Belief Revision Controlled by Meta-abduction

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1 Introduction

We describe an abductive reasoning agent that is able to change its mind and appropriately revise previous conclusions when it encounters a reasoning dilemma. Abductive inference (by which we mean “Inference to the Best Explanation”) is an ampliative inferential process; that is, the conclusion goes beyond merely extracting information already present in the premises, perhaps unobviously. Thus, abductive inference is inherently fallible, and so it is desirable for a reasoning agent relying on abduction to be able to correct mistaken previous conclusions. A number of frameworks have been proposed for how to model and implement the logic of how an agent might change its mind: the non-monotonic reasoning techniques of default reasoning, Justification (and Assumption)-based truth maintenance systems and AGM theory, are prominent examples. These approaches, whatever their differences, share the property that they all seek universal solutions to the problem of belief revision. In contrast, we propose to take advantage of the specific structure of abductive reasoning to identify revision candidates among earlier beliefs, to propose specific revisions, to select among possible revisions, and to make the requisite changes to the system of beliefs. These adjustments are performed through meta-abductive processing over the recorded steps in an abductive agent’s reasoning trace.

A sophisticated rational agent is able to continue to function even when confronted with information that challenges its current beliefs. It is obvious that human beliefs are not static, and that, with the passage of time, and the processing of information, beliefs are revised and not simply monotonically extended. Two major communities addressing the problem of belief revision or theory contraction are comprised of mathematical logicians and of artificial intelligence theorists. Among the logicians, a belief system is commonly treated as a logically closed set of sentences whose behavior under revision is maintained by certain postulates that place restrictions and guide the contraction, i.e., these are attempts to axiomatize belief revision (at least partially). One of the most popular approaches is the AGM-theory by Alchourron, Grefenst and Makison (see [3], for a full account). In general, the choice of change in these approaches stem from notions of epistemic entrenchment, which

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are rough measures of how the specific changes would minimally affect the belief system as a whole. In the community of AI-theorists, typical approaches build on the works of [4] and [5]. They introduce and develop the concept of a reasoning subsystem for updating beliefs by associating with each belief, a set of justifications (in essence the reasons or derivations for that belief) and analyzing the size and strength of the associated set in comparatively determining its truth. For a comprehensive overview, see [6] or [7].

There has been little work reported in the abductive inference literature on dynamic abductors, abductive agents that handle an incoming information stream by producing their best explanations at any point in time, and updating their beliefs in the light of new information. Such a dynamic abducer may be said to perform the task of “maintaining situation awareness” (analogous to perception and situation understanding) by coherently assimilating new information and forming best explanations. A simpler sort of dynamic abducer continually corrects its best estimate of the situation, as the situation changes, but it does not explicitly correct previous estimates of what has become the past situation. Let us say that this sort of abducer performs “shallow” belief revision. The past situation influences and constrains the present, however, and an agent that has a correct estimate of the past has an advantage in reasoning about the present. Thus, a dynamic abducer that is able to correct previous estimates of the past has a reasoning advantage in estimating the current situation. Let us say that this sort of abductive agent performs “deep” belief revision. In this paper, we describe how this sort of abductive agent can work. That is, we describe a reasoning strategy whereby a dynamic abducer is able to appropriately revise previous estimates, under some circumstances, and use the revised estimates to improve its estimates of the current situation. We also describe an implementation of this strategy in ASAS-Smart, a system for entity tracking and re-identification.

The abducer we describe proceeds monotonically, that is, it accumulates beliefs, until anomalous data raises significant doubt regarding the validity of either its beliefs, or the incoming data, and causes it to revise its beliefs in an attempt to improve its estimate of the situation. This belief-revision process makes use of abductive reasoning, where the anomalous data are the to-be-explained, and where mistakes in previous reasoning steps are considered among the alternative hypotheses for doing the explaining.

The general construction principles of this abductive reasoner are domain independent. However, we describe a specific implementation for entity tracking and re-identification for military information fusion, a specific application, and a special case of the general problem of maintaining situation awareness. Entity tracking and re-identification is a core task of the existing military application, the All Source Analysis System (ASAS) [1]. The current implementation of the abductive reasoner (ASAS-Smart) extends and enhances the capabilities of the legacy ASAS system.

Our larger goal has been to develop scientific foundations and technology for situation awareness as a generic task for intelligent systems. Consequently, we are interested in developing generic software for what has been called “multiple-source information fusion”, which is intended to support situation awareness for military and other applications. The aim of this article is to describe how multiple-source information fusion may be framed as a problem of abduction, and how mistakes in abductive reasoning may be repaired using abductive meta-reasoning, that is, by abductively diagnosing apparent faults in the abductive agent’s system of beliefs, and repairing apparent faults by adopting alternative explanations.
Belief Revision in Dynamic Abducers

For dynamic abducers, belief revision is the process of altering existing beliefs (current best estimate of the present or past situation) to coherently assimilate the acquisition of new information. This represents a slight alteration to the traditional formulation of belief revision as altering existing beliefs to resolve a contradiction, in order to allow for belief revision to be triggered by less drastic states of reasoning difficulty.

In a task of situation awareness, an agent assimilates information from senses or sensors, and tries to maintain an accurate and consistent representation of the world. The desired state of the agent is a description as close to reality as is possible, or at least those aspects of reality that are important. This is achieved through a process of “fusion of information” from multiple sources. The inference process, by its very nature of sometimes having to deal with insufficient information, is fallible. Thus, there will be situations in which the agent makes an informed, but incorrect, guess based on the available evidence, makes additional inferences dependent on this guess, and continues until it encounters a discrepancy between new information and its estimate of the situation. Cognitively, the anomalies in the observables (depending on how severe they are) may accumulate to cross some threshold before the agent is aware of the existence of a problem, and is motivated to correct it. The challenge then, in the case of an abductive reasoner, is to confidently identify the incorrect, but abductively supported, conclusions, to retract them, and those conclusions that follow from them, and provide convincing alternative explanations for the previous data and the new data that brought about this self-analysis, in such a way as to maintain consistency, coherence, plausibility and explanatory coverage in the agent’s view of the universe, as much as possible.

A plausible architecture for a sophisticated reasoning agent ought to provide some mechanism for belief revision. For the agent to perform “deep” belief revision, this would seem to require a representation for recording justifications for beliefs (or at least some information from which such justifications may be generated) along with a method or methods for effecting revision of beliefs called for by the acquisition of new information. A reasonable approach would be to: detect an anomaly, analyze the recorded justifications for tenuous conclusions, reassess them with the advantage of hindsight, and choose a best way out of the difficulty. In a dynamic abducer, these basic components of a belief revision strategy correspond to five distinct phases in generic abductive processing, as summarized in the following table.
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Components of a belief revision strategy for a dynamic abducer

<table>
<thead>
<tr>
<th>Phases of generic abductive processing</th>
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<tbody>
<tr>
<td>(i) Detecting a reasoning dilemma (possibly anomalous new data)</td>
</tr>
<tr>
<td>(ii) Identifying relevant, lower-confidence past decisions</td>
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<tr>
<td>(iii) Determining whether the current dilemma would be resolved by suspension of belief, combined with assertion of an alternative explanation, at the point of one or more of these past decisions</td>
</tr>
<tr>
<td>(iv) Choosing the best method of resolving the dilemma, if more than one is available</td>
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<tr>
<td>(v) Performing the indicated repairs on the system of beliefs</td>
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Thus, meta-abductive processing is a plausible and appropriate strategy for belief revision in abductive processing.

3 Description of the ASAS Domain

The purpose of ASAS-Smart is to perform entity tracking and re-identification in an area under surveillance. The system works by analyzing the reports from an Area Of Interest (AOI) populated with sensors, scouts etc., and by fusing the reports of sightings of different types of entities at different locations and times to form a consistent picture of the AOI.

The traditional ASAS works by considering one report at a time and trying to associate it with previously sighted entities in that area based on time, location and type reported in the new sighting. Thus, the fusion problem is already framed as one of abductive inference - the top-level question being ‘How best can this sighting be explained?’ in terms of known entities or hypothesized new entities. In ASAS and ASAS-Smart, automated fusion takes place under human supervisory control.

The application may be enhanced by spatial reasoning about entities near a particular location, and by route or path planning. In our system, support for this spatial reasoning comes from the Diagrammatic Reasoning System (DRS). This is a domain-independent module that provides functionality to the abductive reasoner in support of generating, evaluating and refining hypotheses. The DRS consists of Perceptual Routines that act on diagrams (maps of the AOI, in our system) and derive symbolic information, together with a Problem Solver that drives the routines and interfaces with the abduction engine [8].

The abduction engine is a goal-directed problem solver that uses domain knowledge, ac-
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According to a problem solving strategy, to determine a best explanation for the incoming information. This is done by setting up subgoals in the form of rival candidate hypotheses that are explored and evaluated and then selectively combined or independently chosen as the best explanation. Some of the novel attributes of the abduction engine in fusing information occur in the phases of critiquing hypotheses and in deciding about their acceptance. The evaluation of these hypotheses includes a limited form of prediction or expectation-based reasoning, which derives implications based on the assumption that the individual hypotheses are true, and scores the hypotheses depending on the failure or confirmation of the expectations. That is, the presence (or absence) of expected consequences of a hypothesis strengthens (or weakens) confidence in that hypothesis. In the case of highly ambiguous situations, the system delays making a decision, and waits for sufficient information to confidently resolve the ambiguity. When incoming information is sufficiently anomalous, abductive reasoning identifies those parts of the belief system that plausibly cause the difficulty, and the abduction engine attempts to construct alternative plausible explanations to resolve the difficulty.

3.1 The Entity Re-identification Algorithm in ASAS-Smart

The main algorithm used in ASAS-Smart may be understood by dividing it according to the main phases of abductive processing:

1. Determining what is to be explained. A report arrives asserting the presence of a certain type of entity at a certain place and time. This entity, or more precisely, this report, constitutes data to be explained.

2. Hypotheses generation. The abduction engine generates candidate hypotheses by polling its database for entities of the same type known to be in the AOI, and by hypothesizing that any such entities could have moved to the location of the new report since their last sighting. It also considers the possibility that the newly reported entity is a previously unseen one, and the possibility of the report being false (due to a mistake or due to deception).

3. Hypotheses evaluation. The generated hypotheses are subjected to a series of tests, each of which affects its confidence score.

(a) First, impossible hypotheses are filtered out using a simple speed-distance-time screen based on the last known locations of the entities and the times at which they were last observed. This depends on knowledge of the maximum speed of an entity of a given type.

(b) Next, the abduction engine uses the DRS to determine, for each hypothesized entity, whether or not there is a viable route from the location of its last sighting to the location of the new sighting. Hypotheses without a viable route are given very low confidence scores.

(c) Finally, an observational consequences test is performed, where each of these routes is checked to see if it crosses some sensor field in the area. If it does, the DRS attempts to modify the route to determine if another route exists that avoid the sensors but satisfies the length (i.e., time) constraint. If such a modification is not possible, any crossed sensor field is queried to determine whether an object of the type under consideration passed through it. The confidence of the hypothesis is adjusted depending on the answer. If a path cannot be modified to avoid a sensor field, and the sensor field did
not report an entity of that type at approximately the time in question, the confidence score of the hypothesis is significantly degraded. However, it is known that sensor fields are fallible, and hence a refinement of the hypothesis is possible wherein the entity in question followed the route crossing the sensor field, and the sensor field failed to report it. Since this is effectively the conjunction of two hypotheses, one of which (sensor failure) is presumably a low probability event, the overall confidence score of this hypothesis will be low.

During this process, a hierarchy of hypotheses may be dynamically created. For example, a hypothesis of a specific known entity can take on the added refinements (possibly more than one) of the route that it might have taken, and one or more sensor fields crossed by that route that might have failed to report. These three tests of hypothesis evaluation are instances of a more general strategy according to which expectations of a hypothesis are analyzed (possibly leading to other expectations) until they are confirmed or refuted by domain constraints or by observables. The observational consequences test allows for conclusions to be drawn from negative reports, i.e., evidence of absence may sometimes be inferred from absence of evidence.

4. Hypothesis acceptance. Once the hypotheses have been evaluated, the confidence scores are compared, and, if possible, a best explanation is selected. This is subject to two conditions formulated as thresholds: the PLASIBILITY-THRESHOLD, which is a user-defined value that must be exceeded by the confidence score of a hypothesis for it to be considered to be plausible; and the CLEAR-BEST-THRESHOLD, which is a user-defined value that must be exceeded by difference of two confidence scores for one hypothesis to be considered to be distinctly better than another. If there is a unique best explanation, it is accepted, and becomes a Belief.

Every such acceptance decision is given a confidence score (not to be confused with the confidence score of the hypothesis), which is a function of: how plausible the hypothesis is, how decisively the hypothesis surpasses its nearest rival, how many rival explanations remain plausible, and how exhaustive the search was for alternative explanatory hypotheses. Acceptance decisions are stored with their confidence scores in a reasoning trace to make them available for subsequent reconsideration.

4 Abductive Processing in ASAS-Smart

High-level walkthroughs of two examples follow, which show the capabilities of the system in greater detail. The first example provides an introduction to the system, describing how entity re-identification works, with a simple example of an abductive dilemma, and showing how the system resolves it. The second example shows how the system corrects previous decisions using meta-abduction.

Meta-abductive reasoning has the same form as “object-level” abductive reasoning, going through the same phases of reasoning, but it considers the occurrence of the abductive dilemma as what needs to be explained, and hypotheses about mistakes in previous reasoning steps are considered among the potential explainers. It is “meta-” both in reasoning about reasoning states and steps, instead of reasoning only about observations, and also in relying

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1 In the formulation of the problem just given, there is just one item of data to be explained, and possibly several contending hypotheses. However, a more general treatment of the problem would treat it as hypotheses assembly, where the conjunction of a subset of the generated hypotheses will be chosen to explain a finite set of findings. See the PEIRCE algorithm in [2] - Chapter 9.
on meta-data in its reasoning, namely, the confidences associated with the reasoning steps (which it uses to guide the generation of hypotheses).

4.1 Example 1

4.1.1 Setup

Problem solving begins with Figure 1, representing the system’s view of the world. The map shown is the Area Of Interest (AOI). Two tanks T1 and T2 are believed to have been at location l1, at time t1, and at location l2, at time t2, respectively, on either side of a river, over which they cannot pass, except by using a bridge. The knowledge base also records a sensor field surrounding the entrance to a single bridge across the river, as shown in the diagram. To the system’s best knowledge, the sensor field S1 is functioning correctly, but it is also known that sensor fields are fallible, albeit with a low probability of false negatives. A new sighting of a tank T3 (tentatively so labeled) is reported at location l3 at time t3. The system’s goal is to explain the new report.

![Figure 1](image)

4.1.2 Processing

The hypothesis-generation phase, described previously, provides the system with four plausible rival hypotheses: T1, T2, Previously Unseen Entity, and Noise - any of which could explain the new report. In the process of evaluating the hypotheses, the system establishes that both the T1 and T2 hypotheses pass the first test, the speed-distance-time screen, and are recognized for the time being as equally highly plausible explanations for the new report, while the other two are less plausible.

For the sake of the example, these hypotheses are assumed to be less plausible than those of known entities having traveled to the location of the new report; this can be presumed to be based on sensor coverage in that region being good enough to prevent entities from moving in without being observed, etc. In particular, we assume that these hypotheses are below the PLAUSIBILITY-THRESHOLD described previously.
location of the new report, the DRS determines that T1 has a straight-line path to the
destination, while T2 would have had to follow a path across the river, and hence across
the bridge, and consequently across sensor field S1. Since sensor field S1 does not have
any memory of a tank having crossed it in the time frame in question, the only way that
T2 could explain the new report is by hypothesizing that S1 has malfunctioned. Thus, the
hypothesis T2 is refined by the addition of the route it must have followed across the bridge,
and the additional assumption that S1 must have malfunctioned. Since the malfunctioning
of S1 is presumed to have low probability, the refined hypothesis is given a low plausibility
score.

Next, the hypotheses-acceptance phase considers the candidate hypotheses and chooses
'T1 following a straight path to l3' as the best explanation for T3. That is, it associates
the new report with T1, and decides that T3 is the entity previously identified as T1, which
has moved to location l3. This decision is based on the viability and confidence scores of
the hypotheses. Considerations of parsimony (that a simpler explanation is better, other
things being equal) prevent a composite hypothesis from being considered in this case. This
abductive decision is given a confidence score that is modest, but not strong, since there are
alternative plausible explanations for the data, though not very good ones. The estimated
state of the world is then updated to show this acceptance, as depicted in Figure 2 (ignoring
Tank T4 for the moment).

Next, there comes another report, that of a tank T4 at location l4 at time t4, as depicted
in Figure 2. Here the system runs into a snag. Even though the hypotheses-generation phase
comes up with four hypotheses - T1, T2, Previously Unseen Entity and Noise - the speed-
distance-time screen filters out T1 and T2, since they could not have traveled the required
distance in the available time. Previously Unseen Entity and Noise are not acceptable since
their confidence scores are below the threshold of plausibility. This leaves the agent in
an abductive dilemma - there is no plausible explanation for the incoming data. If there
was no alternative, the agent would have to suspend processing, or guess that that the
new report will need to be explained using one of the implausible hypotheses. However, it is
plausible under the circumstances that a previous decision was incorrect, so the agent decides
to question its previous decisions. This constitutes an extensive search for hypotheses to explain the observed data, but it is undertaken only as required, since it is computationally expensive, and to begin with there seemed to be better explanations available.

So, the reasoning agent (i.e., the system) decides to question its previous decisions, and searches its reasoning trace to locate those decisions with low confidence scores. In this case there is only one: the decision that associated the report of T3 with tank T1. Let us call this decision D. The question is whether any alteration of D would permit a better explanation for T4, and how plausible would that alteration of D be, in comparison with the implausible hypotheses Previously Unseen Entity and Noise.

As an attempt at repair, the system chooses the second-best hypothesis from the set of alternatives at decision D. Recall that there is only the one: ‘T2 along a route over the bridge, and S1 has malfunctioned’, since Previously Unseen Entity and Noise were below the plausibility threshold. Acceptance of this second-best hypothesis (let us call this decision D-Prime) would assume that T3 is the tank T2 having traveled to location l3. D-Prime proposes a specific repair to a previous decision, substituting a second-best explanation for what was the best explanation at the first pass. D-Prime amounts to a hypothesis that is worth considering as a possible way to explain why the abductive dilemma arose. Decision D-Prime leads to the estimated world state shown in Figure 3, for the time at which the report of tank T4 is received.

The system now must determine whether D-Prime leads to resolution of the abductive dilemma. So, tentatively assuming the decision, D-Prime, the abductive processing is redone on all reports received after decision D, in this case just the one report of tank T4. This time, the system determines that T1 can explain the new report T4 (that is, that T1 has moved to l4 at t4). Since this hypothesis passes all tests, and is sufficiently better than the alternatives (suppose), it is accepted at the hypothesis acceptance phase. The system thus determines that the dilemma introduced by the new report T4 is resolved by accepting D-Prime instead of D, and since D-Prime (followed by the new decision identifying T4 with T1) is sufficiently better that either of the implausible hypotheses available for explaining T4 (suppose), the decision is made to accept D-Prime, and to accept the identification of
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T4 with T1 that follows. The resultant world view is then the state depicted in Figure 4.

4.2 Example 2

This example again illustrates the capabilities of the system for entity tracking and re-identification, and also shows how it corrects previous decisions using meta-abduction.

4.2.1 Setup

Figure 5 depicts the initial state of the system. The database contains reports of three tanks in the AOI. These are: ‘Tank T1 at location l1 and time t1’, ‘Tank T2 at location l2 and time t2’, and ‘Tank T3 at location l3 at time t3’. Two sensor fields S1 and S2 are situated around entrances to two bridges across the river. To the best of the system’s knowledge, both sensor fields are functioning correctly. Suppose, also, that sensor field S1 is known to be more reliable than S2.

4.2.2 Processing

A sighting of a tank T4 at location l4 at time t4 is reported, as shown in Figure 5. Processing is similar to that in Example 1. Suppose that T3 is rejected for failing the speed-distance-time screen. The remaining hypotheses are: ‘T1 along a route over the bridge and S1 has malfunctioned’, ‘T2 along a straight route’, Previously Unseen Entity, and Noise. Under the circumstances, hypothesis ‘T2 along a straight route’ is chosen as the best explanation, because there is no reason at this time to doubt the correct functioning of sensor field S1. Consequently, this hypothesis is accepted, and the estimated state of the world is updated to that depicted in Figure 6. Let us call this abductive decision D1; it would be associated with an appropriately modest confidence score because of the availability of an alternative plausible hypothesis (T1) that can also explain the observation, albeit less plausibly.

Next, there arrives a report of a tank T5 at location l5 at time t5, as shown in Figure 6.
Similar processing leads to the decision to associate T5 with T3, choosing this hypothesis as the best from the set: ‘T3 along a straight path’, ‘T1 along a path over the bridge and S2 has malfunctioned’, Previously Unseen Entity, Noise (Supposing that T2 fails the speed-distance-time test). Let us call this decision D2, and suppose that D2 is given a confidence score similar to that of D1. Decision D2 results in the estimated world state shown in Figure 7.

Next, a report arrives of a tank T6 at location l6 at time t6, as shown in Figure 7. Abductive processing leads the system to infer that T6 is tank T3 having moved to that location. This hypothesis is chosen from the set: ‘T3 along a straight route’, Previously Unseen Entity, Noise; assuming that the T1 and T2 hypotheses are eliminated for failing
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Fig. 7.

the speed-distance-time test. Let us call this decision D3. Accepting this hypothesis results in the estimated world state depicted in Figure 8. This hypothesis does not have any plausible explanatory rivals, and so D3 is a highly confident abductive step.

Fig. 8.

A tank T7 is then reported to be at location l7 at time t7, as shown in Figure 8. As suggested by the figure, this causes an abductive dilemma similar to the one in Example 1. No plausible explanation for the observation is available. The only surviving candidates after applying the speed-distance-time test are Previously Unseen Entity and Noise, both of which are assumed to be below the threshold of plausibility.

This is the situation where the reasoning agent uses meta-abductive reasoning and explicitly considers alternative explanations in attempting to resolve the dilemma. As previously
stated, the same “object-level” form of abductive reasoning is utilized at a meta-level to explain the occurrence of the abductive dilemma, and mistakes in previous reasoning steps are considered as hypotheses in comparison with other factors such as imperfect perceptual input etc., as potential explainers.

In the example, the system searches its past decisions, and identifies D1 and D2 as plausible hypotheses (i.e. low confidence past decisions whose alteration may lead to the resolution of the abductive dilemma). These are added to the implausible hypotheses from the “object” level to make the candidate set: D1, D2, Previously Unseen Entity, Noise. (The truth of either of the implausible ones would also explain the occurrence of the dilemma; they are implausible, yet worth considering at this point, especially so that they can be compared with the belief-revision hypotheses.)

The agent then evaluates the hypotheses and determines their relative confidence scores. This is done by tentatively assuming the second-best alternatives for each of the abductive decisions D1 and D2, in turn, and re-processing all subsequent reports to determine whether either results in a resolution of the abductive dilemma. If a revised decision results in a resolution of the dilemma, the implied mistake in the original decision reasonably counts as a possible explanation for why the dilemma arose.

Note that the alternative hypotheses considered in an abductive decision made in the past may not have the same confidence values when they are later reconsidered. Confidences may differ as a result of information that arrived subsequently. Thus, confidences may need to be re-evaluated. The second-best alternative, as the most plausible revision candidate, should be chosen after this rescoring. If the second-best alternative does not work out, the third-best alternative might also be considered, and so on. In the current example, however, there is no new information for scoring the alternatives, and their scores remain the same.

For D1, the second-best alternative is ‘T1 following a route over the bridge and S1 has malfunctioned’ (call this D1-Prime). This is in effect the association of T1 (instead of T2) with the sighting T4. On continuing the processing, with tentative acceptance of D1-Prime, the next report of T5 is associated with tank T3, and the following report of T6 is also associated with tank T3, with the new report being explained by T3 having moved from l5 to l6. This leads to the world state shown in Figure 9a, and after the new report of T7 is considered, the hypothesis ‘T2 along a straight line’ becomes a high-confidence explanation, whose acceptance leads to the world state shown in Figure 9b. This is, therefore, one option for retraction that is quite plausible. That is, it leads to a more plausible account than that the new report was caused by either of the hypotheses: Previously Unseen Entity or Noise.

Alternatively, if decision D2 is retracted, the second-best hypothesis at that point for explaining the sighting of T5 is: ‘T1 along a path through the bridge and S2 has malfunctioned’. In this case, T1, rather than T3, is associated with T5. Call this decision D2-Prime. This decision occurs after T4 was associated with T2. Subsequent processing would then identify the sighting T6 as T1 having moved from l5 to l6. The corresponding estimated world state is shown in Figure 10a. Finally, when sighting T7 is processed, ‘T3 along a straight route’ emerges as the best explanation, and its acceptance leads to the alternative plausible world state shown in Figure 10b.

This leaves the system with a problem. As is obvious, there are two plausible explanations, with corresponding plausible world states, each arising from a different candidate belief revision: Figure 9b shows the state that follows from D1-Prime, and Figure 10b shows the state that follows from D2-Prime. Recall, however, that we assumed that sensor field S1 is known to be more reliable than S2. This consideration reasonably influences the estimate of
the relative confidence of D1-Prime and D2-Prime, with D1-Prime coming out the weaker, since it supposes a malfunction in the more reliable sensor field S1. Consequently, D2-Prime is chosen as the better alternative (let us suppose that it is sufficiently better to pass the threshold to be considered as distinctively better). So D2-Prime is accepted, along with the subsequent decisions that followed its tentative acceptance. The abductive agent’s best estimate of the state of the world is thus shown in Figure 10b.
5 Summary & Discussion

We have described the workings of a dynamic abducer, an abductive reasoning agent that continually fuses information from multiple sources to “maintain situation awareness”, that is, to maintain a best estimate of the situation based on incoming data. In particular, we have described a special class of problems of entity tracking and re-identification, and described in some detail how a dynamic abducer for this problem is able, under some circumstances, to appropriately “change its mind”. and explicitly revise the conclusion of an earlier reasoning step. This ability results from performing “meta-abductive” reasoning in situations where no plausible hypotheses are available for explaining a new observation report. We have also described ASAS-Smart, an implementation of such a dynamic abducer, and illustrated its capabilities by tracing its reasoning on two example cases. Although the present system is in many ways simple, idealized, and domain-specific, we believe that it illustrates principles of reasoning that have broad applicability.

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