems.
  - Map topological relationships, each sensor's "perspective" can overlap to derive permutation of shared information = renders to sparse info.

# To What and Where Do We Look?

- Big Data starts out as a “high dimensional” problem.
  - All or most information is there, but too complex or time-consuming to decipher.
  - One solution = reduce dimensionality from higher to lower, preserving relevant information.
- Look at methods to reduce dimensionality from theoretical mathematics, physics, to stigmergy and multivariate analysis.
  - Most methods use a variety of tools from topology.

# Different Perspectives and reflections



# A better understanding

From this:

Transposed to this:



# But How?

- Information is related through multidisciplinary approaches.
- Different areas to look for a common thread:
  - Communication theory
  - Network traffic patterns
  - Complexity science & Chaos theory
  - Topology:
    - braid / knot theory relationships
    - Topological relationships to multi-agent control
    - Clusters and dimensional reduction methods
    - Quantum entanglement
  - Stigmergy (collective self-organization in nature)
  - Sparse data effects in ecosystems

# Highlights of References (1)

1 Paxson and Floyd: Large-scale network *packet traffic does not follow* the anticipated model of *a Poisson distribution*, *but* instead has *a fractal* quality in the way that the packets self-organize into clusters, producing 'burstiness'.

2 Mandelbrot: Observed scaled [self-] similarity (currently called fractal topology) pattern in communication error clusters for signals on telephony transmission lines.

3 Kurlin: Algorithm using topological aspects of *braid theory* plans the *motions of large numbers of robots*. His objective: robots to *traverse* a connected graph or '*map*' of connected paths, *without collisions*.

4 Huebschmann: *Braid theory* and its mapping as multiple strings which cross, which he refers to a "crossed module structure". He later describes what he calls a "permutahedron" as an overlay of a shape originating from a *polyhedron* that is *mapped to higher dimensions*.



# Topological relationships

Knot or Braid Theory can show the shared points as intersections or overlaps between linear data sets. These points shared in common between multiple data sets *might be* a representation of the same observed object, or may indicate some sort of constraint to the systems as a whole.



# Highlights of References (2)

5 Holden, Karlsen and Risebro: Initially starting from differing locations / trajectories, nonlinear weakly coupled degenerate parabolic systems eventually form an 'orbital' state around an attractor. Gives proof of random yet topologically constrained systems self-organizing towards an attractor.

6 Stremler, Ross, Grover, and Kumar: Reciprocal effort to Holden, et al. - provide a method for the analysis of chaos using a topological approach - in this case, braid theory to bound the topological space.

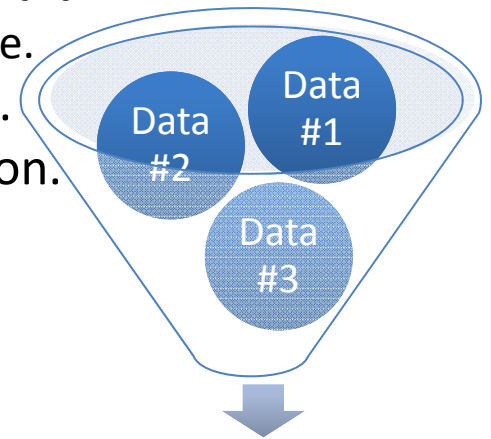
7 Jordache: Nature can cause rules to be created from multi-agent systems interacting with their environment, by a consensus of information, i.e. constraints and convergence for random data in general.

8 Larsen and Speckman: When clusters are not independent, or the clusters are not homogeneous relative to selected dependent variables, this creates a need for multidimensional scaling.

9 Tashkova, Šilc, Atanasova, and Džeroski: Models of ecosystems that are high dimensional and nonlinear with sparse data are tested, and it is shown that global methods are superior to localized methods in this type of case.

# The high dimensional data problem

- Heterogeneous data from many sources – each has its own perspective.
- Composite information is formed from data, but is intractable – why?
  - Because differing time / space observations & sensor resolutions creates multiple, different representations of any object.
  - Each representation may be reduced to a unique dimension, capturing all relevant information. Many representations = many dimensions.
  - Mathematically, n-dimensional matrices computationally hard.
  - N-dimensional topologies are even harder to conceptualize.
- Need to capture relevant details, yet reduce dimensions.
- Algebraically challenging, but possible topological solution.



Composite / aggregate data.

# Highlights of References (3)

**10 Mosseri and Ribeiro:** High dimensional {Hilbert} space may include remotely linked systems or information, defines *quantum entanglement*.

**11 Solomon:** Similar *topological entanglement* = vector cross products shows that entangled state of vector / topological spaces is linked to Braid theory.

**12 Marseguerra and Zoia:** *Multiple inputs from various sensors create a high dimensional* problem space for signal processing. In order to reduce the dimensionality so as to create a more tractable lower dimensional problem space, an autoassociative neural network is chosen.

**13 Yuksel:** *Focused information sharing across distributed systems*, while avoiding some of the dimensionality issues. (Stochastic nestedness). Method uses a Markov chain of distributed information, and incorporates a 'belief' system to supplement missing information. This creates *a recursive optimization pattern of minimum information*. Note that a this type of *recursive pattern is computationally similar to a fractal*. Issue: open question as to whether the selected beliefs would prove valid and sufficient in all cases.

# Highlights of References (4)

**14 Masoumi and Meybodi:** For multi-agent systems of learning automata, a stigmergic learning algorithm with entropy based adaptation can be an improvement over general algorithms.

**15 Sukumar, Jayakumar and Geetha:** High-dimensional problem & methodology - Multiple web services compared, to select the best for certain tasks. Comparisons are made on multiple simultaneous parameters producing mappings that create clusters, each of which represents different criteria (high-dimensional problem).

Dimensional reduction is done using space-filling curves (SFC). The SFC can be thought of as a projection of some higher dimensional data set containing clustered subsets that map to portions of the curve (Fractal structure).

Choosing best SFC: Hilbert SFC shortcomings discussed - limited scalability and mapping irregularities, and failing to successfully map exact cluster patterns. Previous paper cited that mathematically proves the Peano SFC to be superior to the Hilbert SFC.

{Lays groundwork for investigation of novel / adaptive SFCs for better 'fit'.}

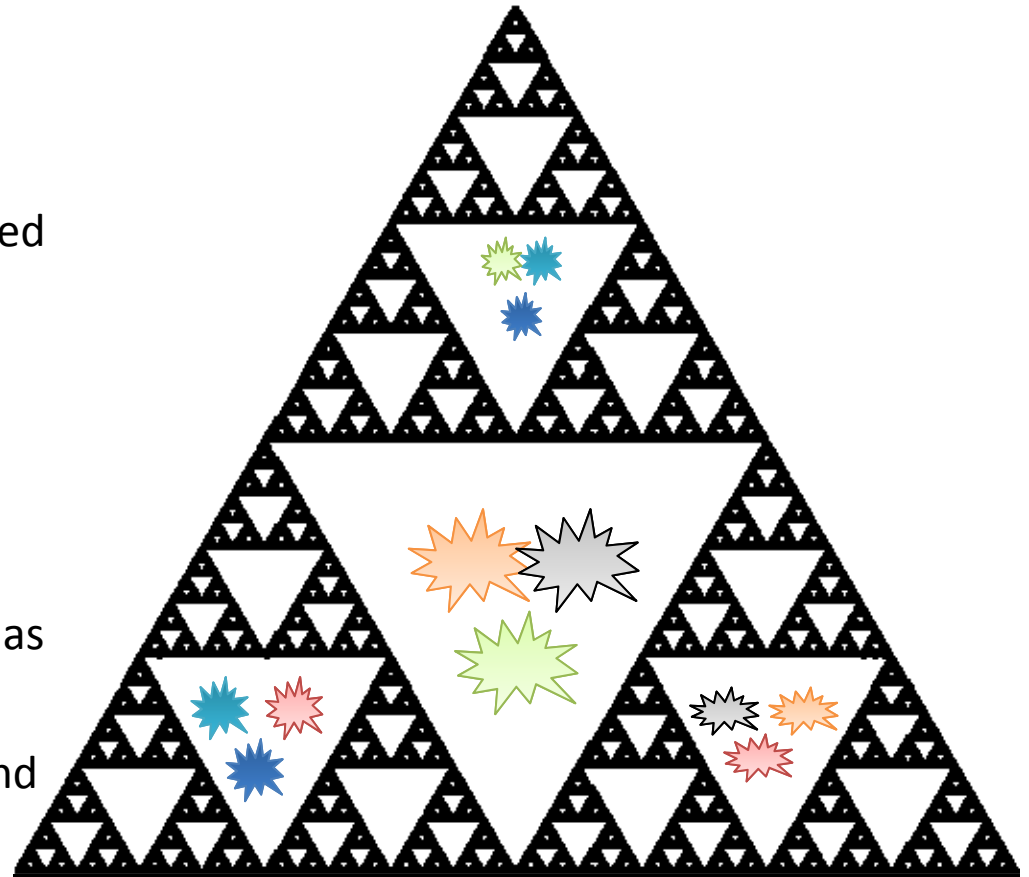
# Conclusions

- Various approaches to large-scale distributed information.
- Topological approaches provide some mathematically tangible methods.
- Fractal curves both can be dimensional reduction of high-dimension space, and provide bounding conditions for multi-cluster relationships.
- Current fractals are statically limited, use an adaptive fractal method.

# Non-overlapping topology relationships – multiple clusters

Capturing relationships for multiple cluster-of-cluster topologies, while reducing dimensionality:

- Non-stochastic solution is needed (preserve interrelationship details).
- Possible non-integer resulting dimensionality.
- Various self-similar curves have had success in the past – e.g. fractal models.
- Resulting curve / map emerges as the abstraction of complex collective interrelationships, dictated by world constraints and objectives or goals the autonomous systems .



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# Acronyms

- SoS – System of systems
- SFC – Space-filling curves