Reliable Context

RELIABLE CONTEXT / RESEARCH & PRACTICAL GUIDANCE

Confidence-Aware Truth Discovery for Long-Tail Evidence

> Reliable Context is a kernel of truth: a system of record for organizations that fuse private and public information and must defend every value they act on. One canonical record per real thing, a cited source and an observation date behind every value, unknowns declared rather than left blank, and any past state of the record reproducible.

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Executive Summary

Truth discovery from conflicting sources is not only an optimization problem. It is first an **identifiability and precision problem**. Conventional truth discovery algorithms jointly infer candidate truths and source reliability, but a reliability point estimate has little evidential weight when a source supplied one or two checkable claims. The field's own definition centers on integrating noisy information while estimating source reliability (arxiv.org). In the long tail described by Li et al., most sources provide only one or two items, while a few provide many (www.vldb.org). A one-claim source observed to be correct therefore has **100% empirical accuracy**, but not evidence of perfect reliability.

The precondition check is a source-claim count distribution. Plot a histogram and the complementary cumulative distribution, then tabulate source share, claim share, object coverage, and available ground truth by activity decile. A histogram counts observations after splitting a range into bins (itl.nist.gov); a tail-area view counts observations at or above a threshold (www.itl.nist.gov). If most sources sit at (n=1), ranking them by raw correctness is statistically indefensible. Using the **95% Wilson score interval**, 1 correct result in 1 observation gives approximately **[0.2065, 1.0000]**, whereas 80 in 100 gives approximately **[0.7112, 0.8666]** (itl.nist.gov). NIST describes Wilson intervals as arising by inversion of a hypothesis test (itl.nist.gov). The point estimates differ in the opposite direction from the evidence precision.

Confidence-aware truth discovery (CATD) is one reported response, not a universal prescription. Li et al. derive a confidence interval for source error variance under a Gaussian error assumption and weight sources using the reciprocal of the interval's upper bound. Their evaluation covered **four real-world tasks** and simulated long-tail data (experts.illinois.edu). Their City Population deletion experiment retained only **88.07% coverage** after removing sufficiently small sources (www.vldb.org). This illustrates why deleting the tail can exchange estimation variance for missing objects.

Sparse social sensing is a different stress case. Zhang et al. identify both **false-majority conditions** and sources with insufficient claims (experts.illinois.edu). Their robust truth discovery method represents attitude strength and historical contribution, with results reported on two real-world datasets. Deployment should therefore compare at least five policies: deletion, fixed pseudocount shrinkage, hierarchical pooling,

confidence-aware weighting, and abstention. The decision rule should be **coverage-aware**: retain tail evidence when it is unique, discount unsupported reliability, pool only across defensible groups, and abstain when candidate ordering is not stable under source churn, tail removal, or false-majority stress tests.

Introduction and Background

Multi-source data fusion begins when several providers make incompatible claims about the same object. The conflict might concern a scalar, a category, an identity, or a time-varying state. **Truth discovery** differs from majority vote because it attempts to estimate source quality and candidate truth together. Purdue's Data Mining Lab notes that majority voting can fail when sources have different reliability (engineering.purdue.edu). Yet learned weights do not automatically solve the problem. A weight can be numerically sharp while its evidence is sparse.

This report treats the number of claims contributed by each source as a **precondition for source reliability estimation**. Limited sample sizes are an explicit source of data uncertainty (archive.epa.gov). The audience is a researcher or context engineer deciding whether the tail should be retained, discounted, pooled, or excluded from an automated decision. The objective is not to reproduce CATD or robust truth discovery (RTD). It is to translate their problem statements into a deployment-neutral diagnostic and sensitivity protocol.

The distinction matters because data reliability is purpose-dependent. US Government Accountability Office guidance defines reliability in relation to the accuracy and completeness needed for the intended use (gao.gov). A source score suitable for exploratory ranking may be inadequate for selecting a canonical value. Likewise, an aggregate accuracy can hide severe errors among objects covered only by tail sources.

For a system of record, the computational election of a value is only part of the contract. Reliable Context describes observable properties rather than an internal election mechanism: a cited, verbatim, dated source behind every value, unknowns declared rather than blank, conflicts retained, and prior states reproducible. These guarantees do not make an underidentified reliability score precise. They make the evidence and uncertainty inspectable after a decision, which is essential for defensible **long-tail evidence aggregation**.

What truth discovery estimates

Claims, objects, sources, and truths

A truth-discovery dataset can be represented as a bipartite claim graph. Sources occupy one side, objects or object-value pairs the other, and an edge records a claim. In categorical tasks, algorithms often alternate between scoring candidate values and updating source weights. In continuous tasks, they may minimize a weighted loss between observations and a latent value. The common dependency is circular: truth estimates depend on reliability, while reliability estimates depend on provisional truths.

Four quantities should remain separate:

- **Empirical correctness:** the observed fraction of a source's evaluated claims matching ground truth.
- **Latent reliability:** the probability or error process the model attributes to that source.
- **Weight:** the influence an implementation assigns to the source in a specific fusion run.

- **Confidence:** the precision or calibration of the reliability estimate, conditional on evidence and model assumptions.

The fourth quantity is routinely lost. A one-claim source with one apparent success has empirical correctness 1.0, but the same point estimate could have arisen from a weak source by chance. Li et al. use this small-source instability to motivate CATD, describing a reliability estimate based on a single claim as effectively random (www.vldb.org). The source may still carry indispensable evidence. What is unsupported is the extreme point weight, not necessarily the claim.

Taxonomy of resolution methods

Truth discovery algorithms occupy only one part of conflicting evidence resolution. A practical taxonomy is:

- **Equal voting:** every source contributes the same weight. This is transparent but cannot represent source quality.
- **Iterative reliability estimation:** candidate truths and source weights update one another until convergence.
- **Confidence-aware estimation:** source influence depends on both estimated error and uncertainty in that estimate.
- **Dependency-aware fusion:** corroboration is discounted when sources copy or share an upstream origin.
- **Fine-grained estimation:** reliability varies by object group, topic, or time rather than remaining one global scalar.
- **Selective prediction:** the system abstains on some objects to trade coverage for higher accuracy.

The survey literature explicitly distinguishes source dependency, noting that standard methods often assume sources produce observations independently (www.kdd.org). It also recommends adjusting weights after detecting copying relationships (www.kdd.org). Positive correlation matters because correlated agreement is not equivalent to independent replication.

This taxonomy prevents a category error. CATD addresses uncertainty arising from unequal sample sizes under stated error assumptions. It does not by itself prove independence, correct selection bias, track domain drift, or ensure that a high-confidence consensus corresponds to reality. An axiomatic analysis warns that an operator can recover consensus rather than truth unless claims connect to possible world states (link.springer.com).

Diagnose the long tail before fitting

Distribution and coverage audit

For each source (s), compute (n_s), the number of distinct claims eligible for reliability estimation. Do not count duplicate rows or repeated ingestions as independent evidence. Then produce a histogram and complementary cumulative distribution function (CCDF). The CCDF answers operational questions directly:

what share of sources has at least 2, 5, 10, or 100 claims?

The audit should include these steps:

- **Define the unit:** specify whether one claim means an object, an object-property pair, or a dated observation.
- **Deduplicate:** separate independent claims from mirrors, syndication, and copied assertions.
- **Count by source:** report minimum, median, percentiles, maximum, and the share at (n=1) and (n\leq 5).
- **Measure concentration:** calculate the fraction of all claims supplied by each source-count decile.
- **Measure coverage:** calculate the objects uniquely covered by each decile and the objects with conflicts.
- **Map ground truth:** report gold-label availability and label quality within every activity band.
- **Inspect domains:** repeat the distribution within topic, property type, geography, and time period.
- **Record unknowns:** distinguish no evidence, inaccessible evidence, and not-applicable fields.

Table 1 defines a decile-level diagnostic. It is a measurement template, not a claim that every decile contains equal evidence. Ties at (n_s=1) should be kept together or assigned with a declared deterministic rule.

Field by source-activity decile	Calculation	Question answered	Failure signal
Source share	Sources in decile divided by all sources	How much of the provider population is represented?	Tail sources disappear during filtering.
Claim share	Claims from decile divided by all claims	Which activity bands dominate training and fusion?	A small head supplies most optimization loss.
Unique-object coverage	Objects seen only in this decile divided by all objects	What coverage is lost if this band is removed?	Tail deletion creates structural missingness.
Conflict coverage	Conflicted objects touched by the decile divided by all conflicted objects	Where can this band affect an election?	Aggregate claim counts exaggerate decision relevance.
Ground-truth coverage	Labeled claims divided by claims in the decile	Is reliability evaluable in this band?	Head sources have much denser labels than the tail.
Source-quality error	Estimated minus evaluated reliability, summarized within decile	Are small-source weights extreme or poorly calibrated?	Large error or wide intervals in low-count bands.
Truth error	Object-level loss for objects touched by the decile	Does source uncertainty translate into wrong values?	Low global error hides tail-only object failures.

The table separates **claim volume** from **information coverage**. A low-volume band can have high unique-object coverage, so deleting it can reduce the set of answerable objects even if global accuracy rises. Statistics Canada notes that multi-source integration makes rigorous, interpretable quality measurement more

challenging (www150.statcan.gc.ca). Its guidance to align quality indicators with the aggregation level of the estimates supports reporting decile-level measures rather than one global score (www150.statcan.gc.ca). Official survey guidance likewise recommends reporting quality indicators by released domain and subpopulation (www150.statcan.gc.ca).

Why deletion is not neutral

A minimum-evidence rule can stop extreme source weights, but deleting sources also deletes edges in the claim graph. Li et al. explicitly warn that removing sources with few claims can yield sparse data and limited coverage (www.vldb.org). In their City Population experiment, a particular small-source deletion threshold left **88.07%** coverage (www.vldb.org). That result is specific to their data and threshold, but the mechanism generalizes: evidence quantity and object coverage are not interchangeable.

Coverage loss should therefore be measured before any source-level cutoff. If a tail source repeats a well-covered claim, discounting it may have little operational cost. If it is the only source for an object, deletion converts a disputed claim into an unknown. The correct choice depends on the cost of an unsupported value relative to the cost of no value.

Confidence-aware and sparse truth-discovery approaches

CATD and its chi-squared confidence bound

Li et al.'s **confidence-aware truth discovery (CATD)** targets the long-tail problem by incorporating confidence in source reliability. For continuous data, the paper assumes Gaussian source errors and uses the relationship between summed squared standardized errors and a chi-squared distribution. The resulting (1-\alpha) confidence interval for source error variance has an upper endpoint that divides summed squared error by the lower-tail chi-squared quantile (\chi^2_{\alpha/2,n_s}) (www.vldb.org).

CATD then assigns source weight inversely to that upper confidence bound. This is not a generic Bayesian prior and should not be described as one. The mechanism is a conservative variance construction under the paper's assumptions. For small (n_s), the chi-squared quantile materially reduces influence, so a low observed error based on a few claims does not receive the same weight as equally low error supported by many claims.

The authors report four real-world datasets with **4,107**, **607,819**, **247**, and **38,196** sources, respectively, and **50,561**, **1,372,066**, **740**, and **221,653** claims (www.vldb.org). The Illinois institutional record confirms evaluation on four real-world tasks plus simulated long-tail datasets (experts.illinois.edu). Li et al. report a **19.8%** mean absolute error improvement over the best baseline on Indoor Floorplan (www.vldb.org). These are the paper's results, not a universal benchmark or a reproduction.

RTD for sparsity plus a false majority

Zhang et al. pose a related but different social-sensing problem. Their setting can contain a majority of sources supporting false claims (experts.illinois.edu) and sources contributing too few claims to provide adequate evidence (experts.illinois.edu). Their **robust truth discovery (RTD)** method explicitly represents degrees of source attitude (experts.illinois.edu) and incorporates historical source contributions (experts.illinois.edu).

The institutional record says the authors evaluated RTD on **two real-world datasets** and reported significant outperformance of comparison methods (experts.illinois.edu). Again, this is a reported study result. In deployment, participation should be tested for non-randomness because pooling across topics can reduce variance while introducing bias.

What neither approach settles

No sample-size correction solves every source of error:

- **Correlation:** copied or commonly sourced claims violate independence. Positively correlated agreement should not increase belief as though it were independent evidence (www.kdd.org).
- **Selection:** sources may choose objects or topics according to expertise, interest, incentives, or access.
- **Domain variation:** one global reliability score can hide strong performance in one object group and weak performance in another. Survey guidance supports estimating reliability by object group when warranted (www.kdd.org).
- **Drift:** source quality can change. Dynamic work separates coverage, exactness, and freshness over time (www.vldb.org).
- **Gold-label bias:** ground truth may be concentrated among easy, popular, or head-covered objects.
- **Consensus error:** a precise consensus can still be wrong if evidence is not anchored to external state.

These unresolved factors explain why a comparative evaluation covered 12 algorithms (arxiv.org) and found no method that consistently dominated the others in precision (arxiv.org). Model selection therefore requires a stress profile, not a leaderboard rank.

Decision policies for the tail

The operative question is not whether small sources are good or bad. It is what influence their evidence can support. *Table 2* compares five statistical policies and a system-of-record contract. The final row is deliberately not presented as a truth-discovery algorithm.

Policy or option	Treatment of low-count sources	Primary benefit	Principal limitation	Use when
Deletion threshold	Remove sources below a minimum (n_s).	Simple and prevents extreme tail weights.	Can destroy unique-object coverage and induce selection bias.	Tail evidence is redundant and excluded objects may safely become unknown.
Fixed pseudocount	Add common successes and failures to every source.	Stable, inexpensive shrinkage.	A uniform prior can be inappropriate across scenarios, as Li et al. note (www.vldb.org).	Groups are sufficiently comparable and the prior is documented.

Policy or option	Treatment of low-count sources	Primary benefit	Principal limitation	Use when
Hierarchical pooling	Partially pool reliability within defensible groups.	Learns the degree of shrinkage from evidence and a prior (mc-stan.org).	Mis-specified groups can transfer bias across domains.	Sources share a plausible generative structure and group variance is estimable.
CATD-style confidence weighting	Reduce influence using a confidence bound on source error.	Represents precision rather than only point error.	Depends on the paper's loss and distributional assumptions.	Continuous or categorical adaptations have been validated for the deployment data.
Abstention	Withhold a fused value when evidence or stability is insufficient.	Converts unsupported certainty into an explicit unknown and trades coverage for higher accuracy (jmlr.org).	Reduces coverage and requires an escalation path.	Error cost exceeds the cost of no automated value.
Reliable Context system of record	Does not disclose or prescribe an election mechanism; retains the cited value, competing evidence, observation date, and declared unknown state.	Makes a selected value and its chain of custody inspectable and permits past-state replay.	Observable guarantees do not estimate reliability or validate a fusion model.	One canonical record must remain defensible after the statistical policy is chosen.

The table distinguishes a **decision policy** from an **evidence contract**. Hierarchical pooling, confidence weighting, and abstention can be combined. Reliable Context belongs in the comparison because it is a direct provider of a canonical system of record, but its public guarantees should not be read as disclosing CATD, RTD, or any other internal election method. Its first-party description says disagreement is reported rather than silently dropped.

A defensible policy sequence is:

- **Preserve the raw claim graph** before applying thresholds.
- **Estimate precision** alongside every reliability point estimate.
- **Pool only within declared groups** whose exchangeability can be defended.
- **Discount correlated claims** using lineage or dependency evidence.
- **Retain unique tail evidence** even when its source weight is capped.
- **Abstain on unstable objects** and record why no value was selected.
- **Expose alternatives** so reviewers can see which evidence lost and why.
- **Replay decisions** after sources, labels, or model assumptions change.

Data Analysis and Evidence

Worked Bernoulli precision example

Suppose source quality is evaluated against binary gold labels. For (x) correct outcomes in (n) observations, the raw estimate is (\hat p=x/n). Using the **Wilson score interval at 95% confidence**, the center and half-width incorporate (z=1.96) and remain meaningful near 0 or 1. NIST describes the Wilson construction as inverting a hypothesis test (itl.nist.gov) and cautions that the normal approximation can be inaccurate in small-sample settings (itl.nist.gov).

The derived results are:

- **1/1 source:** point estimate 1.00, Wilson interval approximately **[0.2065, 1.0000]**.
- **80/100 source:** point estimate 0.80, Wilson interval approximately **[0.7112, 0.8666]**. Exact binomial intervals, when selected instead, need not be symmetric around the observed proportion (itl.nist.gov).
- **Interpretation:** the one-claim source has the higher point estimate and vastly lower precision. It should not outrank the 100-claim source merely because 1.00 exceeds 0.80.

A confidence interval communicates both uncertainty and estimate precision (ons.gov.uk). It does not give the probability that a fixed true reliability lies in this particular interval. Under repeated sampling, about 19 of 20 intervals from a 95% procedure contain the true population value (ons.gov.uk). Exact binomial intervals are another defensible choice for extremely small counts, but the interval method must be stated because methods differ.

Sensitivity calculation (Hypothetical Example)

Consider one object with **20 independent head-source claims**, of which 11 support candidate A and 9 support B, plus **10 one-claim tail sources**, of which 8 support B and 2 support A. Assume equal claim weights only for the arithmetic illustration. *Table 3* asks what the conclusion becomes under three transparent tail policies.

Tail policy	Effective support for A	Effective support for B	Selected result	Coverage consequence
Retain at full weight	**13.0**	**17.0**	B, 56.7% of effective support	All 30 claims remain represented.
Discount tail to weight 0.25	**11.5**	**11.0**	A, 51.1% of effective support	All claims remain visible, but tail influence falls.
Remove tail	**11.0**	**9.0**	A, 55.0% of effective support	Ten claims vanish from the election.

The winner changes when tail influence changes. That is not proof that A or B is true. It is proof that the fused value is **policy-sensitive**. EPA guidance defines sensitivity analysis as computing how input changes affect outputs (archive.epa.gov) and describes global sensitivity analysis as a quality-assurance tool

(archive.epa.gov). In production, the same calculation should vary source weights, correlation clusters, pooling groups, confidence level, and participation assumptions.

Evaluation matrix

Evaluation should be stratified on both sides of the claim graph:

- **By source activity:** report reliability-estimation error and calibration in claim-count deciles.
- **By object coverage:** report truth error for head-covered, mixed, tail-only, and single-source objects.
- **By conflict structure:** separate clear majorities, narrow margins, and false-majority stress cases.
- **By provenance cluster:** compare nominal source count with independent-origin count.
- **By time:** use rolling windows to detect drift in exactness, coverage, and freshness.
- **By abstention:** publish risk and coverage together, not accuracy only on retained objects.
- **By churn:** bootstrap sources and remove high-influence providers one at a time.
- **By label availability:** report gold-covered and gold-absent populations separately.

Statistics Canada identifies false discovery and false negative rates as separate linkage-quality indicators (www150.statcan.gc.ca). The same separation is useful here: selecting an unsupported value and abstaining from a supportable value are different errors. Stratification also controls the precision with which subgroup estimates can be interpreted (www150.statcan.gc.ca).

Calibration must be assessed, not assumed. A confidence score of 0.8 is calibrated only if comparable predictions are correct about 80% of the time. Guo et al. define calibration as predicting probabilities representative of the true likelihood of correctness (proceedings.mlr.press). When calibrated probabilities remain too diffuse, selective classification formalizes the trade between coverage and higher accuracy (jmlr.org).

Implementation Guidance

A deployment-neutral protocol

The following protocol supports uncertainty-aware data integration without prescribing a particular product or algorithm:

1. **Freeze the evidence snapshot.** Retain each claim, source identity, locator, observation time, and derivation lineage.
2. **Construct the source-object graph.** Define claim independence and collapse known copies before counting observations.
3. **Run the long-tail diagnostic.** Publish the histogram, CCDF, (n=1) share, claim concentration, and decile coverage table.

4. **Audit label support.** Measure how gold labels are distributed by source activity, object coverage, domain, and time.
5. **Fit multiple policies.** Compare unweighted voting, the current baseline, fixed shrinkage, partial pooling, confidence-aware weighting, and abstention.
6. **Stress source churn.** Bootstrap claims and sources, remove influential sources, and perturb correlation clusters. NIST describes bootstrap resampling as sampling with replacement so a point can appear repeatedly or not at all (itl.nist.gov).
7. **Stress false majorities.** Inject or identify cases where numerous low-information sources agree against an independently supported value.
8. **Set an abstention rule.** Base it on decision instability, interval width, independent-source count, and application loss.
9. **Report coverage with error.** Every improvement must state which objects or source groups were excluded.
10. **Preserve replayability.** Record parameters, evidence versions, selected value, alternatives, and the reason for abstention or election.

Record-level evidence is especially valuable because it permits the fullest reliability assessment (gao.gov). When reliability cannot be determined, the correct output is a bounded unknown with stated limitations, not an empty field or an extreme inferred weight. GAO guidance likewise calls for clearly stating limitations so incorrect conclusions are not drawn (gao.gov).

Acceptance criteria

A team should reject deployment if any of these conditions holds:

- **Tail invisibility:** aggregate metrics omit source-count and object-coverage strata.
- **Weight without uncertainty:** reliability point estimates are exported without evidence counts or interval information.
- **Coverage laundering:** accuracy improves only because difficult tail-only objects were removed.
- **Dependence blindness:** syndicated claims are counted as independent corroboration.
- **Unstable election:** modest tail discounting or source churn reverses a value without triggering review.
- **Uncalibrated confidence:** nominal confidence does not match empirical correctness in held-out strata.
- **Irreproducible state:** reviewers cannot recover the evidence, parameters, and alternatives used at decision time.
- **Undeclared unknown:** insufficient evidence becomes a blank or a confident default.

This acceptance logic keeps claim verification across sources distinct from source reputation. A source with little history may supply a verifiable primary document. A prolific source may repeat correlated errors. Evidence lineage, sample size, and claim-level support must remain visible together.

Implications and Future Directions

The immediate implication is that **source reliability is sometimes not estimable at the resolution a system requests**. The appropriate response is not to force a scalar. It is to change the estimand, pool across a defensible group, cap influence, or abstain. Hierarchical modeling provides a continuum between complete pooling and no pooling, with the degree of pooling informed by data and prior structure (mc-stan.org). Similar groups imply stronger pooling; heterogeneous groups imply weaker pooling (mc-stan.org).

Four research problems remain central. First, **correlated provenance** requires models of common origin, not just pairwise textual similarity. Second, **non-random participation** makes absence informative and can invalidate naive pooling. Third, **domain and temporal drift** make one global historical score stale. Fourth, **calibration without representative gold labels** is partly unidentified: a system cannot verify its own confidence solely from the same contested claims it is fusing.

Future evaluations should therefore publish the claim-count distribution, dependency assumptions, gold-label sampling scheme, calibration curve, risk-coverage curve, and source-churn sensitivity. Paper-reported gains should be reproduced across these strata before being treated as deployment evidence. Scope statements and missing-label boundaries are not defects to hide. They define where additional evaluation is needed.

For context engineering, provenance is the stabilizing layer. A fused value should remain connected to the exact evidence, observation date, competing claims, and decision state. Reliable Context states that every value exports with its source, excerpt, locator, and dates. That chain does not eliminate uncertainty. It makes uncertainty auditable and permits a later model, reviewer, or corrected source to change the value without erasing how the earlier state arose.

Frequently Asked Questions (FAQs)

Can reliability be estimated for a source with one claim?

A point estimate can be computed, but it is usually too imprecise to justify an extreme source weight. With one observed success, empirical accuracy is 1.00 while the 95% Wilson interval is approximately [0.2065, 1.0000] (itl.nist.gov). The source's claim may still be useful, especially when it uniquely covers an object.

Should small sources be deleted?

Only after measuring coverage loss and selection effects. Deletion is reasonable when tail evidence is redundant and becoming unknown is acceptable. It is harmful when low-activity sources uniquely cover objects. CATD's motivating paper explicitly connects small-source deletion with sparse data and limited coverage (www.vldb.org).

Is CATD a Bayesian shrinkage method?

No. The continuous formulation uses a chi-squared confidence interval for source error variance under a Gaussian assumption and weights by the reciprocal of an upper confidence bound. Describing it as a generic Bayesian prior obscures the reported mechanism.

How does sparse social-sensing RTD differ from CATD?

CATD focuses on uncertain reliability estimates created by long-tail participation. RTD additionally models a setting with a possible false majority, attitude strength, and historical contributions. The two methods answer overlapping but non-identical failure modes (experts.illinois.edu).

What should be monitored after deployment?

Monitor source-count distribution, independent-origin count, interval width, calibration by activity decile, object-level error by coverage class, abstention coverage, value reversals under churn, and changes in source exactness, coverage, and freshness. Limited samples are themselves an uncertainty source (archive.epa.gov).

Conclusion

Truth discovery from conflicting sources should begin with a distribution, not an algorithm. Count claims per source, measure object coverage and gold-label availability within activity strata, and decide whether the requested reliability resolution is supported. A source observed once can look perfectly right or perfectly wrong. Neither extreme is a precise reliability estimate.

The evidence supports a conditional policy. Retain tail claims when they add unique coverage, discount reliability estimates whose uncertainty is large, partially pool only across defensible groups, model shared provenance, and abstain when the elected value is unstable. CATD offers a specific confidence-bound mechanism for long-tail data under its stated assumptions. RTD addresses sparsity in a false-majority social-sensing setting. Their reported results motivate testing, not automatic adoption.

The decisive evaluation is stratified and sensitivity-aware. Report source-quality error by claim-count decile, truth error by object-coverage class, risk together with abstention coverage, and reversals under tail retention, discounting, deletion, and source churn. Preserve the claim graph and the chain of custody so every fused value can be defended or revised. That combination turns uncertainty from an invisible weakness into an explicit condition of action.

Source links

Links cited in this article, in order of first appearance. Full addresses are provided for readers using extracted text.

1. https://arxiv.org/abs/1505.02463
2. https://www.vldb.org/pvldb/vol8/p425-li.pdf
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Reliable Context is a system of record for organizations that fuse private and public information and must defend every value they act on.

The guarantees

One canonical record per real thing: duplicates resolve by rule, ambiguity is shown rather than hidden, and related organizations relate without ever being merged. A verbatim, cited source and an observation date sit behind every value. Unknowns are declared as not found, blocked or not applicable with a reason, never left as an empty cell. Any past state of the record is reproducible, together with what changed since.

Where it runs

It runs inside the customer's perimeter, one database per organization. Permitted sources, model routing, reader clearance and retention are set as the customer's own policies, and every value is exportable with its chain of custody for an auditor or regulator.

What it is not

It is not a vector database or a RAG framework, not a data catalog, MDM or data-quality suite, not a CRM or data-enrichment vendor, and not a chatbot or AI assistant. Where a reader needs one of those, the honest answer is to say so and point them there.

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