Collective Intelligence in Multi-Agent AI Systems: How Aggregation Methods Shape Deliberation Outcomes

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Abstract

When multiple AI agents deliberate on a question, each expresses a position with some degree of confidence. How should we combine these heterogeneous beliefs into a collective judgment? This choice is not merely technical—it encodes fundamental assumptions about expertise, independence, and what "collective wisdom" means. We present a systematic study of 169 aggregation strategies, motivated by the LIDA multi-agent deliberation platform where agents debate policy questions, form coalitions, and reach consensus through mechanisms like prediction markets, quadratic voting, and adversarial collaboration. Our central finding is that **no aggregation method is value-neutral**: weighted averaging assumes compensatory expertise, median voting embodies "one agent, one vote" egalitarianism, log-odds pooling treats agents as independent Bayesian observers, and Dempster-Shafer accumulates corroborating evidence multiplicatively. Through 5,070 experiments, we characterize when each family excels: robust methods (Huber, Tukey) protect against adversarial or miscalibrated agents; density-based methods handle multimodal disagreement; game-theoretic methods (Shapley, nucleolus) fairly attribute influence in coalitions. Three strategies achieve perfect outlier immunity while remaining fast (< 0.03ms): HISTOGRAM_DENSITY, UCB_AGGREGATION, and MAJORITY_VOTE. We release an intelligent meta-aggregator that detects data characteristics and selects appropriate strategies, enabling deliberation protocols to adapt their consensus mechanisms to the structure of agent disagreement.

Keywords: multi-agent deliberation, collective intelligence, AI alignment, belief aggregation, robust consensus, Dempster-Shafer theory, social choice, wisdom of crowds

1 Introduction

A growing body of research suggests that AI systems can be made safer and more reliable through *deliberation*—structured debate among multiple AI agents who critique each other's reasoning, surface hidden assumptions, and collectively arrive at better-justified conclusions. This approach, sometimes called "AI safety via debate" or "scalable oversight," promises to extend human oversight to domains where individual humans lack expertise to evaluate AI outputs directly.

But deliberation requires *aggregation*. When multiple agents express positions with varying confidence, how should we combine them into a collective judgment? This is not a neutral engineering choice. Consider:

- **Weighted averaging** assumes expertise is compensatory—a highly confident expert can offset uncertain novices.

- **Median voting** embodies egalitarianism—each agent's position counts equally regardless of stated confidence.
- **Log-odds pooling** treats agents as independent Bayesian observers sharing private evidence.
- **Dempster-Shafer combination** accumulates corroborating evidence multiplicatively, amplifying agreement.

Each encodes different assumptions about what "collective wisdom" means. The choice shapes which agents have influence, how dissent is weighted, and whether the system favors consensus or preserves uncertainty.

1.1 The LIDA Deliberation Platform

This work emerges from the LIDA multi-agent research platform, designed to study how distributed AI systems reach collective decisions. LIDA simulates complex deliberation scenarios including:

- **Policy wargaming**: AI governance scenarios where agents representing stakeholders (safety researchers, industry, policymakers) debate interventions
- **Prediction markets**: Agents trade on beliefs, with prices reflecting collective confidence
- **Adversarial collaboration**: Structured critique-defense cycles following Kahneman's protocol
- **Quadratic voting**: Agents allocate conviction points with quadratic cost, preventing domination by single voices
- **Coalition dynamics**: Agents form and dissolve alliances, with power balancing and credibility tracking

Each mechanism requires a way to aggregate agent confidences into collective outcomes. LIDA extracts confidence from LLM token-level log probabilities, but the question remains: given n agents with confidences $c_1, \ldots, c_n$ and reliability weights $w_1, \ldots, w_n$, what is the collective confidence $\hat{c}$?

1.2 The Core Problem: Aggregation Encodes Values

Consider a concrete scenario from LIDA: five AI agents debate whether to recommend a 6-month pause on frontier AI training.

Agent (Persona)	Support	Reliability
Safety Researcher	0.92	1.5
AI Lab Executive	0.25	1.2
Policy Expert	0.68	1.3
Academic Ethicist	0.81	1.1
Industry Economist	0.35	1.0

What is the collective position? Different methods give dramatically different answers:

- **Weighted average**: 0.62 (moderate support)
- **Median**: 0.68 (the policy expert's view)
- **Log-odds**: 0.58 (combining independent evidence)
- **Robust Tukey**: 0.71 (downweighting extreme positions)
- **Dempster-Shafer**: 0.89 (three of five support > 0.65)

The range of 0.58 to 0.89 represents the difference between "uncertain, lean yes" and "strong support." This is not a bug—it reflects that the methods disagree about how to handle:

1. **Polarization**: Should extreme positions (0.25, 0.92) be downweighted?

2. **Expertise**: Should reliability weights dominate stated confidence?
3. **Independence**: Are these five opinions truly independent, or correlated through shared training data?
4. **Corroboration**: Does agreement among three agents strengthen the case beyond their individual confidences?

1.3 Research Questions

This paper addresses three questions:

1. **Characterization**: What assumptions does each aggregation family encode, and when do they produce systematically different outcomes?

2. **Robustness**: Which methods are robust to adversarial agents, miscalibration, or strategic manipulation—critical concerns when AI systems debate each other?

3. **Selection**: Can we automatically detect data characteristics (agreement level, outliers, multimodality) and select appropriate aggregation strategies?

1.4 Contributions

1. **Unified framework**: 169 strategies across 20 categories with consistent API, enabling systematic comparison
2. **Value analysis**: Explicit characterization of what assumptions each method encodes about expertise, independence, and consensus
3. **Robustness evaluation**: Identification of methods resistant to outliers and adversarial inputs—essential for AI deliberation where agents may be miscalibrated or manipulative
4. **Intelligent meta-aggregation**: Automatic strategy selection based on detected data characteristics
5. **LIDA integration**: Production implementation powering deliberation mechanisms including prediction markets, quadratic voting, and adversarial collaboration

1.5 Paper Organization

Section 2 reviews related work from social choice theory, robust statistics, and multi-agent systems. Section 3 formalizes the aggregation problem and defines key properties. Section 4 presents the 169 strategies organized by methodological family, with explicit discussion of encoded assumptions. Section 5 describes the LIDA implementation. Section 6 presents experimental evaluation across 5,070 conditions. Section 7 analyzes results with focus on when different families excel. Section 8 demonstrates integration with LIDA deliberation mechanisms. Section 9 discusses implications for AI alignment and multi-agent systems.

2 Related Work

The problem of aggregating beliefs from multiple sources spans social choice theory, statistics, AI, and philosophy. We organize related work by the core question each tradition addresses.

2.1 Social Choice: What Does "Collective Will" Mean?

Arrow's impossibility theorem [3] showed that no voting system satisfies all desirable properties simultaneously—a sobering result for AI deliberation. Condorcet's jury theorem (1785) provides hope: if individual voters are more likely right than wrong, majority voting converges to truth. But this assumes independence; correlated errors (e.g., from shared training data) break the guarantee.

Implication for AI deliberation: We cannot assume LLM agents are independent. Models trained on similar data may share systematic biases, making naive voting unreliable.

2.2 Robust Statistics: What If Sources Are Corrupted?

Huber [16] and Tukey [24] developed estimators robust to outliers and heavy-tailed distributions. The key insight is *breakdown point*: the fraction of corrupted observations before the estimator fails. The mean has breakdown point 0% (one outlier can cause unbounded bias); the median achieves 50%.

Implication for AI deliberation: In adversarial settings, or when some agents are miscalibrated, robust aggregation prevents manipulation by outlier opinions.

2.3 Belief Functions: How Do We Combine Evidence?

Dempster-Shafer theory [8, 22] extends probability to handle uncertainty about uncertainty. Rather than forcing beliefs onto a probability simplex, it allows mass to be assigned to sets of hypotheses, explicitly representing ignorance.

Implication for AI deliberation: When agents express "I don't know," DS can preserve this uncertainty rather than forcing a point estimate. This matters for high-stakes decisions where false precision is dangerous.

2.4 Ensemble Learning: When Do Combinations Beat Individuals?

Breiman's bagging [4] and Wolpert's stacking [27] showed that combining diverse weak learners produces strong learners. The key is diversity—correlated predictors provide redundant information.

Implication for AI deliberation: Diverse agent architectures (different model families, training data, prompting strategies) may be more valuable than multiple copies of the same strong model.

2.5 AI Safety via Debate

Recent work proposes using structured debate between AI systems as a scalable oversight mechanism. The idea: even if humans cannot directly evaluate AI outputs in complex domains, they can judge which of two AI debaters made better arguments.

Implication: Debate requires aggregation—not just of final positions, but of argument quality, evidence strength, and credibility updates. Our framework provides the building blocks for these mechanisms.

2.6 Classical Opinion Pooling (1785–1980)

The mathematical study of belief aggregation began with Condorcet's 1785 analysis of jury voting, establishing that majority rule amplifies correctness when individual jurors have accuracy $p > 0.5$. Laplace extended this to continuous confidence estimates in his analysis of witness testimony reliability.

The 20th century saw formal axiomatization. **(author?)** [23] proposed the linear opinion pool:

$$P(E) = \sum_{i=1}^{n} w_i P_i(E) \tag{1}$$

where P_i are expert probabilities and w_i are non-negative weights summing to 1. This satisfies *unanimity*: if all experts assign probability 1, so does the pool.

(author?) [7] established that under repeated linear averaging with positive weights, opinions converge to consensus. The rate of convergence depends on the second eigenvalue of the weight matrix.

The logarithmic opinion pool (alternatively: geometric mean in probability space) was axiomatized by **(author?)** [12]:

$$P(E) \propto \prod_{i=1}^{n} P_i(E)^{w_i} \tag{2}$$

(author?) [13] proved this is the unique *externally Bayesian* pooling rule: if each expert updates via Bayes' rule, so does the aggregate.

2.7 Robust Statistics (1960–present)

Classical aggregation methods suffer from non-robustness: a single outlier can arbitrarily distort the result. Robust statistics, pioneered by **(author?)** [16] and **(author?)** [14], addresses this through:

M-estimators: Minimize $\sum_i \rho(c_i - \mu)$ for loss function ρ. The Huber loss transitions from quadratic to linear at threshold k:

$$\rho_{\text{Huber}}(x) = \begin{cases} \frac{1}{2}x^2 & |x| \le k \\ k|x| - \frac{1}{2}k^2 & |x| > k \end{cases} \tag{3}$$

Breakdown point: Introduced by **(author?)** [14], this is the fraction of observations that must be corrupted to cause unbounded bias. The median achieves the maximum breakdown point of 50%; the mean has breakdown point 0%.

Influence function: Measures sensitivity to infinitesimal contamination:

$$\text{IF}(x; T, F) = \lim_{\epsilon \to 0} \frac{T((1-\epsilon)F + \epsilon\delta_x) - T(F)}{\epsilon} \tag{4}$$

Bounded influence function implies robustness.

(author?) [24] introduced the biweight (bisquare) M-estimator with redescending influence function, achieving near-optimal efficiency under normality while remaining robust.

2.8 Dempster-Shafer Theory (1967–present)

(author?) [8] introduced upper and lower probabilities; **(author?)** [22] extended this to a theory of evidence with explicit uncertainty representation.

A *mass function* $m : 2^\Omega \to [0,1]$ assigns mass to subsets of frame Ω, with $m(\emptyset) = 0$ and $\sum_{A \subseteq \Omega} m(A) = 1$. Unlike probability, mass can be assigned to composite hypotheses, representing uncertainty about which specific hypothesis holds.

Dempster's rule of combination is:

$$m_{1,2}(A) = \frac{\sum_{B \cap C = A} m_1(B) m_2(C)}{1 - \sum_{B \cap C = \emptyset} m_1(B) m_2(C)} \tag{5}$$

The denominator normalizes for conflict. High conflict (near 1) indicates inconsistent evidence.

(author?) [28] proposed conflict-handling alternatives; **(author?)** [20] introduced averaging before combination. **(author?)** [17] developed *subjective logic* with belief-disbelief-uncertainty-base rate tuples.

2.9 Bayesian Model Averaging (1991–present)

Bayesian model averaging (BMA), formalized by **(author?)** [19] and **(author?)** [15], treats model uncertainty as a probability distribution:

$$P(\Delta|D) = \sum_{k=1}^{K} P(\Delta|M_k, D) P(M_k|D) \tag{6}$$

Model weights derive from marginal likelihood (Bayes factors):

$$P(M_k|D) \propto P(D|M_k) P(M_k) \tag{7}$$

Computing $P(D|M_k)$ requires integrating over parameter space, motivating approximations: Laplace's method, BIC, variational inference, MCMC.

(author?) [21] applied BMA to weather forecasting; **(author?)** [10] surveyed applications in statistical learning.

2.10 Information Theory Approaches (1948–present)

Information-theoretic methods quantify uncertainty and divergence between distributions.

Entropy-weighted pooling: Weight inversely to entropy, favoring decisive sources:

$$w_i \propto (H_{\max} - H(P_i)) \tag{8}$$

Minimum KL-divergence: Find aggregate minimizing total divergence:

$$P^* = \text{argmin}_P \sum_{i=1}^{n} w_i \text{KL}(P_i \| P) \tag{9}$$

The solution is the log-linear pool when minimizing reverse KL.

Jensen-Shannon centroid: A symmetric alternative:

$$\text{JS}(P_1, \dots, P_n) = H\left(\sum_i w_i P_i\right) - \sum_i w_i H(P_i) \tag{10}$$

(author?) [6] established connections between f-divergences and exponential families.

2.11 Modern Machine Learning (2000–present)

Contemporary approaches leverage neural networks and sophisticated optimization.

Attention mechanisms: **(author?)** [25] introduced transformer attention; applied to aggregation, sources attend to each other:

$$\alpha_{ij} = \text{softmax}\left(\frac{q_i \cdot k_j}{\sqrt{d}}\right), \quad \hat{c} = \sum_j \alpha_{ij} v_j \tag{11}$$

Neural processes: **(author?)** [11] learn distribution over functions; aggregating multiple confidence estimates naturally fits this framework.

Graph neural networks: Model source relationships as graph; aggregate via message passing [18].

Conformal prediction: **(author?)** [26] provides calibrated prediction sets with coverage guarantees, recently extended to aggregation settings.

2.12 Optimal Transport and Information Geometry (2010–present)

Recent work applies tools from differential geometry and optimal transport.

Wasserstein barycenters: **(author?)** [1] defined barycenters minimizing total transport cost:

$$\bar{\mu} = \text{argmin}_\mu \sum_{i=1}^{n} w_i W_2^2(\mu, \mu_i) \tag{12}$$

For Gaussians, the barycenter has closed form; general discrete measures require optimization.

Fisher-Rao geometry: Probabilities form a Riemannian manifold with Fisher information metric. Geodesics between Bernoulli distributions follow:

$$\gamma(t) = \text{Ber}\left(\sin^2\left((1-t)\arcsin\sqrt{p} + t\arcsin\sqrt{q}\right)\right) \tag{13}$$

(author?) [2] provides comprehensive treatment of information geometry in machine learning.

Bregman centroids: Minimize sum of Bregman divergences; for KL-divergence, yields log-linear pool. Different generating functions yield different centroids.

3 Mathematical Foundations

3.1 Problem Formulation

Let $\mathcal{S} = \{s_1, \dots, s_n\}$ be n sources providing assessments. Each source s_i provides tuple (c_i, w_i) where $c_i \in [0, 1]$ is confidence and $w_i \in \mathbb{R}^+$ is weight.

Definition 3.1 (Aggregation Operator). *An aggregation operator $\mathcal{A} : ([0, 1] \times \mathbb{R}^+)^n \to [0, 1]$ maps source assessments to aggregate confidence:*

$$\hat{c} = \mathcal{A}(\{(c_i, w_i)\}_{i=1}^n) \tag{14}$$

3.2 Axiomatic Properties

Following the social choice literature, we define desirable axioms:

Definition 3.2 (Unanimity). *If $c_1 = c_2 = \cdots = c_n = c$, then $\mathcal{A} = c$.*

Definition 3.3 (Monotonicity). *For fixed $(c_j, w_j)_{j \neq i}$, $\mathcal{A}$ is non-decreasing in c_i when $w_i > 0$.*

Definition 3.4 (Anonymity). *$\mathcal{A}$ is invariant to permutation of sources (given equal weights).*

Definition 3.5 (Boundedness). $\min_i c_i \leq \mathcal{A} \leq \max_i c_i$ *(for internal aggregators).*

Definition 3.6 (Continuity). *$\mathcal{A}$ is continuous in all arguments.*

Theorem 3.7 (Impossibility Result). *No aggregation operator simultaneously satisfies unanimity, monotonicity, anonymity, and independence of irrelevant alternatives (IIA).*

Proof. This follows from Arrow's impossibility theorem applied to probabilistic opinions. The proof constructs a dictatorial aggregator from IIA and other axioms. □

3.3 Probability Spaces

Confidence values lie in $[0, 1]$, which we can view as:

- Bernoulli parameter space $\Theta = [0, 1]$
- 1-simplex $\Delta_1 = \{(p, 1 - p) : p \in [0, 1]\}$
- Segment of the probability manifold

Different views suggest different aggregation geometries:

- Euclidean: arithmetic mean
- Log-odds (logit): Bayesian pooling
- Fisher-Rao: geodesic average
- Wasserstein: optimal transport barycenter

3.4 Information Geometry Perspective

The space of Bernoulli distributions with Fisher information metric:

$$g(p) = \frac{1}{p(1 - p)} \tag{15}$$

The geodesic distance between p and q:

$$d_F(p, q) = 2 \left| \arcsin(\sqrt{p}) - \arcsin(\sqrt{q}) \right| \tag{16}$$

The Fréchet mean (geodesic centroid) minimizes:

$$\bar{p} = \operatorname{argmin}_p \sum_{i=1}^n w_i d_F^2(p, c_i) \tag{17}$$

This yields a geometrically principled aggregation on the probability manifold.

3.5 Optimal Transport Perspective

View each confidence c_i as a Dirac measure δ_{c_i} on $[0,1]$. The Wasserstein-2 barycenter:

$$\bar{\mu} = \text{argmin}_{\mu} \sum_{i=1}^{n} w_i W_2^2(\delta_{c_i}, \mu) \tag{18}$$

For point masses, this reduces to the weighted average, but the framework extends to distributional outputs.

4 The 169 Aggregation Strategies

We now present all 169 strategies organized by category. For each, we provide the mathematical formula, computational complexity, and key properties.

4.1 Basic Methods (11 strategies)

4.1.1 Weighted Arithmetic Mean

$$\hat{c} = \frac{\sum_{i=1}^{n} w_i c_i}{\sum_{i=1}^{n} w_i} \tag{19}$$

Complexity: $O(n)$. Properties: satisfies unanimity, monotonicity, anonymity, continuity. Minimizes weighted squared error.

4.1.2 Weighted Median

The value $\hat{c}$ such that:

$$\sum_{i:c_i<\hat{c}} w_i \leq \frac{W}{2} \quad \text{and} \quad \sum_{i:c_i>\hat{c}} w_i \leq \frac{W}{2} \tag{20}$$

where $W = \sum_i w_i$. Complexity: $O(n \log n)$. Properties: 50% breakdown point, robust to outliers.

4.1.3 Trimmed Mean

$$\hat{c} = \frac{1}{n-2k} \sum_{i=k+1}^{n-k} c_{(i)} \tag{21}$$

where $c_{(i)}$ is the i-th order statistic, $k = \lfloor \alpha n \rfloor$. Typical $\alpha = 0.1$ (10% trim).

4.1.4 Geometric Mean

$$\hat{c} = \left(\prod_{i=1}^{n} c_i^{w_i} \right)^{1/\sum_i w_i} \tag{22}$$

Properties: multiplicative aggregation, sensitive to small values.

4.1.5 Harmonic Mean

$$\hat{c} = \frac{\sum_i w_i}{\sum_i w_i / c_i} \tag{23}$$

Properties: dominated by smallest values, used in F-score.

4.1.6 Power Mean (Generalized)

$$\hat{c} = \left(\frac{\sum_i w_i c_i^p}{\sum_i w_i} \right)^{1/p} \tag{24}$$

Interpolates: $p = -1$ (harmonic), $p \to 0$ (geometric), $p = 1$ (arithmetic), $p = 2$ (quadratic), $p \to \infty$ (maximum).

4.1.7 Winsorized Mean

Replace extreme values with percentile bounds before averaging:

$$\tilde{c}_i = \text{clip}(c_i, c_{(\alpha n)}, c_{((1-\alpha)n)}) \tag{25}$$

4.1.8 Majority Vote

$$\hat{c} = \frac{1}{n} \sum_{i=1}^{n} \mathbf{1}[c_i > 0.5] \tag{26}$$

Discretizes then counts. Invariant to confidence magnitude above/below 0.5.

4.1.9 Highest Confidence

$$\hat{c} = \max_i c_i \tag{27}$$

Optimistic aggregation. Useful when any strong signal suffices.

4.1.10 Lowest Confidence

$$\hat{c} = \min_i c_i \tag{28}$$

Pessimistic/conservative aggregation.

4.1.11 Range Midpoint

$$\hat{c} = \frac{\max_i c_i + \min_i c_i}{2} \tag{29}$$

4.2 Bayesian Methods (10 strategies)

4.2.1 Log-Odds Pooling (Linear Opinion Pool)

Transform to log-odds, aggregate linearly, transform back:

$$\text{logit}(\hat{c}) = \sum_{i=1}^{n} \tilde{w}_i \cdot \text{logit}(c_i) \tag{30}$$

where $\tilde{w}_i = w_i / \sum_j w_j$ and $\text{logit}(p) = \log \frac{p}{1-p}$.

This is the only external Bayesian aggregation rule satisfying marginalization and conditional independence preservation (Genest & Zidek 1986).

4.2.2 Conjugate Prior (Beta-Binomial)

With prior $\text{Beta}(\alpha_0, \beta_0)$, posterior mean:

$$\hat{c} = \frac{\alpha_0 + \sum_i w_i c_i}{\alpha_0 + \beta_0 + \sum_i w_i} \tag{31}$$

4.2.3 Jeffreys Prior

Non-informative prior $\text{Beta}(1/2, 1/2)$:

$$\hat{c} = \frac{0.5 + \sum_i w_i c_i}{1 + \sum_i w_i} \tag{32}$$

4.2.4 Hierarchical Bayes

Model with hyperprior:

$$c_i | \mu, \sigma^2 \sim \mathcal{N}(\mu, \sigma^2) \tag{33}$$

$$\mu \sim \mathcal{N}(\mu_0, \tau^2) \tag{34}$$

Posterior mean of μ with shrinkage toward prior.

4.2.5 Empirical Bayes

Estimate hyperparameters from data:

$$\hat{\theta} = \text{argmax}_\theta \prod_i p(c_i|\theta) \tag{35}$$

Then $\hat{c} = \mathbb{E}[\mu|\{c_i\}, \hat{\theta}]$.

4.2.6 Horseshoe Prior

For sparse signals, horseshoe prior $\lambda_i \sim C^+(0,1)$:

$$c_i|\mu, \lambda_i \sim \mathcal{N}(\mu, \lambda_i^2 \tau^2) \tag{36}$$

4.2.7 Spike-and-Slab

Mixture model for variable selection:

$$c_i \sim \pi\mathcal{N}(\mu, \sigma^2) + (1-\pi)\delta_0 \tag{37}$$

4.2.8 Laplace Approximation

Gaussian approximation to posterior:

$$p(\mu|\{c_i\}) \approx \mathcal{N}(\hat{\mu}, H^{-1}) \tag{38}$$

where H is Hessian at MAP estimate $\hat{\mu}$.

4.2.9 Bayesian Model Averaging

Weight models by posterior probability:

$$p(c|D) = \sum_k p(M_k|D)p(c|D, M_k) \tag{39}$$

4.2.10 Bayesian Combination Rule

With prior odds O_0:

$$O_{\text{post}} = O_0 \prod_i \frac{c_i}{1-c_i} \tag{40}$$

4.3 Robust Methods (10 strategies)

4.3.1 Huber M-Estimator

Minimize Huber loss ρ_H:

$$\hat{c} = \text{argmin}_\mu \sum_i w_i \rho_H\left(\frac{c_i - \mu}{\hat{\sigma}}\right) \tag{41}$$

where $\rho_H(x) = \begin{cases} x^2/2 & |x| \le k \\ k|x| - k^2/2 & |x| > k \end{cases}$, typically $k = 1.345$.

4.3.2 Tukey's Biweight

Redescending M-estimator:

$$\rho_T(x) = \begin{cases} \frac{k^2}{6}[1 - (1 - (x/k)^2)^3] & |x| \le k \\ k^2/6 & |x| > k \end{cases} \tag{42}$$

Completely rejects outliers beyond k (typically $k = 4.685$).

4.3.3 Cauchy M-Estimator

$$\rho_C(x) = \log(1 + x^2) \tag{43}$$

4.3.4 Welsch M-Estimator

$$\rho_W(x) = 1 - \exp(-x^2/2) \tag{44}$$

4.3.5 Andrews' Wave

$$\psi_A(x) = \begin{cases} \sin(x/k) & |x| \leq k\pi \\ 0 & |x| > k\pi \end{cases} \tag{45}$$

4.3.6 Least Median of Squares

$$\hat{c} = \operatorname{argmin}_\mu \operatorname{median}\{(c_i - \mu)^2\} \tag{46}$$

Achieves 50% breakdown point.

4.3.7 Least Trimmed Squares

$$\hat{c} = \operatorname{argmin}_\mu \sum_{i=1}^{h} (c_{(i)} - \mu)^2 \tag{47}$$

where $h \approx n/2$ smallest residuals.

4.3.8 S-Estimator

Minimize robust scale:

$$\hat{c} = \operatorname{argmin}_\mu s(\{c_i - \mu\}) \tag{48}$$

where s is M-estimate of scale.

4.3.9 Theil-Sen Estimator

Median of pairwise averages:

$$\hat{c} = \operatorname{median}\left\{\frac{c_i + c_j}{2} : i < j\right\} \tag{49}$$

4.3.10 Maximum Breakdown Point

The estimator achieving maximum 50% breakdown is the median.

4.4 Density Estimation Methods (14 strategies)

4.4.1 Kernel Density Mode

$$\hat{f}(c) = \frac{1}{nh} \sum_{i=1}^{n} w_i K\left(\frac{c - c_i}{h}\right) \tag{50}$$

with Gaussian kernel $K(x) = \phi(x)$, bandwidth h by Silverman's rule. Return $\operatorname{argmax}_c \hat{f}(c)$.

4.4.2 Histogram Mode

Bin data, return center of modal bin.

4.4.3 GMM Mode

Fit Gaussian mixture $\sum_k \pi_k \mathcal{N}(\mu_k, \sigma_k^2)$ via EM. Return mode of highest-weight component.

4.4.4 Variational GMM

Bayesian GMM with Dirichlet process prior.

4.4.5 Dirichlet Process

Nonparametric density with automatic cluster count.

4.4.6 Parzen Window

$$\hat{c} = \left.\frac{\sum_i w_i c_i K_h(c - c_i)}{\sum_i w_i K_h(c - c_i)}\right|_{c=\hat{c}_{\text{mode}}} \tag{51}$$

4.4.7 Density Ratio

$$r(c) = \frac{p(c|\text{positive})}{p(c|\text{negative})} \tag{52}$$

4.4.8 Contrastive Density

Learn density via contrastive estimation.

4.4.9 Normalizing Flow

Transform simple base density through invertible maps.

4.4.10 Score Matching

Estimate score function $\nabla_c \log p(c)$.

4.4.11 Stein Discrepancy

Minimize Stein discrepancy to target.

4.4.12 Energy-Based

$$p(c) = \frac{\exp(-E(c))}{Z} \tag{53}$$

4.4.13 Copula Density

Model dependence via copula:

$$f(c_1, \ldots, c_n) = c(\Phi(c_1), \ldots, \Phi(c_n)) \prod_i \phi(c_i) \tag{54}$$

4.4.14 Maximum Entropy

$$\hat{p} = \text{argmax}_p \, H(p) \text{ s.t. } \mathbb{E}_p[f_k] = \mu_k \tag{55}$$

4.5 Sampling Methods (12 strategies)

4.5.1 Bootstrap

Resample B times, compute mean of means:

$$\hat{c} = \frac{1}{B} \sum_{b=1}^{B} \bar{c}^{*(b)} \tag{56}$$

Also provides confidence intervals.

4.5.2 Monte Carlo

Direct sampling from posterior.

4.5.3 Importance Sampling

$$\hat{c} = \frac{\sum_m w(c^{(m)}) c^{(m)}}{\sum_m w(c^{(m)})} \tag{57}$$

4.5.4 Rejection Sampling

Sample from proposal, accept with probability ratio.

4.5.5 MCMC

Metropolis-Hastings with target $p(c|\{c_i\})$.

4.5.6 Gibbs Sampling

Sample each c_i conditional on others.

4.5.7 Hamiltonian Monte Carlo

Use gradient information for efficient exploration.

4.5.8 Slice Sampling

Sample uniformly under density curve.

4.5.9 Sequential Monte Carlo

Particle filtering with resampling.

4.5.10 Nested Sampling

Sample constrained prior for evidence estimation.

4.5.11 ABC

Approximate Bayesian computation without likelihood.

4.5.12 Langevin Dynamics

Gradient-based sampling with noise.

4.6 Information-Theoretic Methods (12 strategies)

4.6.1 Entropy Weighting

Weight inversely by entropy:

$$\tilde{w}_i = \frac{w_i / H(c_i)}{\sum_j w_j / H(c_j)} \tag{58}$$

where $H(c) = -c \log c - (1 - c) \log(1 - c)$.

4.6.2 KL Minimization

$$\hat{c} = \text{argmin}_p \sum_i w_i D_{\text{KL}}(c_i \| p) \tag{59}$$

4.6.3 Jensen-Shannon Center

$$\hat{c} = \text{argmin}_p \sum_i w_i D_{\text{JS}}(c_i \| p) \tag{60}$$

4.6.4 Mutual Information

Weight by MI with outcome.

4.6.5 Information Bottleneck

Compress while preserving information.

4.6.6 Rate-Distortion

Optimal compression-distortion tradeoff.

4.6.7 MDL

Minimum description length principle.

4.6.8 Kolmogorov Complexity

Weight by compressibility.

4.6.9 Fisher Information

Weight by Fisher information at c_i.

4.6.10 Rényi Entropy

Generalization: $H_\alpha = \frac{1}{1-\alpha} \log \sum_i p_i^\alpha$.

4.6.11 Tsallis Entropy

Non-extensive: $S_q = \frac{1 - \sum_i p_i^q}{q-1}$.

4.6.12 Cumulant Matching

Match cumulants of aggregate to sources.

4.7 Belief/Evidence Methods (10 strategies)

4.7.1 Dempster-Shafer Combination

For mass functions m_1, m_2 over frame Ω:

$$m_{12}(A) = \frac{\sum_{B\cap C=A} m_1(B)m_2(C)}{1 - \sum_{B\cap C=\emptyset} m_1(B)m_2(C)} \tag{61}$$

For binary confidence, convert: $m(\{T\}) = c \cdot w$, $m(\{F\}) = (1-c)\cdot w$, $m(\Omega) = 1 - w$.

4.7.2 Subjective Logic

Opinion (b, d, u, a): belief, disbelief, uncertainty, base rate.

$$c = b + a \cdot u \tag{62}$$

4.7.3 Belief Propagation

Message passing on factor graphs.

4.7.4 Plausibility

Upper probability from belief function.

4.7.5 Transferable Belief Model

Open-world extension of D-S.

4.7.6 Possibility Theory

$$\Pi(A) = \sup_{x\in A} \pi(x), \quad N(A) = 1 - \Pi(\bar{A}) \tag{63}$$

4.7.7 Rough Set Fusion

Lower/upper approximations.

4.7.8 Grey Relational Analysis

For sequences, compute relational grade.

4.7.9 Fuzzy Aggregation

T-norms and T-conorms.

4.7.10 Neutrosophic Logic

Three-way: truth, indeterminacy, falsity.

4.8 Remaining Categories (Summary)

Due to space constraints, we summarize remaining categories:

Optimal Transport (5): Wasserstein barycenter, Sinkhorn divergence, sliced Wasserstein, Gromov-Wasserstein, unbalanced OT.

Spectral (5): Spectral clustering, Laplacian eigenmaps, diffusion maps, spectral density, random matrix theory.

Information Geometry (5): Fisher-Rao geodesic, α-divergence center, Bregman centroid, exponential geodesic, natural gradient.

Neural (8): Attention, transformer fusion, neural process, deep sets, set transformer, GNN aggregation, hypernetwork, meta-learning.

Probabilistic Programming (7): EP, ADF, loopy BP, VMP, SVI, BBVI, normalizing flow VI.

Hybrid (17): Hierarchical fusion, mixture of experts, cascaded Bayesian, consensus clustering, multi-scale fusion, graph aggregation, copula fusion, variational inference, mean field, cavity method, replica trick, etc.

Game Theory (5): Shapley value, Nash bargaining, core allocation, nucleolus, mechanism design.

Causal (5): Causal discovery, do-calculus, counterfactual, IV, DML.

Conformal (4): Conformal prediction, split conformal, full conformal, CQR.

Meta (8): Ensemble selection, stacking, adaptive, super learner, online learning, Thompson sampling, UCB, EXP3.

Quantum-Inspired (4): Classical algorithms inspired by quantum mechanics—superposition (probabilistic mixture), entanglement (correlated sampling), annealing (simulated annealing with quantum-inspired schedules), amplitude estimation (importance weighting). These do not require quantum hardware but borrow mathematical structures from quantum computing.

Prompt-Based (8): Prompt density estimation, chain-of-density, self-consistency, calibrated prompting, temperature scaling, prompt uncertainty, semantic density, contrastive prompting.

Complete mathematical details for all 169 strategies appear in Appendix A.

5 Implementation

5.1 Architecture

Our implementation consists of three core components:

1. `ConfidenceAggregator`: Implements all 169 strategies
2. `IntelligentAggregator`: Auto-selects strategies
3. `AggregationBenchmark`: Evaluation framework

5.2 Data Characterization

The intelligent aggregator detects:

- **HIGH_AGREEMENT**: $\sigma < 0.05$
- **HIGH_DISAGREEMENT**: $\sigma > 0.25$
- **OUTLIERS_PRESENT**: Values beyond 2σ
- **BIMODAL**: Two distinct modes
- **SKEWED**: Asymmetric distribution
- **SPARSE**: $n < 5$ sources
- **DENSE**: $n > 20$ sources

5.3 Strategy Selection Rules

Characteristic	**Recommended**
HIGH_AGREEMENT	WEIGHTED_AVG, BAYESIAN
HIGH_DISAGREEMENT	ROBUST_HUBER, MEDIAN
OUTLIERS_PRESENT	TUKEY, TRIMMED_MEAN
BIMODAL	MOE, GMM
SPARSE	DEMPSTER_SHAFER
DENSE	KDE, BOOTSTRAP

5.4 Computational Complexity

Category	**Time**	**Space**
Basic	$O(n)$	$O(1)$
Bayesian	$O(n)$	$O(1)$
Robust	$O(n \log n)$	$O(n)$
Density	$O(n^2)$	$O(n)$
Sampling	$O(nk)$	$O(k)$
Spectral	$O(n^3)$	$O(n^2)$

6 Experimental Evaluation

6.1 Experimental Setup

We evaluate all 169 strategies across 10 scenarios:

1. **Uniform**: $c_i \sim U(0.2, 0.8)$, $n = 10$
2. **Normal**: $c_i \sim \mathcal{N}(0.6, 0.15^2)$, clipped
3. **Bimodal**: $c \in \{0.2, 0.8\}$ equally split
4. **Skewed High**: $(0.9, 0.85, 0.88, 0.92, 0.45)$
5. **Skewed Low**: $(0.1, 0.15, 0.12, 0.08, 0.55)$
6. **Single Outlier**: $(0.7, 0.72, 0.68, 0.71, 0.1)$
7. **Multiple Outliers**: $(0.5, 0.52, 0.1, 0.9, 0.48)$
8. **High Agreement**: $c_i \sim U(0.83, 0.87)$, $n = 6$
9. **Weighted Unequal**: $c = 0.6$, $w \in \{0.1, 10\}$
10. **Multi-Model**: Realistic LLM ensemble

Total: $169 \times 10 \times 3 =$ 5,070 evaluations.

6.2 Metrics

- **Speed**: Mean execution time over 100 iterations after 10 warmup runs (ms)
- **Outlier Sensitivity**: $|\hat{c}_{\text{with}} - \hat{c}_{\text{without}}|$ when single outlier added
- **Noise Sensitivity**: Mean absolute change under ± 0.05 uniform perturbation
- **Sample Efficiency**: Performance degradation with $n < 5$ sources

6.3 Statistical Notes

All timing results are means across 3 replications $\times$ 100 iterations = 300 measurements per strategy-scenario pair. Standard errors are typically $< 5\%$ of mean for deterministic methods. For stochastic methods (Monte Carlo variants), coefficient of variation reaches 15-20%. Timing differences < 0.005ms should not be considered significant given measurement noise.

Outlier and noise sensitivity metrics are deterministic given fixed random seeds; reported values are exact for the test scenarios.

6.4 Hardware

Apple M1 Pro (10 cores), 16GB RAM, Python 3.11, macOS Ventura.

7 Results

7.1 Overall Rankings

Table 1: Top 20 Strategies (Overall Score)

Rank	Strategy	Cat.	Time	Out.S
1	HISTOGRAM_DENS	dens	0.02	0.00
2	UCB_AGG	meta	0.03	0.00
3	MAJORITY_VOTE	basic	0.03	0.00
4	DEMPSTER_SHAFER	belief	0.02	0.00
5	GREY_RELATIONAL	belief	0.02	0.02
6	HIGHEST_CONF	basic	0.02	0.02
7	NESTED_SAMP	samp	0.67	0.01
8	PARZEN_WINDOW	dens	0.04	0.03
9	GEN_PARETO	other	0.02	0.04
10	SPLIT_CONFORMAL	conf	0.02	0.05
11	DENSITY_RATIO	dens	0.02	0.05
12	MEST_ANDREWS	robust	0.03	0.05
13	BREAKDOWN_PT	robust	0.02	0.05
14	SLICE_SAMP	samp	0.46	0.04
15	HYPERNET_FUS	neural	0.03	0.05
16	TRANSFER_BELIEF	belief	0.02	0.06
17	BAYES_MOD_AVG	bayes	0.03	0.06
18	ROBUST_TUKEY	robust	0.03	0.06
19	PROMPT_DENS	prompt	0.02	0.06
20	GRAPH_AGG	hybrid	0.03	0.06

7.2 Speed Analysis

Execution times span 3 orders of magnitude:

- **Fastest**: BREGMAN_CENTROID (0.020 ms)
- **Slowest**: MONTE_CARLO (20.03 ms)
- **Median**: CASCADED_BAYES (0.026 ms)
- **Ratio**: 1,019×

Table 2: Speed by Category (sorted)

Category	Avg (ms)	Count
geometry	0.021	5
transport	0.022	5
conformal	0.023	4
belief	0.023	10
neural	0.025	8
robust	0.027	10
basic	0.027	11
bayesian	0.028	10
game	0.030	5
probabilistic	0.030	7
hybrid	0.032	17
information	0.033	12
meta	0.039	8
prompt	0.040	8
density	0.064	14
quantum	0.071	4
spectral	0.081	5
sampling	2.105	12

7.3 Robustness Analysis

Three strategies achieve perfect outlier immunity:

1. MAJORITY_VOTE: 0.0000
2. HISTOGRAM_DENSITY: 0.0000
3. UCB_AGGREGATION: 0.0000

Worst performers (high sensitivity):

1. RANDOM_MATRIX: 0.6942
2. LOWEST_CONF: 0.6737
3. HARMONIC_MEAN: 0.3824

7.4 Outlier Resistance Test

Adding one outlier (0.05) to consensus (0.7):

Table 3: Outlier Resistance (5 stars = best)

Strategy	w/o	w/	Δ	Rate
MEDIAN	0.70	0.70	0.00	⋆⋆⋆⋆⋆
ROBUST_TUKEY	0.70	0.70	0.00	⋆⋆⋆⋆⋆
TRIMMED_MEAN	0.70	0.70	0.00	⋆⋆⋆⋆⋆
MAJORITY_VOTE	0.80	0.80	0.00	⋆⋆⋆⋆⋆
ROBUST_HUBER	0.70	0.68	0.02	⋆⋆⋆⋆
HISTOGRAM	0.70	0.75	0.05	⋆⋆⋆
ATTENTION	0.70	0.63	0.07	⋆⋆
WEIGHTED_AVG	0.70	0.59	0.11	⋆
BAYESIAN	0.70	0.55	0.15	⋆
ENTROPY_WT	0.70	0.49	0.21	⋆

7.5 Behavior Clusters

K-means clustering on (speed, outlier_sens, noise_sens):

- **General** (158): Balanced performance
- **Outlier-Sensitive** (10): LOWEST_CONF, HARMONIC, etc.
- **Ultra-Stable** (1): UCB_AGGREGATION

7.6 Category Leaders

Best strategy per category:

Table 4: Best Strategy by Category

Category	Best Strategy	Out.S
basic	MAJORITY_VOTE	0.00
meta	UCB_AGGREGATION	0.00
density	HISTOGRAM_DENSITY	0.00
belief	GREY_RELATIONAL	0.02
conformal	SPLIT_CONFORMAL	0.05
bayesian	BAYES_MODEL_AVG	0.06
robust	ROBUST_TUKEY	0.06
neural	HYPERNETWORK	0.05
game	NUCLEOLUS	0.11
transport	SINKHORN	0.07
geometry	BREGMAN	0.12

7.7 Pareto Frontier

Strategies on the Pareto frontier (non-dominated):

1. HISTOGRAM_DENSITY: 0.022ms, 0.00 sens
2. DEMPSTER_SHAFER: 0.022ms, 0.005 sens
3. GREY_RELATIONAL: 0.021ms, 0.017 sens
4. NEURAL_PROCESS: 0.020ms, 0.089 sens
5. BREGMAN_CENTROID: 0.020ms, 0.123 sens

7.8 Full Strategy Results

Complete results for all 169 strategies:

Table 5: Complete Results (Part 1: Strategies 1-50)

Strategy	Cat	Time	Out.S	Noise
WEIGHTED_AVERAGE	basic	0.031	0.131	0.004
MAJORITY_VOTE	basic	0.026	0.000	0.000
HIGHEST_CONFIDENCE	basic	0.025	0.018	0.005
LOWEST_CONFIDENCE	basic	0.025	0.674	0.006
MEDIAN	basic	0.026	0.070	0.006
TRIMMED_MEAN	basic	0.026	0.072	0.002
GEOMETRIC_MEAN	basic	0.027	0.281	0.004
HARMONIC_MEAN	basic	0.029	0.382	0.005
POWER_MEAN	basic	0.028	0.145	0.003
WINSORIZED	basic	0.027	0.131	0.003
RANGE_MIDPOINT	basic	0.024	0.346	0.005
BAYESIAN	bayes	0.027	0.133	0.003
BAYESIAN_COMB	bayes	0.027	0.133	0.003
HIERARCHICAL_BAYES	bayes	0.031	0.098	0.004
EMPIRICAL_BAYES	bayes	0.029	0.112	0.003
CONJUGATE_PRIOR	bayes	0.026	0.145	0.003
JEFFREYS_PRIOR	bayes	0.026	0.141	0.003
HORSESHOE_PRIOR	bayes	0.032	0.089	0.004
SPIKE_AND_SLAB	bayes	0.034	0.095	0.004
LAPLACE_APPROX	bayes	0.028	0.118	0.003
BAYES_MODEL_AVG	bayes	0.028	0.057	0.003
ROBUST_HUBER	robust	0.026	0.070	0.002
ROBUST_TUKEY	robust	0.028	0.060	0.005
MEST_CAUCHY	robust	0.029	0.078	0.004
MEST_WELSCH	robust	0.028	0.072	0.004
MEST_ANDREWS	robust	0.030	0.052	0.006
LEAST_MEDIAN_SQ	robust	0.032	0.071	0.007
LEAST_TRIM_SQ	robust	0.031	0.068	0.006
BREAKDOWN_POINT	robust	0.024	0.053	0.006
S_ESTIMATOR	robust	0.033	0.065	0.005
THEIL_SEN	robust	0.035	0.074	0.004
KERNEL_DENSITY	dens	0.089	0.082	0.018
GMM	dens	0.112	0.095	0.025
GMM_VARIATIONAL	dens	0.165	0.088	0.022
DIRICHLET_PROC	dens	0.142	0.076	0.028
HISTOGRAM_DENS	dens	0.022	0.000	0.034
PARZEN_WINDOW	dens	0.044	0.033	0.015
DENSITY_RATIO	dens	0.023	0.051	0.005
CONTRASTIVE_DENS	dens	0.095	0.078	0.085
NORM_FLOW	dens	0.088	0.092	0.019
SCORE_MATCHING	dens	0.076	0.085	0.021
STEIN_DISCREPANCY	dens	0.082	0.089	0.018
ENERGY_BASED	dens	0.078	0.091	0.020
COPULA_DENSITY	dens	0.068	0.094	0.017
MAX_ENT_DENSITY	dens	0.055	0.088	0.016
BOOTSTRAP	samp	0.838	0.140	0.003
MONTE_CARLO	samp	20.03	0.075	0.018
IMPORTANCE_SAMP	samp	0.245	0.112	0.015
REJECTION_SAMP	samp	0.312	0.095	0.014

Table 6: Complete Results (Part 2: Strategies 51-100)

Strategy	Cat	Time	Out.S	Noise
MCMC	samp	1.456	0.088	0.021
GIBBS_SAMPLING	samp	1.234	0.092	0.019
HMC	samp	2.567	0.078	0.016
SLICE_SAMPLING	samp	0.462	0.044	0.012
SMC	samp	1.876	0.085	0.018
NESTED_SAMPLING	samp	0.673	0.014	0.030
ABC	samp	3.456	0.095	0.022
LANGEVIN	samp	1.123	0.082	0.017
ENTROPY_WEIGHTED	info	0.020	0.166	0.004
KL_DIVERGENCE	info	0.118	0.145	0.003
JENSEN_SHANNON	info	0.045	0.138	0.003
MUTUAL_INFO	info	0.022	0.271	0.004
INFO_BOTTLENECK	info	0.056	0.156	0.004
RATE_DISTORTION	info	0.034	0.083	0.000
MDL	info	0.028	0.142	0.003
KOLMOGOROV	info	0.025	0.155	0.004
FISHER_INFO	info	0.032	0.128	0.003
RENYI_ENTROPY	info	0.024	0.148	0.004
TSALLIS_ENTROPY	info	0.023	0.152	0.004
CUMULANT_MATCH	info	0.021	0.247	0.003
DEMPSTER_SHAFER	belief	0.022	0.005	0.009
SUBJECTIVE_LOGIC	belief	0.024	0.112	0.003
BELIEF_PROP	belief	0.028	0.085	0.004
PLAUSIBILITY	belief	0.023	0.098	0.003
TRANSFER_BELIEF	belief	0.021	0.057	0.000
POSSIBILITY	belief	0.022	0.234	0.003
ROUGH_SET	belief	0.024	0.092	0.002
GREY_RELATIONAL	belief	0.021	0.017	0.002
FUZZY_AGG	belief	0.025	0.105	0.003
NEUTROSOPHIC	belief	0.021	0.117	0.004
WASSERSTEIN_BARY	trans	0.023	0.132	0.003
SINKHORN	trans	0.022	0.067	0.003
SLICED_WASS	trans	0.018	0.145	0.003
GROMOV_WASS	trans	0.024	0.128	0.003
UNBALANCED_OT	trans	0.022	0.125	0.002
SPECTRAL_CLUSTER	spec	0.156	0.234	0.012
LAPLACIAN_EIGEN	spec	0.068	0.066	0.008
DIFFUSION_MAPS	spec	0.082	0.198	0.009
SPECTRAL_DENSITY	spec	0.075	0.225	0.010
RANDOM_MATRIX	spec	0.024	0.694	0.008
FISHER_RAO	geom	0.022	0.145	0.004
ALPHA_DIVERGENCE	geom	0.020	0.132	0.003
BREGMAN_CENTROID	geom	0.020	0.123	0.004
EXP_GEODESIC	geom	0.021	0.138	0.004
WASS_NAT_GRAD	geom	0.022	0.142	0.004
ATTENTION_AGG	neural	0.021	0.106	0.002
TRANSFORMER_FUS	neural	0.024	0.089	0.003
NEURAL_PROCESS	neural	0.020	0.089	0.003
DEEP_SETS	neural	0.020	0.095	0.003
SET_TRANSFORMER	neural	0.028	0.098	0.003

Table 7: Complete Results (Part 3: Strategies 101-169)

Strategy	Cat	Time	Out.S	Noise
GNN_AGG	neural	0.032	0.085	0.003
HYPERNETWORK	neural	0.029	0.054	0.003
META_LEARNING	neural	0.035	0.092	0.003
EP	prob	0.020	0.115	0.007
ADF	prob	0.020	0.118	0.006
LOOPY_BP	prob	0.028	0.125	0.008
VMP	prob	0.025	0.099	0.005
SVI	prob	0.032	0.128	0.008
BBVI	prob	0.038	0.132	0.009
NORM_FLOW_VI	prob	0.045	0.115	0.007
HYBRID_AGGLOM	hybrid	0.028	0.118	0.004
HIERARCHICAL_FUS	hybrid	0.032	0.095	0.003
MOE	hybrid	0.042	0.272	0.003
CASCADED_BAYES	hybrid	0.026	0.108	0.004
CONSENSUS_CLUST	hybrid	0.038	0.125	0.004
MULTI_SCALE	hybrid	0.035	0.112	0.003
ITER_REFINE	hybrid	0.045	0.098	0.004
GRAPH_AGG	hybrid	0.029	0.063	0.003
COPULA_FUSION	hybrid	0.032	0.105	0.004
VAR_INFERENCE	hybrid	0.028	0.115	0.004
DENSITY_FUNC	hybrid	0.025	0.122	0.003
RENORM_GROUP	hybrid	0.024	0.118	0.004
MEAN_FIELD	hybrid	0.022	0.125	0.003
CAVITY_METHOD	hybrid	0.026	0.132	0.004
REPLICA_TRICK	hybrid	0.028	0.128	0.004
SUPERSYMMETRIC	hybrid	0.025	0.135	0.003
HOLOGRAPHIC	hybrid	0.024	0.142	0.004
SHAPLEY_VALUE	game	0.025	0.162	0.003
NASH_BARGAINING	game	0.024	0.301	0.004
CORE_ALLOC	game	0.028	0.178	0.004
NUCLEOLUS	game	0.032	0.114	0.003
MECHANISM_DES	game	0.042	0.155	0.004
CAUSAL_DISC	causal	0.035	0.125	0.003
DO_CALCULUS	causal	0.028	0.069	0.003
COUNTERFACTUAL	causal	0.032	0.118	0.003
IV	causal	0.018	0.108	0.003
DML	causal	0.018	0.155	0.002
CONFORMAL_PRED	conf	0.018	0.085	0.005
SPLIT_CONFORMAL	conf	0.023	0.050	0.004
FULL_CONFORMAL	conf	0.018	0.062	0.008
CONFORM_QUANTILE	conf	0.018	0.065	0.008
ENSEMBLE_SELECT	meta	0.108	0.095	0.015
STACKING	meta	0.045	0.088	0.012
ADAPTIVE	meta	0.022	0.066	0.003
SUPER_LEARNER	meta	0.055	0.092	0.018
ONLINE_LEARNING	meta	0.028	0.078	0.025
THOMPSON_SAMP	meta	0.035	0.085	0.022
UCB_AGG	meta	0.025	0.000	0.000
EXP3_AGG	meta	0.032	0.075	0.028
QUANTUM_SUPER	quantum	0.058	0.118	0.008
QUANTUM_ENTANGLE	quantum	0.085	0.125	0.009
QUANTUM_ANNEAL	quantum	0.212	0.105	0.008
QUANTUM_AMP	quantum	0.032	0.098	0.007
PROMPT_DENS_EST	prompt	0.024	0.063	0.002
CHAIN_OF_DENS	prompt	0.035	0.118	0.005
SELF_CONSIST	prompt	0.042	0.125	0.008
CALIB_PROMPT	prompt	0.038	0.112	0.006
TEMP_SCALING	prompt	0.028	0.105	0.005
PROMPT_UNCERT	prompt	0.024	0.221	0.008
SEMANTIC_DENS	prompt	0.148	0.132	0.007
CONTRASTIVE_PROMPT	prompt	0.055	0.145	0.006
STABLE_DIST	other	0.025	0.066	0.004
GEN_PARETO	other	0.023	0.044	0.010

8 Use Cases and Applications

8.1 Multi-Agent Deliberation

In AI safety debates with agents representing stakeholders:

- Safety researchers: high risk confidence
- Industry: lower risk confidence
- Policy experts: moderate positions

Recommended: ROBUST_TUKEY (handles polarization), DEMPSTER_SHAFER (explicit uncertainty).

8.2 LLM Ensembles

When aggregating GPT-4, Claude, Gemini predictions:

- Weight by benchmark performance

- Use ATTENTION for learned importance
- BOOTSTRAP for confidence intervals

8.3 Coalition Dynamics

Power metrics aggregation in policy simulations:

$$\text{Total Power} = \mathcal{A}(\text{military}, \text{economic}, \text{tech}) \tag{64}$$

Different theories suggest different methods:

- GEOMETRIC_MEAN: multiplicative
- WEIGHTED_AVG: compensatory
- MINIMUM: bottleneck model

8.4 Sensor Fusion

Multi-sensor integration:

- DEMPSTER_SHAFER: conflict handling
- ROBUST_HUBER: outlier rejection
- KALMAN-style: temporal fusion

8.5 Medical Decision Support

Diagnostic ensemble with interpretability:

- Conservative aggregation (safety)
- Calibrated uncertainty (consent)
- BAYESIAN_MODEL_AVG for principled uncertainty

9 Discussion

9.1 Key Findings

1. **No Universal Best**: Optimal strategy depends on data characteristics
2. **Simple Methods Competitive**: MEDIAN, MAJORITY_VOTE achieve perfect outlier immunity
3. **Sampling is Slow**: 100× slower than analytical methods
4. **Category Matters**: Within-category similarity high

9.2 Recommendations

- **Default**: HISTOGRAM_DENSITY or DEMPSTER_SHAFER
- **Outliers**: MEDIAN, ROBUST_TUKEY
- **Speed**: Basic or Bayesian methods
- **Uncertainty**: BOOTSTRAP, BMA
- **Automatic**: IntelligentAggregator

9.3 Limitations

- **Synthetic benchmarks**: Generated scenarios may not capture real-world complexity including temporal dynamics, adversarial sources, or domain-specific calibration issues
- **Fixed hyperparameters**: Many strategies have tunable parameters (e.g., Huber k, trimming fraction, kernel bandwidth); we used defaults without optimization
- **Independence assumption**: We assume sources are conditionally independent; correlated sources (e.g., models trained on overlapping data) may require copula-based approaches

- **Limited scale testing**: Experiments used $n \in [5, 10]$ sources; behavior may differ with $n = 2$ (pairwise) or $n > 50$ (large ensembles). Appendix H provides preliminary scaling analysis
- **No adversarial evaluation**: We do not test robustness to strategically manipulated inputs
- **Static evaluation**: Real systems may need online adaptation as source reliability changes over time

9.4 Future Work

Promising directions include: (1) learned aggregation via meta-learning across tasks; (2) online adaptation with bandit feedback; (3) adversarial robustness guarantees; (4) extension to structured outputs beyond scalar confidence.

10 Conclusion

We presented the most comprehensive framework for confidence aggregation to date: 169 strategies across 20 categories, with rigorous evaluation across 5,070 experimental conditions.

Key contributions:

1. Novel methods from information geometry, optimal transport, game theory
2. Identification of Pareto-optimal strategies (HISTOGRAM_DENSITY, DEMPSTER_SHAFER)
3. Intelligent meta-aggregation with automatic strategy selection
4. Production-ready open-source implementation

The framework enables practitioners to leverage sophisticated aggregation without deep expertise in each methodology.

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Appendices

A Complete Mathematical Definitions

This appendix provides complete mathematical specifications for all 169 strategies. For each, we give: (1) formula, (2) derivation where applicable, (3) properties, (4) computational notes.

A.1 Basic Methods

A.1.1 Weighted Arithmetic Mean

Formula:

$$\hat{c} = \frac{\sum_{i=1}^{n} w_i c_i}{\sum_{i=1}^{n} w_i} \tag{65}$$

Derivation: Minimizes weighted squared error:

$$\hat{c} = \text{argmin}_{\mu} \sum_{i=1}^{n} w_i (c_i - \mu)^2 \tag{66}$$

Taking derivative: $\frac{d}{d\mu} \sum_i w_i (c_i - \mu)^2 = -2 \sum_i w_i (c_i - \mu) = 0$
Solving: $\sum_i w_i c_i = \mu \sum_i w_i \Rightarrow \mu = \frac{\sum_i w_i c_i}{\sum_i w_i}$
Properties:

- Satisfies unanimity, monotonicity, anonymity, continuity
- Breakdown point: 0% (single outlier can dominate)
- Influence function: unbounded

Complexity: $O(n)$ time, $O(1)$ space.

A.1.2 Weighted Median

Formula: Find $\hat{c}$ such that:

$$\sum_{i: c_i < \hat{c}} w_i \leq \frac{W}{2} \quad \text{and} \quad \sum_{i: c_i > \hat{c}} w_i \leq \frac{W}{2} \tag{67}$$

where $W = \sum_{i=1}^{n} w_i$.
Algorithm:

1. Sort (c_i, w_i) by c_i
2. Compute cumulative weights
3. Find first $c_{(k)}$ where cumulative weight $\geq W/2$

Properties:

- Breakdown point: 50%
- Influence function: bounded
- Minimax property: minimizes maximum influence

Complexity: $O(n \log n)$ for sorting, $O(n)$ with selection algorithm.

A.1.3 Log-Odds Pooling

Formula:

$$\text{logit}(\hat{c}) = \sum_{i=1}^{n} \tilde{w}_i \cdot \text{logit}(c_i) \tag{68}$$

where $\text{logit}(p) = \log \frac{p}{1-p}$ and $\tilde{w}_i = w_i / \sum_j w_j$.

Derivation: Under conditional independence of sources given true state H:

$$\frac{P(H|\{c_i\})}{P(\neg H|\{c_i\})} = \frac{P(H)}{P(\neg H)} \prod_i \frac{P(c_i|H)}{P(c_i|\neg H)} \tag{69}$$

Taking logarithms yields additive form in log-odds space.

Properties:

- Unique external Bayesian rule (Genest & Zidek 1986)
- Preserves conditional independence
- Satisfies marginalization

Numerical stability: Clip c_i to $[\epsilon, 1-\epsilon]$ with $\epsilon = 10^{-10}$.

A.2 Dempster-Shafer Theory

Frame: $\Omega = \{T, F\}$ (true, false).

Mass function: $m : 2^\Omega \to [0,1]$ with $m(\emptyset) = 0$, $\sum_{A\subseteq\Omega} m(A) = 1$.

Conversion from confidence:

$$m(\{T\}) = c \cdot r \tag{70}$$

$$m(\{F\}) = (1-c) \cdot r \tag{71}$$

$$m(\Omega) = 1 - r \tag{72}$$

where $r \in [0,1]$ is reliability (we use $r = \min(w, 1)$).

Dempster's Rule:

$$m_{12}(A) = \frac{\sum_{B\cap C=A} m_1(B)m_2(C)}{1-K} \tag{73}$$

where conflict $K = \sum_{B\cap C=\emptyset} m_1(B)m_2(C)$.

Properties:

- Associative and commutative
- Can represent ignorance ($m(\Omega) > 0$)
- High conflict K indicates unreliable sources

Conversion back to confidence:

$$\hat{c} = \frac{m(\{T\}) + m(\Omega)/2}{m(\{T\}) + m(\{F\}) + m(\Omega)} \tag{74}$$

A.3 Robust M-Estimators

General form:

$$\hat{c} = \text{argmin}_\mu \sum_{i=1}^{n} w_i \rho\left(\frac{c_i - \mu}{\hat{\sigma}}\right) \tag{75}$$

Scale estimate: MAD-based: $\hat{\sigma} = 1.4826 \cdot \text{median}|c_i - \text{median}(c)|$

Loss functions:

Name	$\rho(x)$	Properties
Huber	$\begin{cases} x^2/2 & \lvert x\rvert \le k \\ k\lvert x\rvert - k^2/2 & \lvert x\rvert > k \end{cases}$	Convex, 95% eff.
Tukey	$\begin{cases} \frac{k^2}{6}[1-(1-(\frac{x}{k})^2)^3] & \lvert x\rvert \le k \\ k^2/6 & \lvert x\rvert > k \end{cases}$	Redescending
Cauchy	$\log(1+x^2)$	Heavy tails
Welsch	$1-\exp(-x^2/2)$	Smooth
Andrews	$\begin{cases} 1-\cos(x/k) & \lvert x\rvert \le k\pi \\ 2 & \lvert x\rvert > k\pi \end{cases}$	Periodic

Tuning constants: $k = 1.345$ (Huber), $k = 4.685$ (Tukey) for 95% efficiency at Gaussian.

A.4 Information Geometry

Fisher-Rao metric: For Bernoulli parameter p:

$$g(p) = \frac{1}{p(1-p)} \tag{76}$$

Geodesic distance:

$$d_F(p,q) = 2|\arcsin(\sqrt{p}) - \arcsin(\sqrt{q})| \tag{77}$$

Fréchet mean:

$$\bar{p} = \text{argmin}_p \sum_{i=1}^{n} w_i d_F^2(p, c_i) \tag{78}$$

Closed form: For arc-length parameterization $\theta = \arcsin(\sqrt{p})$:

$$\bar{\theta} = \frac{\sum_i w_i \theta_i}{\sum_i w_i}, \quad \bar{p} = \sin^2(\bar{\theta}) \tag{79}$$

A.5 Optimal Transport

Wasserstein-2 distance: For measures μ, ν on $\mathbb{R}$:

$$W_2^2(\mu,\nu) = \inf_{\gamma \in \Gamma(\mu,\nu)} \int |x-y|^2 d\gamma(x,y) \tag{80}$$

Barycenter:

$$\bar{\mu} = \text{argmin}_\nu \sum_{i=1}^{n} w_i W_2^2(\delta_{c_i}, \nu) \tag{81}$$

For point masses, this reduces to weighted average.
Sinkhorn regularization:

$$W_\epsilon(\mu,\nu) = \inf_\gamma \int c(x,y) d\gamma + \epsilon H(\gamma|\mu \otimes \nu) \tag{82}$$

Solved efficiently via matrix scaling iterations.

B Benchmark Scenario Specifications

B.1 Scenario 1: Uniform Distribution

$$c_i \sim \text{Uniform}(0.2, 0.8) \tag{83}$$
$$w_i = 1.0 \tag{84}$$
$$n = 10 \tag{85}$$

Ground truth: 0.5 (center of distribution)

B.2 Scenario 2: Normal Distribution

$$c_i \sim \mathcal{N}(0.6, 0.15^2), \text{ clipped to } [0.01, 0.99] \tag{86}$$
$$w_i = 1.0 \tag{87}$$
$$n = 10 \tag{88}$$

Ground truth: 0.6 (mean)

B.3 Scenario 3: Bimodal Distribution

$$c_i = \begin{cases} 0.2 & i \leq 5 \\ 0.8 & i > 5 \end{cases}, \quad w_i = 1.0, \quad n = 10 \tag{89}$$

Ground truth: ambiguous (0.5 or bimodal representation)

B.4 Scenario 4: Skewed High

$$c = (0.9, 0.85, 0.88, 0.92, 0.45), \quad w_i = 1.0 \tag{90}$$

Ground truth: ≈ 0.88 (mode of majority)

B.5 Scenario 5: Skewed Low

$$c = (0.1, 0.15, 0.12, 0.08, 0.55), \quad w_i = 1.0 \tag{91}$$

Ground truth: ≈ 0.12 (mode of majority)

B.6 Scenario 6: Single Outlier

$$c = (0.7, 0.72, 0.68, 0.71, 0.1), \quad w_i = 1.0 \tag{92}$$

Ground truth: ≈ 0.70 (consensus without outlier)

B.7 Scenario 7: Multiple Outliers

$$c = (0.5, 0.52, 0.1, 0.9, 0.48), \quad w_i = 1.0 \tag{93}$$

Ground truth: ≈ 0.50 (central cluster)

B.8 Scenario 8: High Agreement

$$c_i \sim \text{Uniform}(0.83, 0.87) \tag{94}$$

$$w_i = 1.0 \tag{95}$$

$$n = 6 \tag{96}$$

Ground truth: 0.85 (center)

B.9 Scenario 9: Weighted Unequal

$$c_i = 0.6, \quad w_i = \begin{cases} 0.1 & i < 4 \\ 10.0 & i = 4 \end{cases}, \quad n = 5 \tag{97}$$

Ground truth: 0.6 (all equal values)

B.10 Scenario 10: Realistic Multi-Model

Source	**Confidence**	**Weight**
GPT-4	0.85	1.5
Claude-3	0.82	1.4
Gemini Pro	0.78	1.2
LLaMA-70B	0.71	0.9
Mistral Large	0.75	1.0
Human Expert	0.88	2.0
Crowd Average	0.65	0.5

Ground truth: weighted by expertise ≈ 0.80

C Statistical Analysis

C.1 Significance Testing

Paired Wilcoxon signed-rank tests comparing top strategies (Bonferroni corrected, $\alpha = 0.05/10 = 0.005$):

	HISTOGRAM	UCB	DEMPSTER	GREY
UCB	0.892	–	–	–
DEMPSTER	0.043	0.051	–	–
GREY	0.012	0.018	0.234	–
MAJORITY	0.876	0.945	0.056	0.021

No significant differences among top-3 strategies.

C.2 Effect Sizes

Cohen's d for outlier sensitivity between top and bottom strategies:

$$d = \frac{\mu_{\text{bottom}} - \mu_{\text{top}}}{\sigma_{\text{pooled}}} = \frac{0.45 - 0.02}{0.18} = 2.39 \quad \text{(large)} \tag{98}$$

C.3 Bootstrap Confidence Intervals

95% bootstrap CI (10,000 resamples) for category means:

Category	**Outlier Sens. CI**	**Time CI (ms)**
basic	[0.12, 0.22]	[0.024, 0.031]
bayesian	[0.09, 0.15]	[0.025, 0.032]
robust	[0.05, 0.10]	[0.024, 0.030]
sampling	[0.06, 0.11]	[1.2, 3.1]
belief	[0.07, 0.12]	[0.021, 0.026]

C.4 Correlation Analysis

Pearson correlations between metrics:

	Time	Outlier S.	Noise S.
Time	1.00	-0.12	0.35
Outlier S.	-0.12	1.00	0.18
Noise S.	0.35	0.18	1.00

Weak negative correlation between speed and robustness (faster methods slightly more sensitive).

D Proofs

Theorem D.1 (Weighted Average Optimality). *The weighted average $\hat{c} = \sum_i w_i c_i / \sum_i w_i$ is the unique minimizer of weighted squared error among unbiased linear estimators.*

Proof. Consider linear estimators $\hat{c} = \sum_i a_i c_i$. For unbiasedness: $\mathbb{E}[\hat{c}] = \sum_i a_i \mathbb{E}[c_i] = c_{\text{true}}$ requires $\sum_i a_i = 1$.

Variance: $\text{Var}(\hat{c}) = \sum_i a_i^2 \sigma_i^2$.

Using Lagrange multipliers to minimize $\sum_i a_i^2 / w_i$ subject to $\sum_i a_i = 1$:

$$\mathcal{L} = \sum_i \frac{a_i^2}{w_i} - \lambda\left(\sum_i a_i - 1\right) \tag{99}$$

$\frac{\partial \mathcal{L}}{\partial a_i} = \frac{2a_i}{w_i} - \lambda = 0 \Rightarrow a_i = \frac{\lambda w_i}{2}$
From constraint: $\sum_i \frac{\lambda w_i}{2} = 1 \Rightarrow \lambda = \frac{2}{\sum_i w_i}$
Thus $a_i = \frac{w_i}{\sum_j w_j}$, yielding the weighted average. □

Theorem D.2 (Median Breakdown Point)**.** *The sample median has breakdown point* $\varepsilon^* = \lfloor (n+1)/2 \rfloor / n \to 0.5$ *as* $n \to \infty$*.*

Proof. See Appendix F for complete proof. The key insight is that corrupting fewer than $\lceil n/2 \rceil$ observations leaves the median bounded within the range of uncorrupted values. □

Theorem D.3 (Log-Odds Uniqueness)**.** *Log-odds pooling is the unique external Bayesian aggregation rule satisfying:*

1. *Independence preservation*
2. *Marginalization*
3. *Zero-preservation*

Proof. See Genest & Zidek (1986), Theorem 3.1. The key insight is that the functional equation for marginal consistency has unique solution in the log-odds family. □

E Implementation Code

E.1 Core Aggregator

```
class ConfidenceAggregator:
    def aggregate(
        self,
        sources: List[Tuple[str, float, float]],
        strategy: AggregationStrategy
    ) -> float:
        # Extract values and weights
        vals = [s[1] for s in sources]
        weights = [s[2] for s in sources]

        # Dispatch to strategy implementation
        method = getattr(self, f'_{strategy.name.lower()}')
        return method(vals, weights)

    def _weighted_average(self, vals, weights):
        return sum(v*w for v,w in zip(vals,weights)) / sum(weights)

    def _median(self, vals, weights):
        sorted_pairs = sorted(zip(vals, weights))
        cumsum = 0
        total = sum(weights)
        for v, w in sorted_pairs:
            cumsum += w
            if cumsum >= total / 2:
                return v
        return sorted_pairs[-1][0]

    def _bayesian(self, vals, weights):
        EPS = 1e-10
        vals = [max(EPS, min(1-EPS, v)) for v in vals]
```

```
        log_odds = sum(w * math.log(v/(1-v))
                       for v,w in zip(vals,weights))
        log_odds /= sum(weights)
        return 1 / (1 + math.exp(-log_odds))
```

E.2 Intelligent Aggregator

```
class IntelligentAggregator:
    def analyze_data(self, sources):
        vals = [s[1] for s in sources]
        profile = DataProfile(
            n_sources=len(sources),
            mean=statistics.mean(vals),
            std=statistics.stdev(vals) if len(vals)>1 else 0,
            min=min(vals),
            max=max(vals),
        )

        # Detect characteristics
        if profile.std < 0.05:
            profile.characteristics.append(
                DataCharacteristic.HIGH_AGREEMENT)
        if profile.std > 0.25:
            profile.characteristics.append(
                DataCharacteristic.HIGH_DISAGREEMENT)

        return profile

    def recommend_strategies(self, profile):
        strategies = []

        if HIGH_AGREEMENT in profile.characteristics:
            strategies.extend([
                AggregationStrategy.WEIGHTED_AVERAGE,
                AggregationStrategy.BAYESIAN,
            ])

        if OUTLIERS_PRESENT in profile.characteristics:
            strategies.extend([
                AggregationStrategy.ROBUST_TUKEY,
                AggregationStrategy.MEDIAN,
            ])

        return strategies[:20]
```

F Extended Proofs and Derivations

This appendix provides complete proofs for theorems stated in the main text and additional results.

F.1 Proof of Condorcet's Jury Theorem

Theorem F.1 (Condorcet, 1785)**.** *Let n independent voters each have probability $p > 0.5$ of voting correctly. The probability that the majority votes correctly approaches 1 as $n \to \infty$.*

Proof. Let $X_i \in \{0, 1\}$ indicate correct vote by voter i, with $P(X_i = 1) = p$. Let $S_n = \sum_{i=1}^{n} X_i$ be the total correct votes. Majority correct requires $S_n > n/2$.

By the law of large numbers:

$$\frac{S_n}{n} \xrightarrow{P} p > \frac{1}{2} \tag{100}$$

For finite n, using the normal approximation to binomial:

$$P(S_n > n/2) = P\left(\frac{S_n - np}{\sqrt{np(1-p)}} > \frac{n/2 - np}{\sqrt{np(1-p)}}\right) \tag{101}$$

The right-hand side equals:

$$\frac{n(1/2 - p)}{\sqrt{np(1-p)}} = -\frac{\sqrt{n}(p - 1/2)}{\sqrt{p(1-p)}} \to -\infty \tag{102}$$

as $n \to \infty$ since $p > 1/2$. Thus $P(S_n > n/2) \to \Phi(\infty) = 1$. □

F.2 Proof of Log-Odds Uniqueness

Theorem F.2 (Genest & Zidek, 1986)**.** *The logarithmic opinion pool is the unique externally Bayesian pooling function.*

Proof sketch. A pooling function T is *externally Bayesian* if for all priors P and likelihoods L:

$$T(P_1(\cdot|D), \ldots, P_n(\cdot|D)) = T(P_1, \ldots, P_n)(\cdot|D) \tag{103}$$

where $P_i(\theta|D) \propto P_i(\theta)L(D|\theta)$.

Define T on log-odds scale: $f(\mathbf{x}) = T(x_1, \ldots, x_n)$ where $x_i = \log \frac{p_i}{1-p_i}$.

External Bayesianity requires:

$$f(\mathbf{x} + \mathbf{l}) = f(\mathbf{x}) + g(\mathbf{l}) \tag{104}$$

where $l_i = \log \frac{P(D|H)}{P(D|\neg H)}$ is common to all experts.

This functional equation, together with continuity and symmetry, implies:

$$f(\mathbf{x}) = \sum_{i=1}^{n} w_i x_i \tag{105}$$

Converting back: $\text{logit}(\hat{p}) = \sum_i w_i \text{logit}(p_i)$, which is the log-odds pool. □

F.3 Proof of Median Breakdown Point

Theorem F.3. *The sample median has breakdown point $\lfloor (n+1)/2 \rfloor / n$, approaching 50% as $n \to \infty$.*

Proof. Let $x_1 \leq x_2 \leq \cdots \leq x_n$ be the ordered sample.

The median is $x_{(m)}$ where $m = \lceil n/2 \rceil$ for odd n or the average of $x_{(n/2)}$ and $x_{(n/2+1)}$ for even n.

To move the median to $+\infty$, we must replace enough observations so that the m-th order statistic becomes arbitrarily large.

If we corrupt k observations, the smallest possible m-th order statistic occurs when we make the k corrupted values arbitrarily large. The m-th order statistic is then:

$$\tilde{x}_{(m)} = x_{(m-k)} \text{ of original sample} \tag{106}$$

For the median to be unbounded, we need $m - k < 1$, i.e., $k \geq m = \lceil n/2 \rceil$.

Thus the breakdown point is $\lceil n/2 \rceil / n = \lfloor (n+1)/2 \rfloor / n$.

For $n = 2m + 1$: breakdown $= (m + 1)/(2m + 1) \to 1/2$. For $n = 2m$: breakdown $= m/(2m) = 1/2$. □

F.4 Wasserstein Barycenter Characterization

Theorem F.4 (Agueh & Carlier, 2011)**.** *For measures $\mu_1, \ldots, \mu_n$ on $\mathbb{R}^d$ with finite second moments, the Wasserstein-2 barycenter exists and is characterized by:*

$$\bar{\mu} = \text{argmin}_\mu \sum_{i=1}^{n} w_i W_2^2(\mu, \mu_i) \tag{107}$$

Proof for Gaussian case. Let $\mu_i = \mathcal{N}(m_i, \Sigma_i)$. The Wasserstein-2 distance between Gaussians is:

$$W_2^2(\mu_i, \mu_j) = \|m_i - m_j\|^2 + \text{tr}(\Sigma_i + \Sigma_j - 2(\Sigma_j^{1/2}\Sigma_i\Sigma_j^{1/2})^{1/2}) \tag{108}$$

The barycenter mean is the Euclidean barycenter: $\bar{m} = \sum_i w_i m_i$.

The barycenter covariance satisfies the fixed-point equation:

$$\bar{\Sigma} = \sum_{i=1}^{n} w_i (\bar{\Sigma}^{1/2}\Sigma_i\bar{\Sigma}^{1/2})^{1/2} \tag{109}$$

This can be solved iteratively:

$$\bar{\Sigma}_{k+1} = \bar{\Sigma}_k^{1/2} \left(\sum_{i=1}^{n} w_i (\bar{\Sigma}_k^{1/2}\Sigma_i\bar{\Sigma}_k^{1/2})^{1/2} \right) \bar{\Sigma}_k^{1/2} \tag{110}$$

□

F.5 Dempster-Shafer Combination Properties

Theorem F.5. *Dempster's rule of combination is commutative and associative.*

Proof. **Commutativity:** The combination formula is symmetric in m_1 and m_2:

$$m_{1,2}(A) = \frac{\sum_{B \cap C = A} m_1(B) m_2(C)}{1 - K} \tag{111}$$

where $K = \sum_{B \cap C = \emptyset} m_1(B) m_2(C)$.

Since intersection is commutative and multiplication is commutative, swapping indices gives identical result.

Associativity: Let $m_{12} = m_1 \oplus m_2$ and $m_{23} = m_2 \oplus m_3$.

Define the *commonality function* $Q(A) = \sum_{B \supseteq A} m(B)$.

It can be shown that:

$$Q_{12}(A) \propto Q_1(A) \cdot Q_2(A) \tag{112}$$

Since multiplication of commonality functions is associative, so is the combination rule. □

F.6 Fisher-Rao Geodesic Derivation

Theorem F.6. *The geodesic connecting Bernoulli distributions Ber(p) and Ber(q) under the Fisher information metric is:*

$$\gamma(t) = \sin^2\left((1-t)\theta_p + t\theta_q\right) \tag{113}$$

where $\theta_p = \arcsin(\sqrt{p})$.

Proof. The Fisher information for Bernoulli is:

$$g(p) = \frac{1}{p(1-p)} \tag{114}$$

The geodesic equation in 1D is:

$$\ddot{p} + \frac{1}{2}\frac{\partial \log g}{\partial p}(\dot{p})^2 = 0 \tag{115}$$

With $g(p) = [p(1-p)]^{-1}$, we have:

$$\frac{\partial \log g}{\partial p} = -\frac{1}{p} + \frac{1}{1-p} = \frac{2p-1}{p(1-p)} \tag{116}$$

Substituting the parameterization $p = \sin^2\theta$:

$$\frac{dp}{d\theta} = 2\sin\theta\cos\theta = \sin(2\theta) \tag{117}$$

$$\frac{d^2p}{d\theta^2} = 2\cos(2\theta) \tag{118}$$

Geodesics in θ coordinates are straight lines: $\theta(t) = (1-t)\theta_0 + t\theta_1$. □

G Complete Category Analysis

This section provides detailed analysis for each of the 20 strategy categories.

G.1 Basic Methods (11 strategies)

Strategy	Time	Out.S
WEIGHTED_AVG	0.031	0.131
MAJORITY_VOTE	0.026	0.000
HIGHEST_CONF	0.025	0.018
LOWEST_CONF	0.025	0.674
MEDIAN	0.026	0.070
TRIMMED_MEAN	0.026	0.072
GEOMETRIC_MEAN	0.027	0.281
HARMONIC_MEAN	0.029	0.382
POWER_MEAN	0.028	0.145
WINSORIZED	0.027	0.131
RANGE_MIDPOINT	0.024	0.346

Analysis: Basic methods span the robustness spectrum. MAJORITY_VOTE achieves perfect outlier immunity through discretization. LOWEST_CONFIDENCE and HARMONIC_MEAN are extremely sensitive (0.67 and 0.38 respectively) due to small-value bias.

G.2 Bayesian Methods (10 strategies)

Strategy	Time	Out.S
BAYESIAN	0.027	0.133
BAYESIAN_COMB	0.027	0.133
HIERARCHICAL_BAYES	0.031	0.098
EMPIRICAL_BAYES	0.029	0.112
CONJUGATE_PRIOR	0.026	0.145
JEFFREYS_PRIOR	0.026	0.141
HORSESHOE_PRIOR	0.032	0.089
SPIKE_AND_SLAB	0.034	0.095
LAPLACE_APPROX	0.028	0.118
BAYES_MODEL_AVG	0.028	0.057

Analysis: Bayesian methods cluster around 0.028ms average time. Hierarchical and shrinkage priors (horseshoe, spike-and-slab) provide better robustness through regularization. BMA achieves best category robustness (0.057) through model averaging.

G.3 Robust Methods (10 strategies)

Strategy	Time	Out.S
ROBUST_HUBER	0.026	0.070
ROBUST_TUKEY	0.028	0.060
MEST_CAUCHY	0.029	0.078
MEST_WELSCH	0.028	0.072
MEST_ANDREWS	0.030	0.052
LEAST_MEDIAN_SQ	0.032	0.071
LEAST_TRIM_SQ	0.031	0.068
BREAKDOWN_POINT	0.024	0.053
S_ESTIMATOR	0.033	0.065
THEIL_SEN	0.035	0.074

Analysis: Robust methods deliver on their promise with outlier sensitivity consistently under 0.08. Andrews sine and breakdown point estimators achieve best results (0.052, 0.053). All methods remain fast (<0.04ms).

G.4 Density Methods (14 strategies)

Strategy	Time	Out.S
KERNEL_DENSITY	0.089	0.082
GMM	0.112	0.095
GMM_VARIATIONAL	0.165	0.088
DIRICHLET_PROC	0.142	0.076
HISTOGRAM_DENS	0.022	0.000
PARZEN_WINDOW	0.044	0.033
DENSITY_RATIO	0.023	0.051
CONTRASTIVE	0.095	0.078
NORM_FLOW	0.088	0.092
SCORE_MATCH	0.076	0.085
STEIN_DISCREPANCY	0.082	0.089
ENERGY_BASED	0.078	0.091
COPULA	0.068	0.094
MAX_ENTROPY	0.055	0.088

Analysis: HISTOGRAM_DENSITY is the standout performer with perfect outlier immunity (0.000) and fastest time (0.022ms). Complex density estimators (GMM, flows) are slower but do not improve robustness.

G.5 Sampling Methods (12 strategies)

Strategy	Time	Out.S
BOOTSTRAP	0.838	0.140
MONTE_CARLO	20.03	0.075
IMPORTANCE	0.245	0.112
REJECTION	0.312	0.095
MCMC	1.456	0.088
GIBBS	1.234	0.092
HMC	1.567	0.085
NUTS	1.823	0.081
NESTED	0.672	0.012
SLICE	0.456	0.044
REPLICA	2.345	0.078
PARTICLE	0.567	0.065

Analysis: Sampling methods are 10-1000x slower due to Monte Carlo iterations. NESTED sampling achieves excellent robustness (0.012) but at 0.67ms. MONTE_CARLO at 20ms is the slowest strategy overall.

H Sensitivity Analysis

This section examines how strategy performance varies with input characteristics.

H.1 Effect of Number of Sources

We tested all strategies with $n \in \{3, 5, 10, 20, 50, 100\}$ sources:

Table 8: Execution Time Scaling by Source Count

Strategy	$n = 3$	$n = 5$	$n = 10$	$n = 20$	$n = 50$	$n = 100$
WEIGHTED_AVERAGE	0.018	0.021	0.028	0.042	0.089	0.165
MEDIAN	0.019	0.023	0.032	0.051	0.112	0.218
BAYESIAN	0.020	0.024	0.033	0.052	0.115	0.221
DEMPSTER_SHAFER	0.025	0.045	0.125	0.445	2.56	10.2
MONTE_CARLO	18.2	18.5	19.2	20.5	24.8	32.1

Observations:

- Linear methods (weighted average, median) scale as $O(n)$
- DEMPSTER_SHAFER scales poorly due to 2^n subset combinations with n sources
- Monte Carlo is dominated by iteration count, with sublinear growth in n

H.2 Effect of Agreement Level

Testing with varying standard deviation in source confidences:

Table 9: Outlier Sensitivity by Agreement Level

Strategy	$\sigma = 0.02$	$\sigma = 0.10$	$\sigma = 0.25$	$\sigma = 0.40$
WEIGHTED_AVERAGE	0.045	0.112	0.185	0.231
MEDIAN	0.012	0.045	0.089	0.125
ROBUST_TUKEY	0.008	0.032	0.067	0.098
DEMPSTER_SHAFER	0.002	0.018	0.045	0.078
HISTOGRAM_DENSITY	0.000	0.000	0.000	0.000

Observations:

- HISTOGRAM_DENSITY maintains perfect robustness regardless of agreement
- All methods degrade with increasing disagreement
- Robust methods (Tukey, DS) degrade more slowly than simple averaging

H.3 Effect of Outlier Magnitude

Testing with single outlier at various distances from mean:

Table 10: Output Shift by Outlier Distance (baseline = 0.7)

Strategy	$c_{out} = 0.5$	$c_{out} = 0.3$	$c_{out} = 0.1$	$c_{out} = 0.0$
WEIGHTED_AVERAGE	0.66	0.58	0.50	0.46
MEDIAN	0.70	0.70	0.70	0.70
TRIMMED_MEAN	0.70	0.70	0.70	0.70
BAYESIAN	0.68	0.61	0.52	0.47
HARMONIC_MEAN	0.63	0.47	0.28	0.00

Observations:

- MEDIAN and TRIMMED_MEAN are completely immune to single outlier
- HARMONIC_MEAN collapses to 0 when any input is 0
- WEIGHTED_AVERAGE and BAYESIAN shift proportionally

I Computational Complexity Analysis

Table 11: Theoretical Complexity by Category

Category	Time	Space	Notes
Basic (most)	$O(n)$	$O(1)$	Single pass
Median-based	$O(n \log n)$	$O(n)$	Requires sorting
Bayesian	$O(n)$	$O(1)$	Log-odds transform
Robust M-est	$O(n \cdot k)$	$O(n)$	k IRLS iterations
Dempster-Shafer	$O(n \cdot 2^m)$	$O(2^m)$	m hypotheses
Kernel density	$O(n^2)$	$O(n)$	Pairwise kernels
GMM	$O(n \cdot k \cdot t)$	$O(nk)$	k components, t EM steps
MCMC	$O(s \cdot n)$	$O(s)$	s samples
Optimal transport	$O(n^3 \log n)$	$O(n^2)$	Linear programming
Graph-based	$O(n^2)$	$O(n^2)$	Adjacency matrix

J Extended Examples

This section provides worked examples demonstrating key strategies.

J.1 Example 1: Medical Diagnosis Ensemble

Five AI systems evaluate a chest X-ray for pneumonia:

System	Confidence	Reliability
Model A (specialized)	0.82	0.95
Model B (general)	0.75	0.80
Model C (legacy)	0.68	0.70
Model D (new)	0.88	0.85
Model E (outlier)	0.25	0.60

Strategy Comparison:

$$\begin{aligned}\text{Weighted Average} &= \frac{0.82(0.95) + 0.75(0.80) + 0.68(0.70) + 0.88(0.85) + 0.25(0.60)}{0.95 + 0.80 + 0.70 + 0.85 + 0.60} \\ &= \frac{2.694}{3.90} = 0.691\end{aligned} \tag{119}$$

$$\text{Median (weighted)} = 0.75 \text{ (Model B)} \tag{120}$$

$$\begin{aligned}\text{Log-Odds (Bayesian)}: &\quad \sum w_i \log \frac{c_i}{1 - c_i} = 0.95(1.52) + 0.80(1.10) + 0.70(0.75) \\ &\qquad + 0.85(1.99) + 0.60(-1.10) = 4.95 \\ \text{Normalized}: &\quad \frac{4.95}{3.90} = 1.27 \Rightarrow c = \frac{1}{1 + e^{-1.27}} = 0.781\end{aligned} \tag{121}$$

$$\text{Robust Tukey (biweight)}: \quad \hat{c} = 0.78 \text{ (downweights outlier)} \tag{122}$$

Analysis: The outlier (Model E at 0.25) significantly affects weighted average (0.691) but is handled by robust methods (0.78) and median (0.75). For medical diagnosis where false negatives are costly, robust aggregation is preferred.

J.2 Example 2: Multi-Agent Debate

Seven agents debate whether to recommend a policy:

Agent	Position	Confidence
Economist	Support	0.85
Ethicist	Support	0.72
Lawyer	Oppose	0.35
Scientist	Support	0.78
Politician	Support	0.65
Activist	Oppose	0.20
Neutral	Uncertain	0.52

Dempster-Shafer Analysis:
Convert to mass functions with reliability $r = 0.8$:

$$m_{\text{Economist}}(\text{Support}) = 0.85 \times 0.8 = 0.68 \tag{123}$$
$$m_{\text{Economist}}(\text{Oppose}) = 0.15 \times 0.8 = 0.12 \tag{124}$$
$$m_{\text{Economist}}(\Omega) = 0.20 \tag{125}$$

After combining all sources:

$$\text{Bel}(\text{Support}) = 0.71 \tag{126}$$
$$\text{Pl}(\text{Support}) = 0.89 \tag{127}$$
$$\text{Uncertainty} = 0.18 \tag{128}$$

Interpretation: Strong support (belief 0.71) with moderate uncertainty (0.18). The two opposing voices create conflict mass of 0.15, handled by DS normalization.

J.3 Example 3: Sensor Fusion

Temperature readings from five sensors with known noise characteristics:

Sensor	Reading (°C)	σ	Weight $w = 1/\sigma^2$
S1	22.3	0.5	4.0
S2	22.8	0.8	1.56
S3	21.9	0.6	2.78
S4	35.0	1.0	1.0 (faulty)
S5	22.1	0.4	6.25

Weighted Average (including faulty S4):

$$\hat{T} = \frac{22.3(4) + 22.8(1.56) + 21.9(2.78) + 35(1) + 22.1(6.25)}{15.59} = 23.1°\text{C} \tag{129}$$

Robust M-estimator (Huber, $k = 1.5$): After IRLS convergence: $\hat{T} = 22.2$°C (correctly ignores faulty sensor)
Median: $\hat{T} = 22.3$°C
Lesson: For sensor fusion, robust methods provide crucial protection against hardware faults.

K Strategy Selection Guide

K.1 Decision Tree

1. **Are sources highly correlated?**
   - Yes → Use SHRINKAGE_ESTIMATOR or HIERARCHICAL_BAYES
   - No → Continue
2. **Is speed critical (< 0.1ms)?**
   - Yes → Use WEIGHTED_AVERAGE, MEDIAN, or HISTOGRAM_DENSITY
   - No → Continue
3. **Are outliers expected?**
   - Yes → Use ROBUST_TUKEY, MEDIAN, or HISTOGRAM_DENSITY
   - No → Continue
4. **Is uncertainty quantification needed?**
   - Yes → Use MONTE_CARLO, BAYESIAN, or CONFORMAL
   - No → Use WEIGHTED_AVERAGE or BAYESIAN

K.2 Quick Reference by Use Case

Table 12: Recommended Strategies by Application

Application	Recommended Strategies
LLM ensemble	BAYESIAN, ATTENTION_BASED, WEIGHTED_AVERAGE
Medical diagnosis	ROBUST_TUKEY, DEMPSTER_SHAFER, CONFORMAL
Sensor fusion	KALMAN_FILTER, ROBUST_HUBER, MEDIAN
Crowd annotation	DAWID_SKENE, BAYESIAN, MAJORITY_VOTE
Weather forecasting	BAYES_MODEL_AVG, ENSEMBLE_AVERAGE
Financial prediction	ROBUST_TUKEY, HISTOGRAM_DENSITY, MEDIAN
Multi-agent debate	DEMPSTER_SHAFER, SHAPLEY_VALUE, NUCLEOLUS
Real-time systems	HISTOGRAM_DENSITY, WEIGHTED_AVERAGE, MEDIAN
Research analysis	MONTE_CARLO, BOOTSTRAP, CONFORMAL

L Reproducibility Checklist

To reproduce our experiments:

L.1 Software Requirements

```
Python >= 3.9
numpy >= 1.21
scipy >= 1.7
scikit-learn >= 1.0
torch >= 1.10 (optional, for neural methods)
```

L.2 Hardware Used

- CPU: Apple M1 Pro (10 cores)
- RAM: 32 GB
- OS: macOS Ventura 13.0

L.3 Timing Methodology

- Cold start: 10 warmup iterations discarded
- Measurement: Mean of 100 iterations
- Timer: `time.perf_counter_ns()`
- Isolation: Single-threaded, no other processes

L.4 Random Seeds

- Base seed: 42
- Replication seeds: 0, 1, 2 (for 3 iterations)
- NumPy: `np.random.seed(seed)`
- Python: `random.seed(seed)`

L.5 Data Generation

```
def generate_scenario(scenario_type, n=10, seed=42):
    np.random.seed(seed)
    if scenario_type == "consensus":
        return np.random.normal(0.7, 0.05, n)
    elif scenario_type == "bimodal":
        modes = [0.3, 0.8]
        return np.concatenate([
            np.random.normal(m, 0.05, n//2)
            for m in modes])
    elif scenario_type == "outlier":
        base = np.random.normal(0.7, 0.05, n-1)
        return np.append(base, 0.05)
    # ... additional scenarios
```

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N Glossary

Aggregation Combining multiple values into one summary.
Barycenter Center of mass; optimal transport centroid.
Belief Function Mass assignment over power set.
Breakdown Point Fraction of outliers before failure.
Confidence Probability estimate in $[0, 1]$.
Dempster-Shafer Evidence combination framework.
Entropy Uncertainty measure: $H = -\sum p \log p$.
Fisher Information Curvature of log-likelihood.
Geodesic Shortest path on manifold.
Huber Loss Quadratic for small, linear for large errors.
Kernel Density Nonparametric distribution estimate.
Log-Odds $\log(p/(1-p))$; logit transform.
M-Estimator Minimizer of sum of losses.
Optimal Transport Minimum-cost mass transfer.
Pareto Optimal Non-dominated solution.
Robust Statistics Outlier-resistant methods.
Shapley Value Fair allocation in coalitions.
Subjective Logic Belief-disbelief-uncertainty tuples.
Wasserstein Distance Optimal transport metric.
Winsorizing Clamping extreme values.