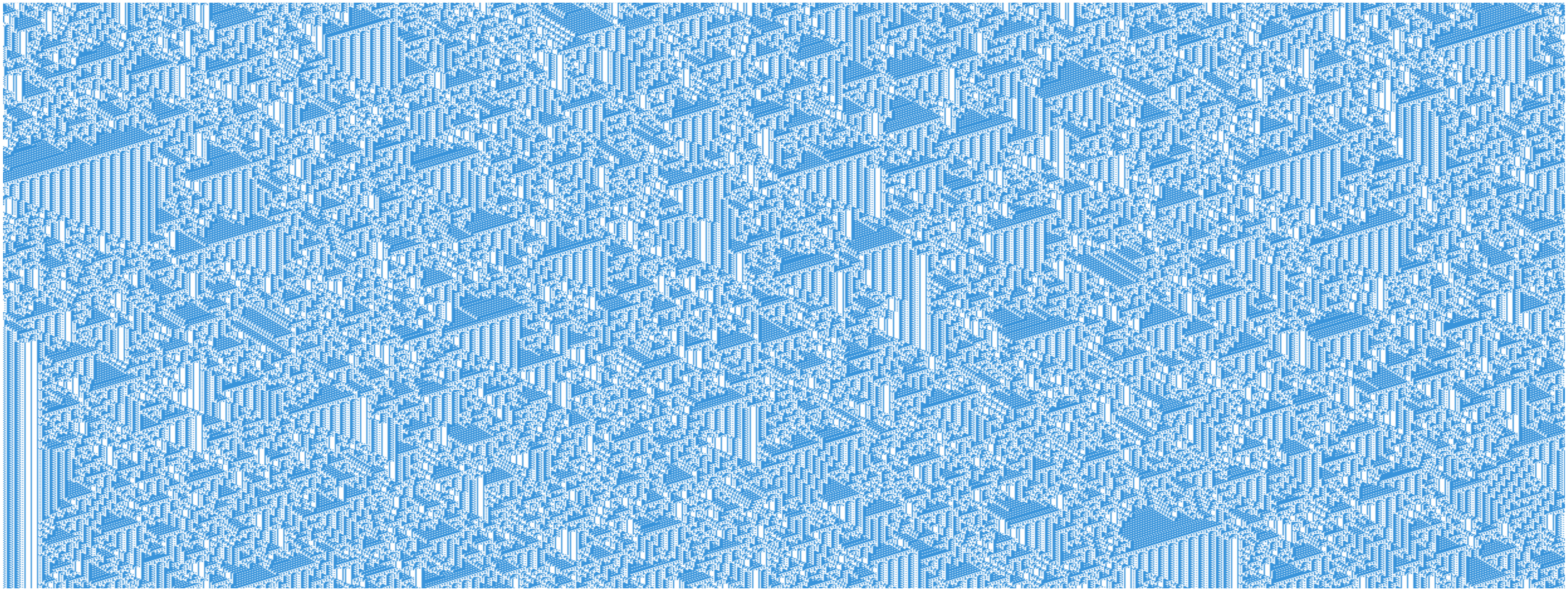
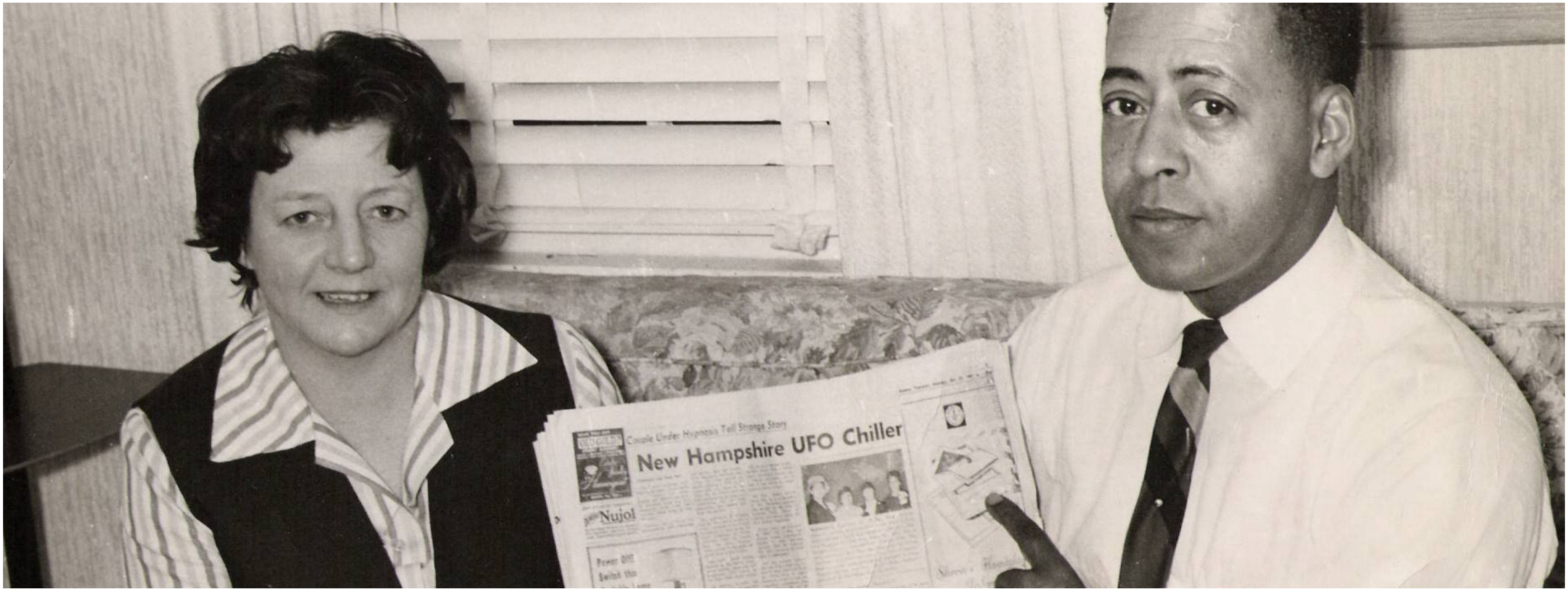


ITERATED ABDUCTION

Joshua Eckroth
Math/CS Colloquium
Stetson University
October 21, 2015



THE ABDUCTION OF BARNEY AND BETTY HILL

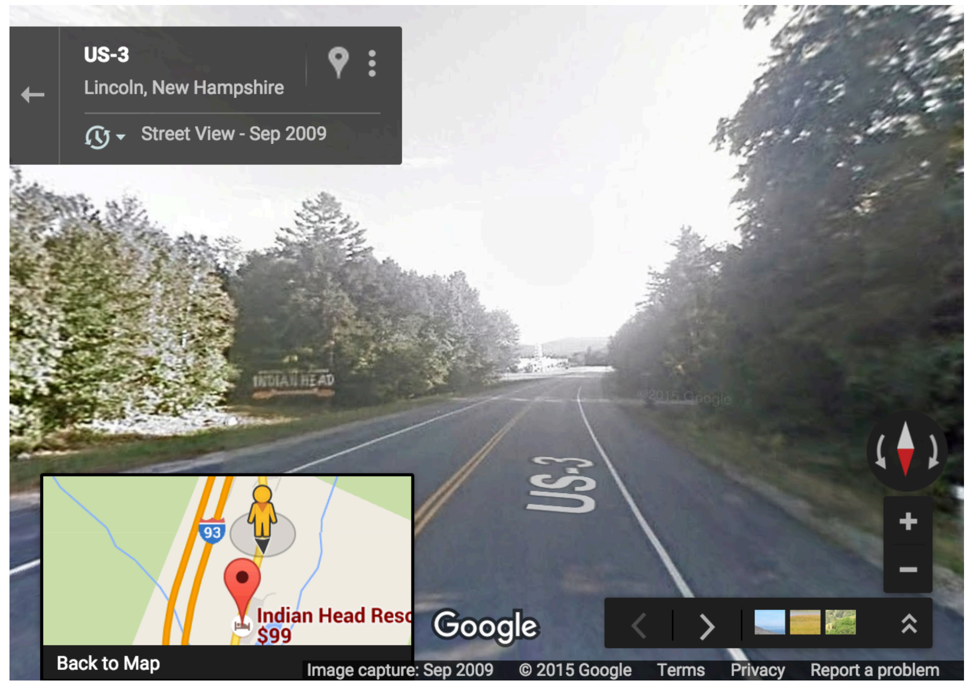
September 20, 1961
New Hampshire, USA

THE EVIDENCE

Barney and Betty were driving south on Route 3 near Lincoln, New Hampshire. Around 2am on September 20, 1961, they noticed a strange object in the sky.

They watched the object for several minutes, then stepped out of their car and observed it with binoculars.

They later reported the object approached to within a few hundred feet and appeared to be a flying machine of unknown origin. They could see humanoid faces in the windows.



THE EVIDENCE

While looking at the faces in the windows, they both experienced short bursts of loud buzzing in their heads.

They quickly got back in their car and drove away, arriving shortly after in Ashland, 30 minutes to the south.

Later, they could not account for 2 hours of missing time. Nor did they remember driving to Ashland.

Under hypnosis a year later, they both stated they were taken aboard the craft, and were subjected to tests.

Betty said the aliens were five feet tall, had bluish-gray skin, dark hair, large noses, eyes like a cat.

Barney said the aliens had large craniums, metallic gray skin, large eyes that continued to side of head, no nose (just nostril slits).

WHAT CAN EXPLAIN THEIR STORY?

THE EVIDENCE (PART 2)

Jacques Vallee stated in 1989 that military radar at Pease Air Force Base had recorded the object seen by the Hills that night.

The Hills were very stressed out around the time of the incident, partly due to social pressure about being an inter-racial couple, their involvement in civil rights campaigns, and their drive home to avoid bad weather.

Twelve days before Barney Hill stated, under hypnosis, that the aliens had eyes that wrapped around the side of their heads and no nose, an episode of *The Outer Limits* aired with aliens having similar eyes and nose.

ABDUCTION VS. ABDUCTION

Barney and Betty Hill may have been abducted.

abduction: from the Latin *abductionem*;
derived from the verb *abducere*,
from *ab*- “away” and *ducere* “to lead”

Deciding whether that is the case, not from deduction but from hypothesizing, testing hypotheses, and selecting the best consistent set of hypotheses that are most explanatory, is called **abduction**, a.k.a., **abductive reasoning, abductive inference.**

CHARLES S. PEIRCE (1839-1914)

Peirce coined the term “abduction” to mean a kind of non-deductive inference that was distinct from *induction*. A kind of **reverse deduction**.

“*Abduction is the process of forming explanatory hypotheses. It is the only logical operation which introduces any new idea*.”

Deduction is for testing theories (prediction). The result is “already known” in a sense.

Induction is for reaching a verdict on hypotheses, based on the number of testable hypotheses that have been verified.

DEDUCTION, INDUCTION, ABDUCTION

DEDUCTION

I took a marble from that bag.

All the marbles in that bag are blue.

Therefore, this marble is blue.

DEDUCTION (AGAIN)

All the marbles in that bag are blue.

I took a marble from that bag.

Therefore, this marble is blue.

Propositional logic:

Bag → Blue

Bag

∴ Blue

INDUCTION

I took a marble from that bag.

The marble is blue.

I took another marble, and it is blue also…

Therefore, all marbles in that bag are blue.

INDUCTION

I took a marble from that bag.

The marble is blue.

I took another marble, and it is blue also…

Therefore, all marbles in that bag are blue.

Propositional logic:

Bag $\wedge$ Blue

Bag $\wedge$ Blue …

$\therefore$ Bag $\rightarrow$ Blue

ABDUCTION

All the marbles in that bag are blue.

This marble is [oddly] blue.

Therefore, this marble came from that bag.

ABDUCTION

All the marbles in that bag are blue.

This marble is [oddly] blue.

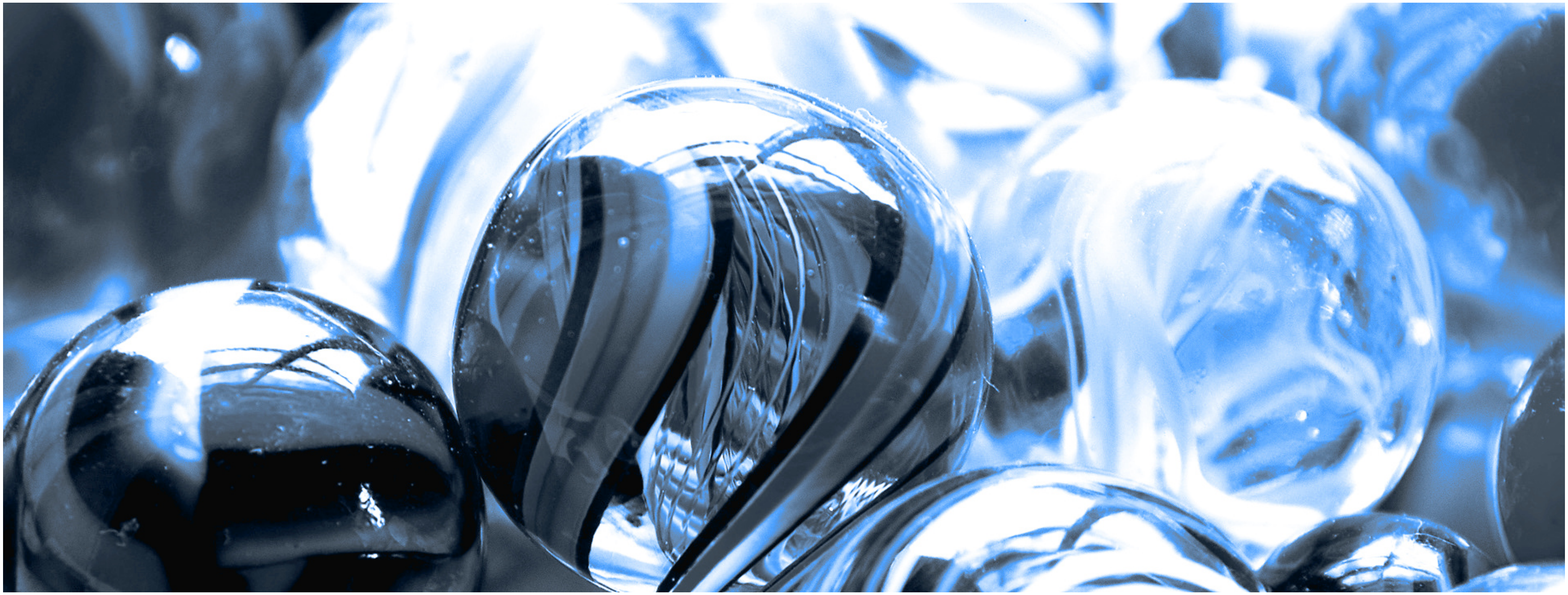
Therefore, this marble came from that bag.

Propositional logic:

Bag → Blue

Blue

∴ Bag



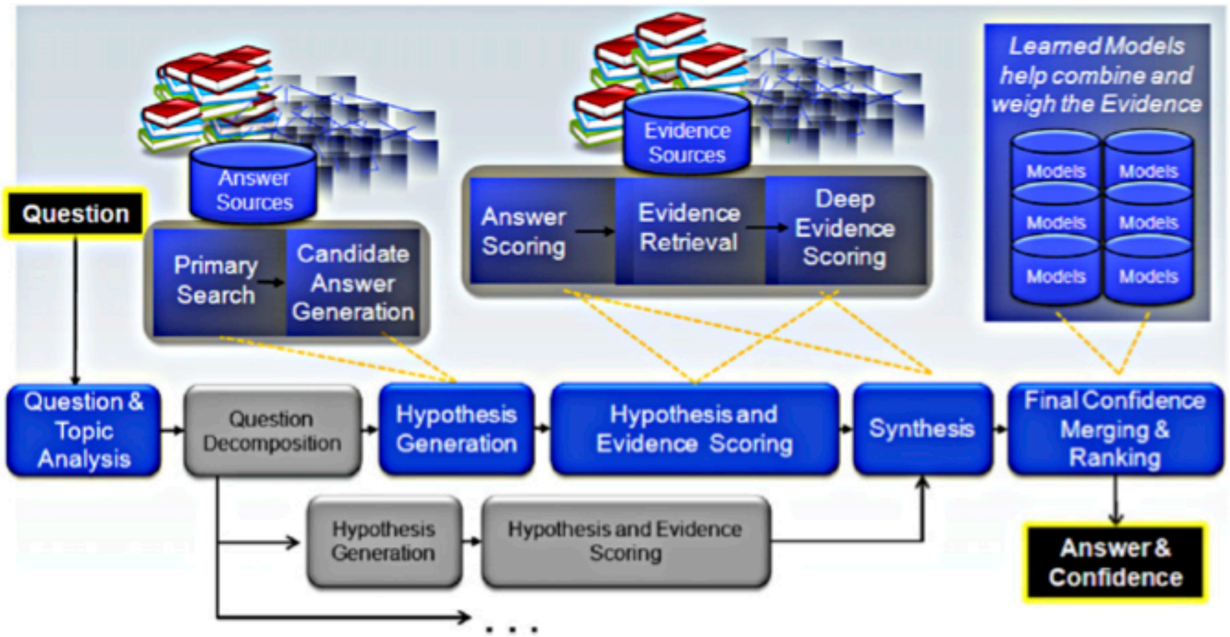
ABDUCTION IN THE WILD

IBM WATSON

IBM's *Jeopardy!*-winning Watson system explicitly used abductive reasoning.

"DeepQA analyzes an input question to determine precisely what it is asking for and generates many possible *candidate answers* through a broad search of large volumes of content. For each of these candidate answers, a *hypothesis* is formed […] For each hypothesis, DeepQA spawns an independent thread that attempts to prove it. […] The final result of this process is a ranked list of candidate answers, each with a confidence score indicating the degree to which the answer is believed correct, along with links back to the evidence." [1]

WATSON'S DEEP-QA ARCHITECTURE



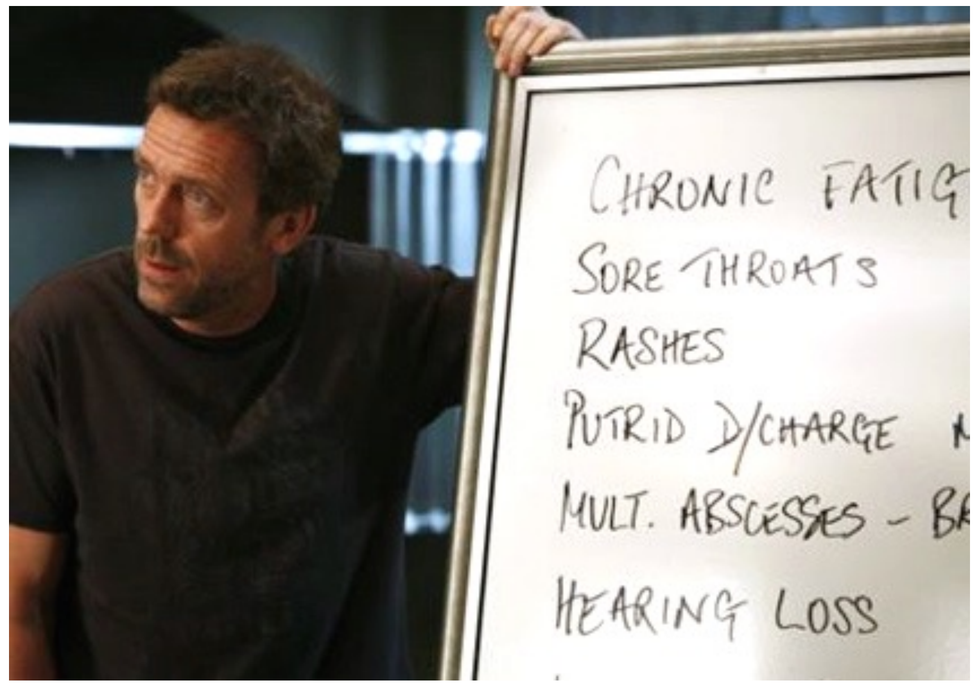
MEDICAL DIAGNOSIS

"First, I obtain the case facts from the patient's history, physical examination, and laboratory tests.

Second, I evaluate the relative importance of the different signs and symptoms.

Third, I list all the diseases which the specific case can reasonably resemble.

Then I exclude one disease after another…" [2]



COMMONSENSE REASONING

"You come into your house late at night, and notice that the light in your room, which is always left on, is off.

It has been raining very heavily, and so you think some power line went down, but the lights in the rest of the house work fine. […]

Finally, a simpler explanation crosses your mind. Maybe the light bulb in your lamp is out, and needs replacing." [3]

SCIENTIFIC REASONING

The Scientific Method is explicitly abductive:

1. Generate a hypothesis.
2. Gather evidence to test the hypothesis.
3. Ultimately, evaluate this hypothesis against others in light of the evidence.
4. The hypothesis that explains best is *probably* correct.

SUMMARY

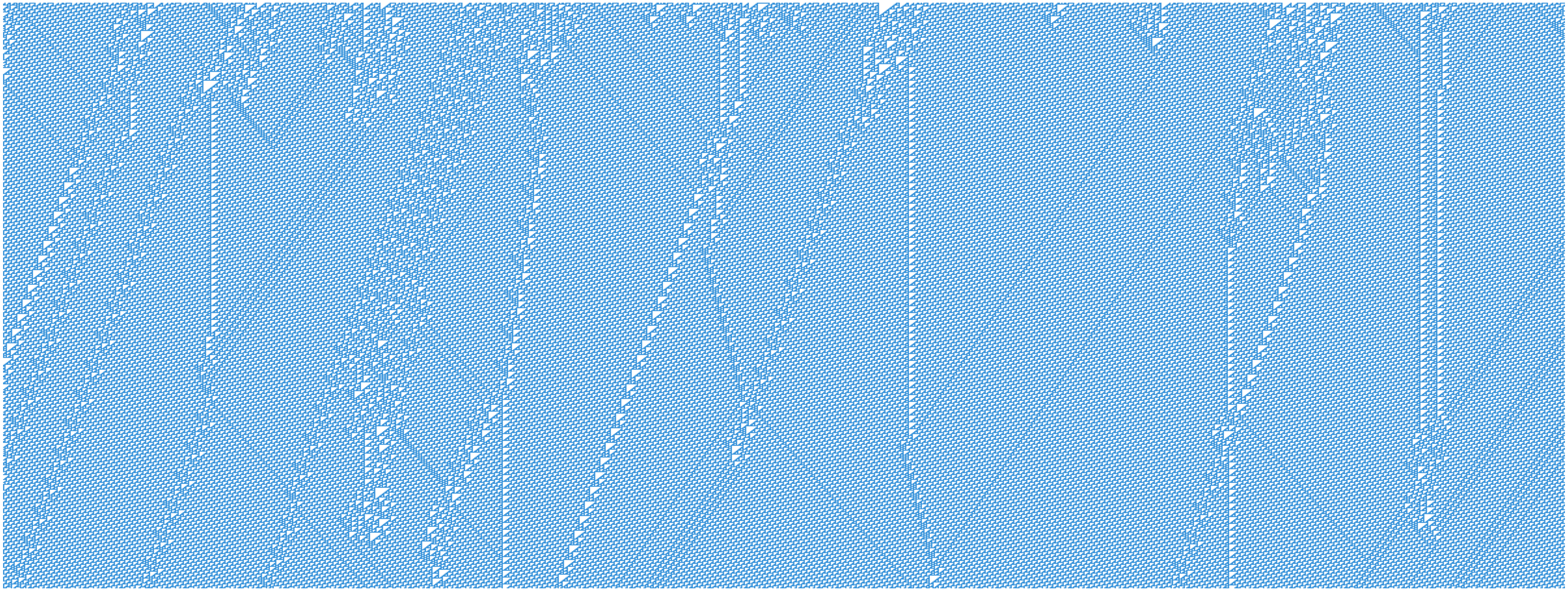
Abduction is a kind of reverse-deduction:

What would have to be true
for the evidence to make sense?

Abduction is *ampliative*: it introduces new knowledge.

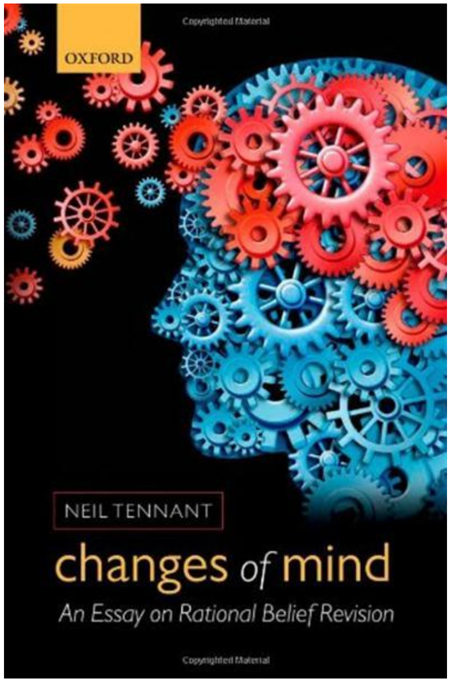
It is a common feature of cognition and truth-seeking.

What (may have) happened to the Hills has the same etymology but, technically, isn't the same thing.

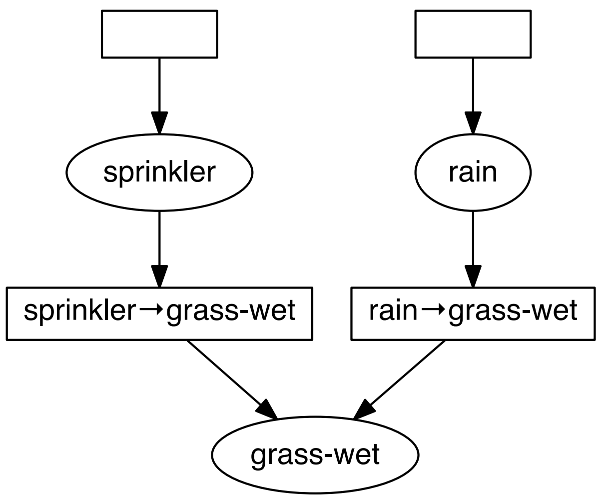


BELIEF DYNAMICS

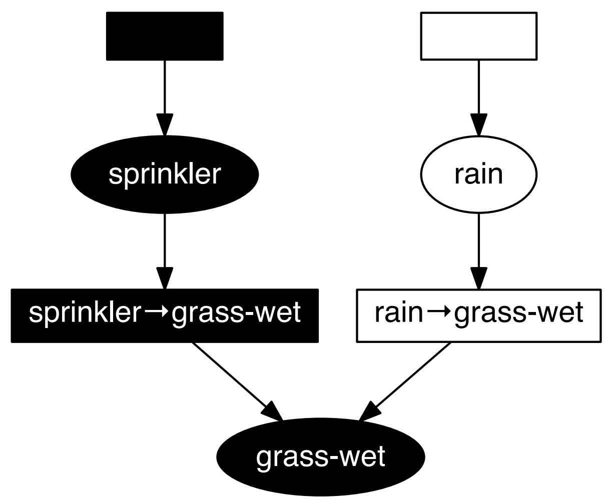
TENNANT'S "FINITE DEPENDENCY NETWORKS"



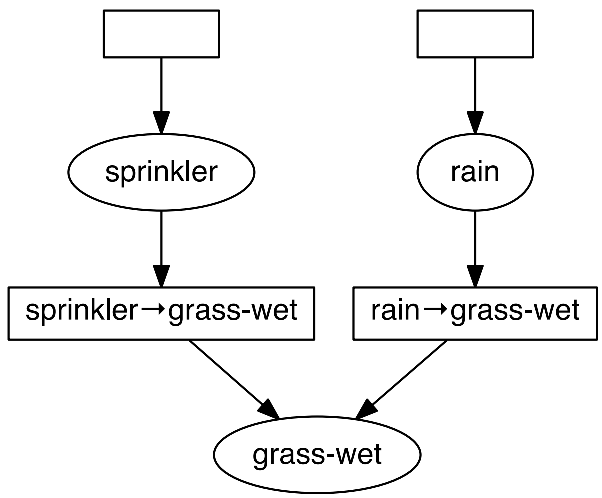
HOW GRASS IS MADE WET



EXPANDING BY "SPRINKLER"



CONTRACTING BY “GRASS WET”



MORE EXAMPLES

FDN RULES

A finite dependency network consists of **nodes, strokes,** and **arrows.**

A black node is **believed,** a white node is **disbelieved**.

Each node points to one or more strokes with an arrow.

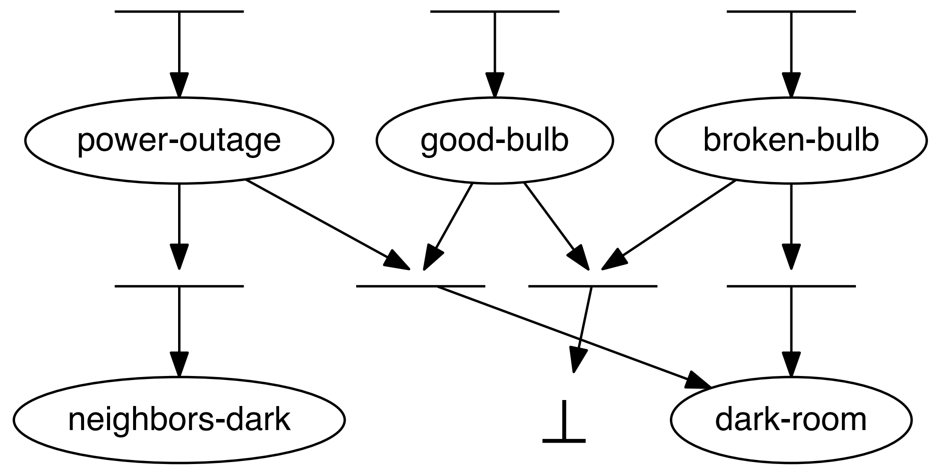
Each stroke points to exactly one node.

A stroke with no incoming nodes is a **starting stroke.**

A node with incoming arrows only from starting strokes is an **initial node.**

FDN RULES

Inconsistencies can be represented using a special node known as ⊥ ("bottom"), which must stay white.



FDN RULES

(C1) Every black node receives an arrow from some black stroke.

(C2) Every white node receives arrows (if any) only from white strokes.

(C3) Every black stroke receives arrows (if any) only from black nodes.

(C4) Every white stroke that receives an arrow receives an arrow from some white node.

(C5) The special node $\perp$ (“bottom”) is always white.

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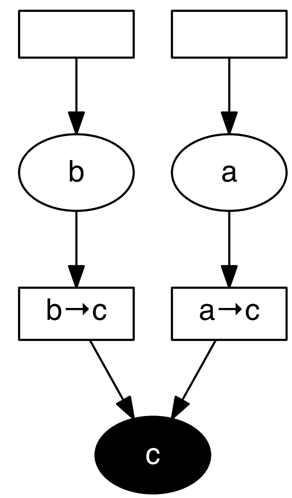

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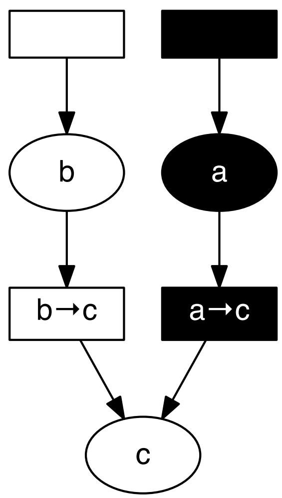

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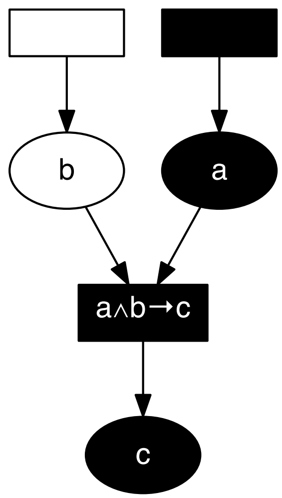

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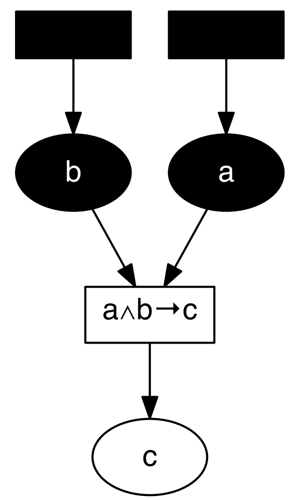

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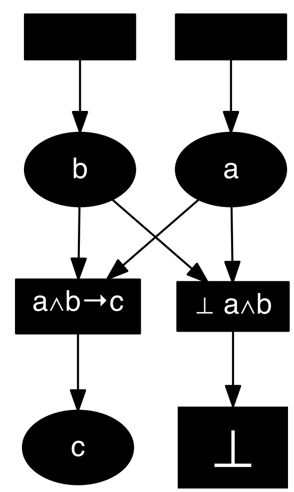
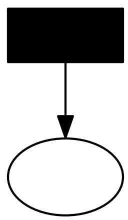
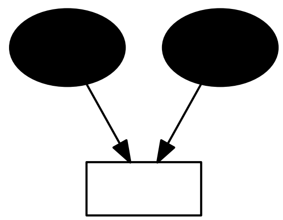


EXPANSION (SPREADING BLACK)

Deterministic expansion patterns:



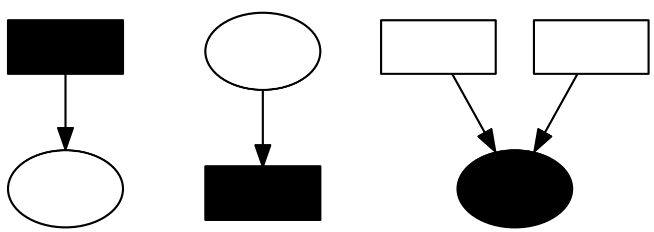


EXPANSION ALGORITHM

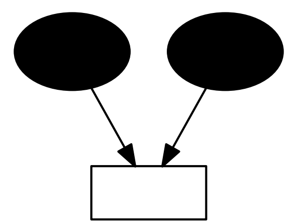
1. If the network satisfies all rules, we are done.
2. Otherwise, find all deterministic “bad” nodes and strokes and color them black. Repeat from step (1).

CONTRACTION (SPREADING WHITE)

Deterministic contraction patterns:



Nondeterministic contraction pattern:



CONTRACTION ALGORITHM

1. If the network satisfies all rules, we are done.
2. Otherwise, find all deterministic "bad" nodes and strokes and color them white. Repeat from step (1).
3. If no deterministic bad nodes or strokes exist, gather all non-deterministic bad nodes. Choose one such node, according to a heuristic, and color it white. Repeat from step (1).

P≠NP

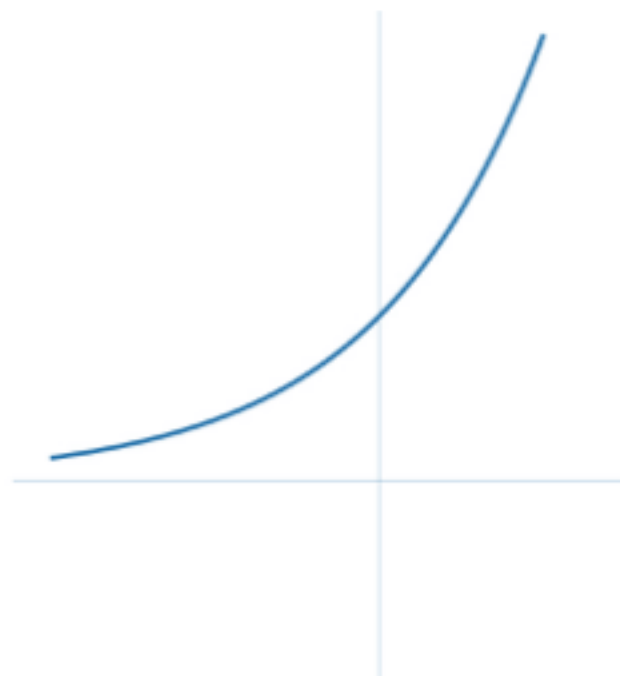
Finding a minimal contraction is NP-complete.

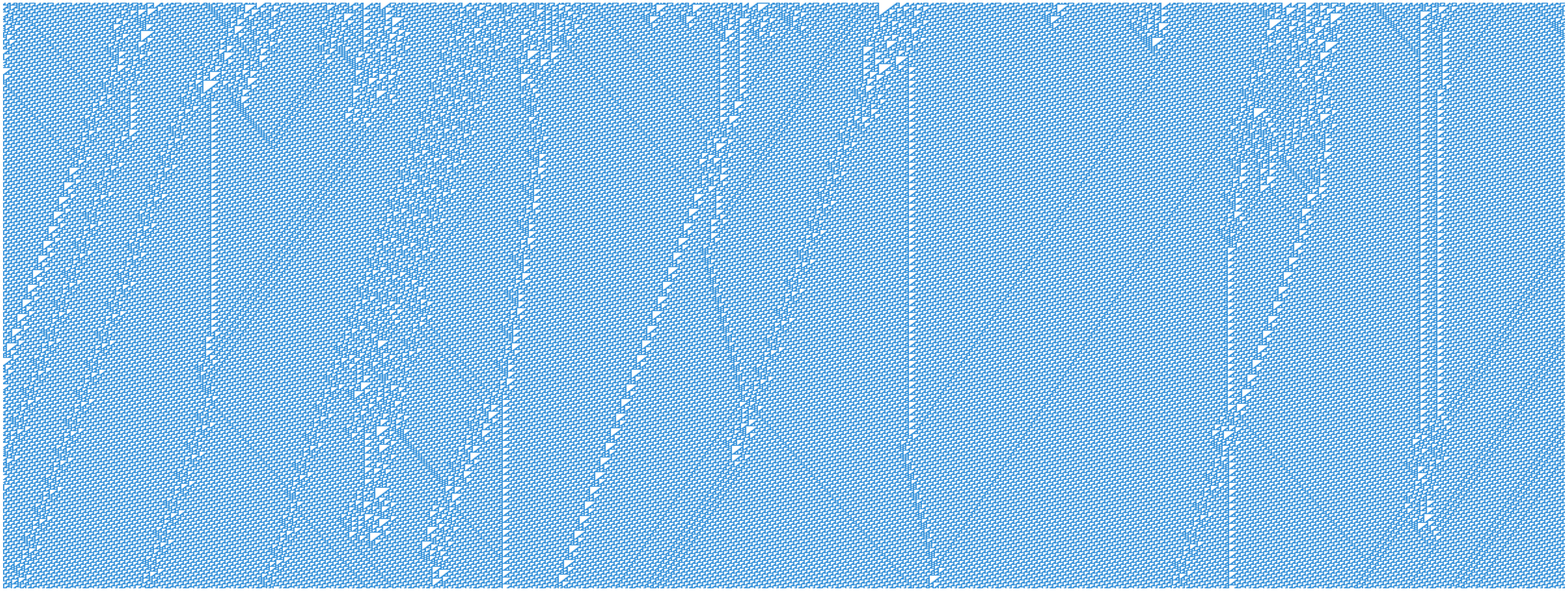
(Technically, the decision-problem variant is NP-complete, by reduction to Vertex Cover.)

So there is no hope in efficiently finding a minimal contraction for all scenarios.

Heuristics are needed.

Heuristics are *only* needed for *nondeterministic* node selection.





BEYOND EXPANSION AND CONTRACTION: ABDUCTION AND ITERATED ABDUCTION

DESIDERATA FOR AUTOMATED REASONING

1. Supports deduction.
2. Supports abduction.
3. Supports contraction: taking back a belief also takes back whatever the belief implies, whatever implies the belief, etc. recursively.
4. Supports iterated abduction: if an explanation is contracted, and an alternative explanation is available, assert the alternative.

NEW SYSTEM: PARAGON

1. Starts with Tennant's finite dependency networks.
2. Adds abduction.
3. Adds iterated abduction.
4. Supports custom contraction and abduction heuristics.
5. Adds visualization.
6. Published as a Clojure/Java library with a permissive license.

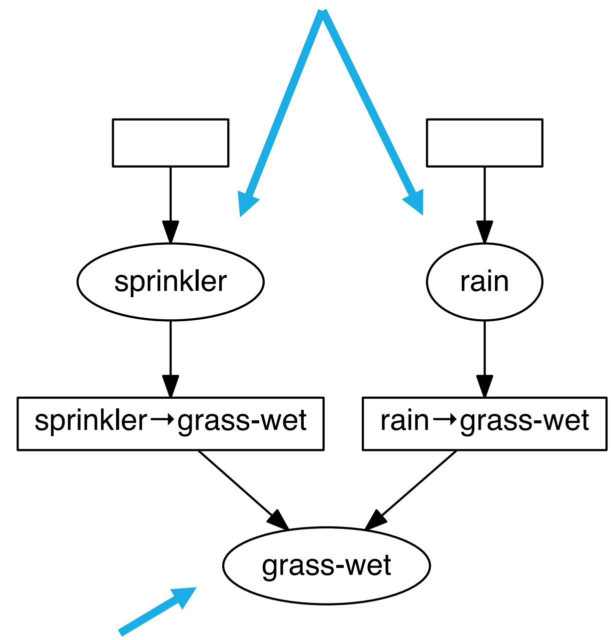
PARAGON ASSUMPTION

In terms of **abduction:**

A node with incoming non-starting strokes is a node that **requires explanation.**

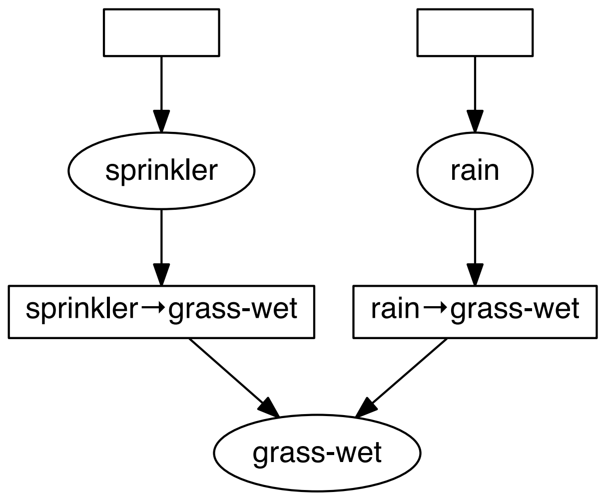
An initial node is a node that **does not require explanation.**

Does not require explanation

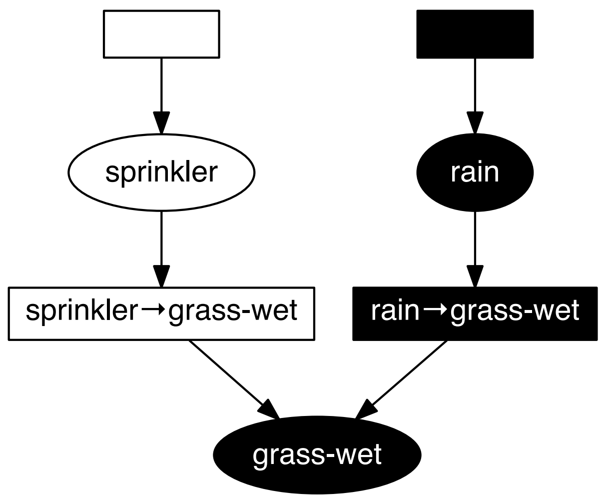


Requires explanation

HOW GRASS IS MADE WET

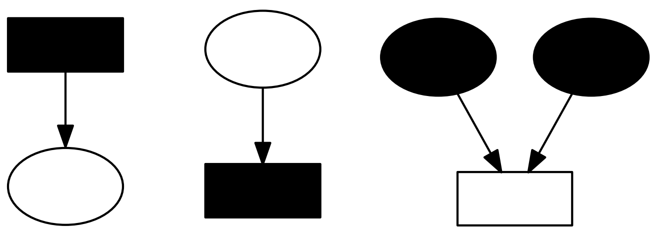


ABDUCING AN EXPLANATION FOR WET GRASS

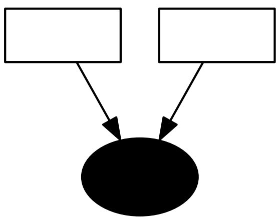


ABDUCTION (SPREADING BLACK)

Deterministic abduction patterns:



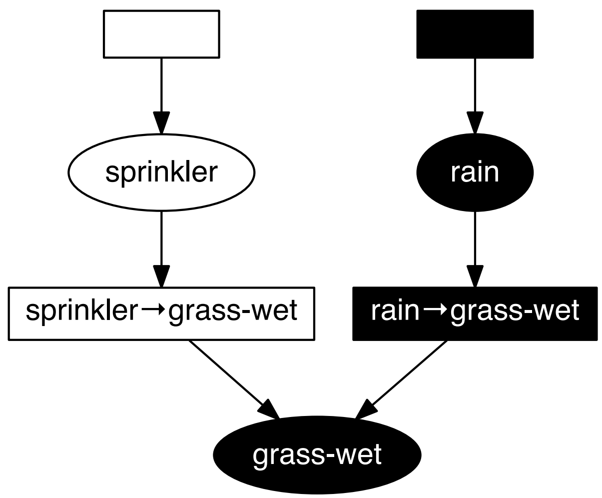
Nondeterministic abduction pattern:



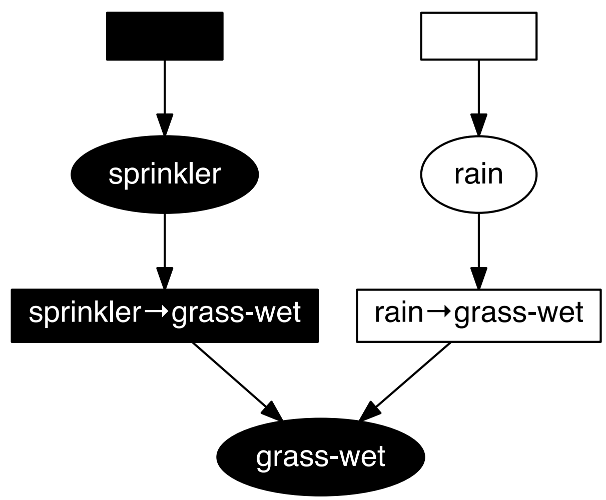
ABDUCTION ALGORITHM

1. If the network satisfies the rules, including (C5) regarding the $\perp$ node, then we are done. If the rules are satisfied except (C5), then $\perp$ has been colored black (from abduction); finish by contracting by $\perp$.
2. Otherwise, find all deterministic bad nodes and strokes and color them black. Repeat from step (1).
3. If no deterministic bad nodes or strokes exist, gather all nondeterministic bad strokes. Choose one such stroke, according to a heuristic, and color it black. Repeat from step (1).

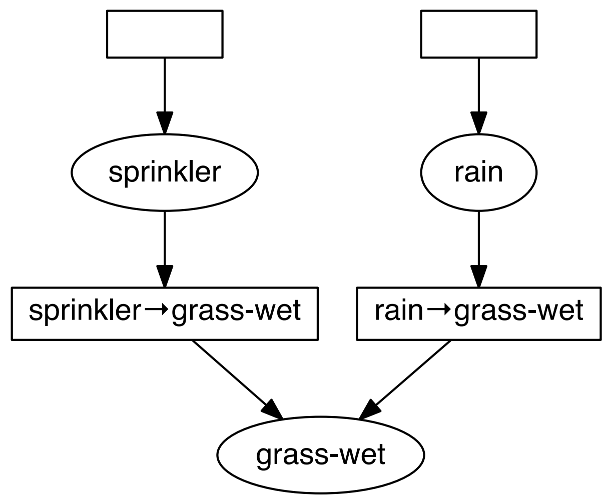
ABDUCING AN EXPLANATION FOR WET GRASS



…AND THEN LEARNING THERE WAS NO RAIN



...AND THEN LEARNING SPRINKLER DIDN'T HAPPEN



ITERATED ABDUCTION WITH PRIORITIES

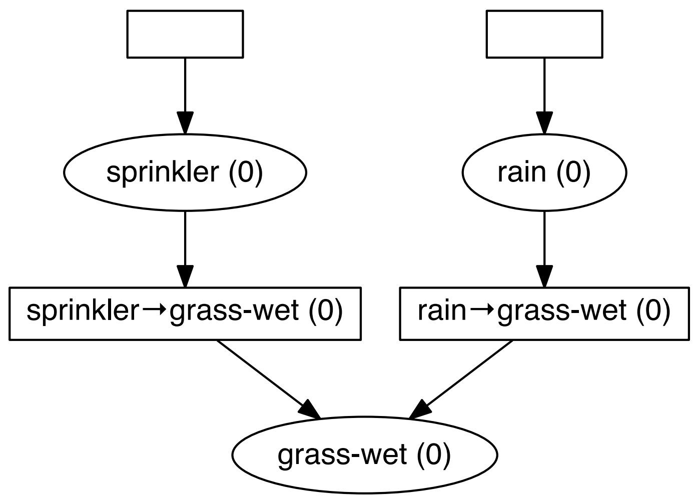
Every stroke and node has a priority (integer).

When a node is contracted or abduced, the global priority counter increments.

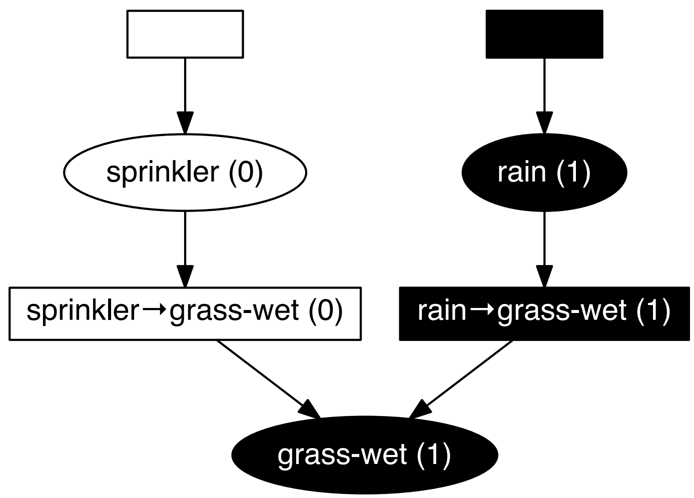
Whenever a stroke or node changes color, its priority is changed to the current global priority counter.

Assume node $\perp$ has infinite priority.

THIS TIME WITH PRIORITY LABELS



THIS TIME WITH PRIORITY LABELS



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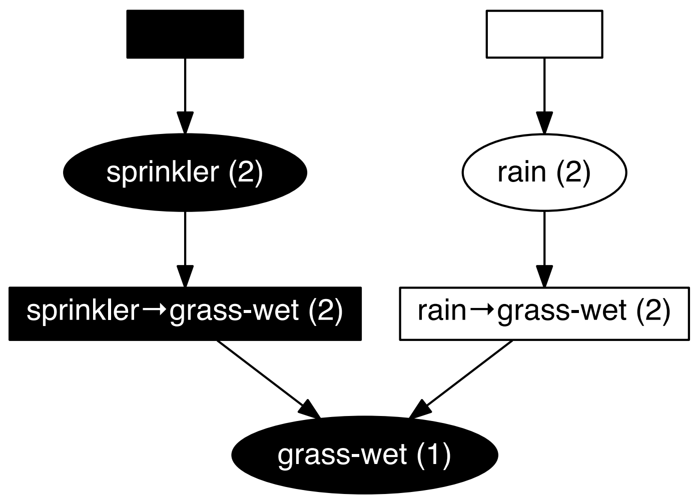
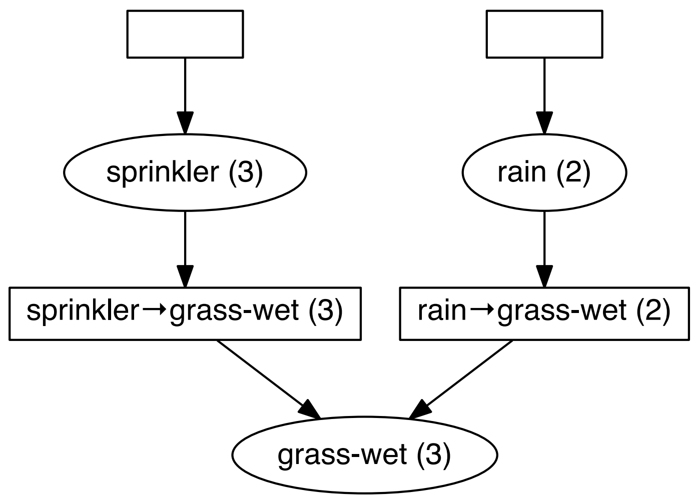


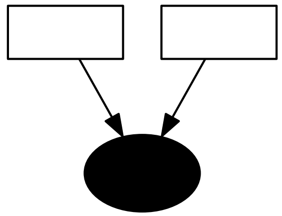
THIS TIME WITH PRIORITY LABELS



CONTRACTING BAD NODES (WITH PRIORITIES)

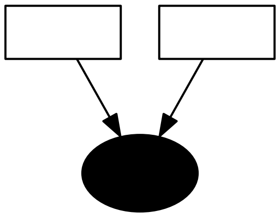
Deterministic "bad node" criteria:

1. Let p be the priority of this node n.
2. Let $min\text{-}p$ be the minimum priority of incoming strokes of n.
3. Then n is a bad node whenever:
   - n is black, and
   - every incoming stroke is white, and
   - $p \leq min\text{-}p$



ABDUCING BAD STROKES (WITH PRIORITIES)

Nondeterministic “bad stroke” criteria:

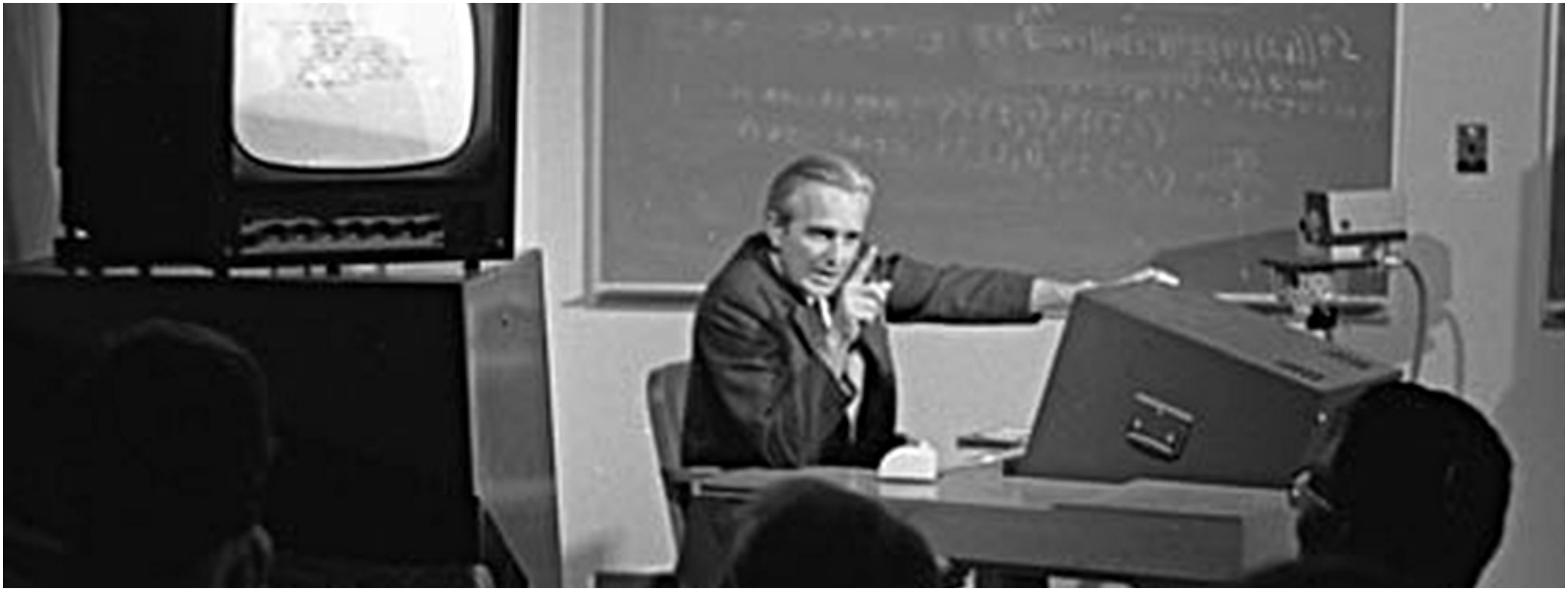


1. Let p be the priority of this stroke s.
2. Let *out-p* be the priority of the (single) outgoing node n of s.
3. Then s is a bad stroke whenever:
   - s is white, and
   - n is black, and
   - every incoming stroke of n is white, and
   - $p \leq$ *out-p*

PARAGON SUMMARY

We have examined how Paragon supports:

1. Deduction and contraction using Tennant's finite dependency networks.
2. Abduction using a *reverse-deduction* procedure.
3. Iterated abduction using priorities, which modifies the contraction and abduction algorithms.



UNSCRIPTED DEMO

FUTURE WORK

1. Evaluate contraction and abduction heuristics.
   - In terms of minimality.
   - In terms of explanatory coverage.
   - In terms of recovery.
2. Add fluents (variables).
   - E.g., *loves*(X, Y) can explain *married*(X, Y) and *friends*(X, Y).
3. Evaluate performance on benchmark cases.
   - E.g., plan recognition, story understanding, et al.
4. Evaluate scalability.
   - E.g., adapt to description logics (semantic web) and “ABox abduction.”

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[2] Ledley, R. S. & Lusted, L. B. Reasoning Foundations of Medical Diagnosis: Symbolic logic, probability, and value theory aid our understanding of how physicians reason. *Science*, American Association for the Advancement of Science, 1959, 130, 9-21

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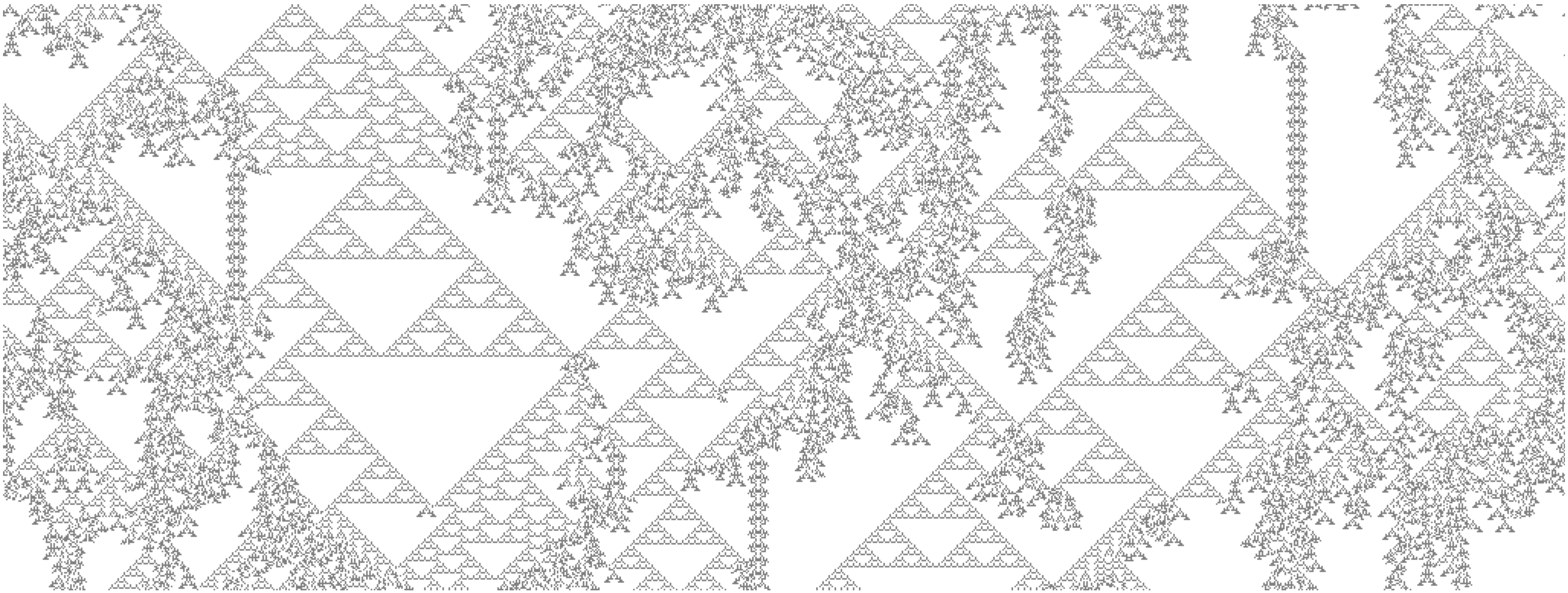

QUESTIONS