

Moral Entropy: Auditing Bias and Uncertainty in Moral Judgment

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Abstract

Most work in computational ethics treats annotator disagreement on moral content as noise to be voted away, collapsed into *majority* vote or the more permissive *any-annotator* rule which assigns a label as soon as any annotator flags it. We argue this uncertainty should instead be modeled and learned from. We introduce **Moral Entropy**, a Bayesian framework that estimates a full posterior over the true label and decomposes its entropy into *aleatoric* uncertainty (irreducible disagreement about the moral content) and *epistemic* uncertainty (from insufficient or noisy annotation). This lets any heuristic consensus rule be audited against a calibrated ground truth via entropy methods such as cross-entropy/KL, Brier score, and expected calibration error. Running this model on over 100,000 posts from three corpora spanning fifteen discourse domains, we audit the standard aggregation rules against the resulting posterior and reveal systematic differences in moral labels. Across MFTC and MFRC, the any-annotator rule yields mean false-positive rates of 10.2–19.9% and mean false-negative rates of 38.9–54.8% relative to the Bayesian consensus, while majority-vote and two-vote rules miss 63–83% of reference-positive labels.

Keywords: Computational Ethics, Moral Foundations Theory, Bayesian modeling, calibration, proper scoring rules, annotator disagreement

1 Introduction

1.1 Motivation

Annotators disagree on moral judgments, and often for good reason: Moral Foundations Theory itself predicts systematic disagreement across ideological and cultural lines (Graham et al., 2013; Haidt, 2012; Haidt and Graham, 2007). Almost every MFT-annotated corpus use discards this signal before anyone downstream can use it. The standard way to turn raw annotator votes into a single

Different posts. The same extra flag.

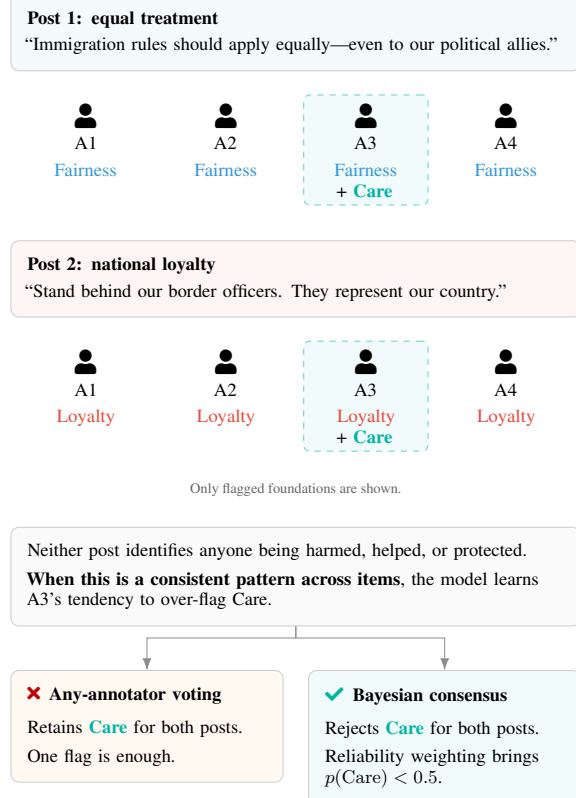


Figure 1: Different posts, the same extra flag. One stresses equal treatment; the other, national loyalty. A3 flags both as Care. In this illustrative example, the broader annotation history reveals a systematic tendency to over-flag Care. Accounting for this reliability lowers the Care posterior below the decision threshold, so Bayesian consensus rejects both Care assignments.

training label is a heuristic consensus rule: majority vote, or the more permissive *any-annotator* rule (positive, if flagged by any annotator) (Bulla et al., 2025; Hoover et al., 2020; Hopp et al., 2021; Preniqi et al., 2024; Trager et al., 2022; Zangari et al., 2025). Both are attractive because they are cheap and assumption-free. Both also discard exactly the information a moral-psychology

researcher should care about most: how much and why annotators agreed.

This matters for two distinct reasons. First, a dataset with high inter-annotator disagreement may be capturing a real moral phenomenon rather than noisy labeling — MFT does not predict convergence. Second, aggregation rules like any-annotator are statistically biased in a way no one reports: because the rule is a logical OR over J noisy binary votes, its false-positive rate grows mechanically with J even when every individual annotator is well calibrated. A downstream classifier trained on such labels inherits this bias with no way to detect it, since the heuristic consensus reports no uncertainty by construction.

We argue both problems are solvable by a Bayesian consensus model, that yields a full posterior over the true label rather than a single bit. The entropy of that posterior is a natural, principled uncertainty measure — what we call **Moral Entropy** — and it decomposes cleanly into the two uncertainty types above. Once this posterior is available, any heuristic consensus rule can be audited against it directly, with tools from statistical decision theory (such as proper scoring rules).

1.2 Contribution

Auditing consensus rules. We introduce **Moral Entropy** — the entropy of the Bayesian posterior over a moral-foundation label. Cross-entropy, Brier score, and calibration error are all Bregman divergences of an entropy function — one family, many possible diagnostics; we instantiate the 0/1-loss case in the main text and the remainder in the supplement. Across three corpora (106,627 texts carrying over 250,000 annotations), heuristic consensus rules disagree with the Bayesian posterior on a large, corpus-dependent share of items: substantial bias, whose direction depends on the rule.

Entropy-based uncertainty analysis. We decompose Moral Entropy into aleatoric (irreducible disagreement) and epistemic (model-parameter) uncertainty, showing that the former dominates across corpora and foundations.

Soft-label fine-tuning. Training classifiers on the calibrated posterior instead of collapsed hard labels yields consistent 2–3% accuracy gains, driven by the greater consistency of soft targets.

1.3 Related Work

Moral Foundations Theory (Graham et al., 2013; Haidt and Graham, 2007) posits five innate moral

 Care	DEF: Aversion to others' suffering; underlies kindness and nurturance. EX: "My heart breaks seeing children separated from families at the border."
 Fairness	DEF: Demand for equal treatment and reciprocity; underlies justice. EX: "Everyone deserves equal access to healthcare regardless of income."
 Authority	DEF: Deference to rank and tradition; underlies respect and duty. EX: " Respect your elders and follow traditional values that built this nation."
 Loyalty	DEF: Allegiance to the in-group over outsiders; underlies patriotism. EX: " Stand with our troops — they sacrifice everything for our freedom."
 Sanctity	DEF: Reverence for the pure and untainted; underlies chastity and restraint. EX: " Marriage is sacred and should be protected from secular corruption."

Table 1: The original five moral foundations, with brief definitions adapted from [MoralFoundations.org](https://moralfoundations.org) (Sanctity is also termed Purity) and illustrative social-media examples. Key moral cues highlighted in foundation color (Skorski and Landowska, 2025b).

intuitions — Care, Fairness, Loyalty, Authority, Sanctity — universal in kind, variable in weight; that variance is what drives ideological disagreement. A fixed, theory-derived label set maps naturally onto multi-label classification, arguably making MFT the moral-psychology framework best suited to computational treatment: a growing body of work fine-tunes language models to detect which foundations a text invokes (Bulla et al., 2025; Hoover et al., 2020; Hopp et al., 2021; Preniqi et al., 2024; Trager et al., 2022; Zangari et al., 2025). This research line trains on hard labels: annotator votes are collapsed once, by majority or any-annotator rule, upstream of the classifier. We depart in kind, not merely in degree — not a hard label, not an ad hoc soft label (the raw agreement fraction), but a soft label estimated as the posterior of a fully Bayesian consensus model, with calibrated rather than heuristic uncertainty.

Probabilistic treatment of noisy annotations has a long history, most notably Dawid–Skene (Dawid and Skene, 1979) and its Bayesian extensions (Paun and Simpson, 2021), which our model builds on directly. The empirical benefits have been demonstrated in label recovery (Paun et al., 2018) and uncertainty-guided annotation (Simpson and Gurevych, 2019). A growing body of recent research challenges the practice of collapsing disagreement into a single ground truth (Munir, 2026). Aleatoric/epistemic uncertainty decomposition is common in Bayesian deep learning; we apply it to posterior label uncertainty in annotator aggregation. To our knowledge, this combination has not been used to audit consensus-labeling heuristics across Moral Foundations corpora.

The paper is methodologically complementary to Skorski and Landowska (2025a), which uses a similar Bayesian consensus model to compare LLM and human accuracy; here we extend the approach with approximate Bayesian posterior inference and demonstrate its use for auditing consensus rules, entropy-based uncertainty analysis, and more balanced fine-tuning on soft-labels, beyond the evaluation of pre-trained models.

2 Methods

2.1 Bayesian Consensus Model

We adapt a Dawid–Skene-style model (Dawid and Skene, 1979) with weak Dirichlet priors, following the specification in Skorski and Landowska (2025a). There are N items, each with a true label drawn from K possible classes with prevalence $\pi \sim \text{Dir}(\alpha)$. Each of J annotators has a confusion matrix Θ_j , whose rows $\theta_{jk} \sim \text{Dir}(\beta_k)$ encode a weak prior belief that annotators are more often right than wrong. For item i , given its annotations y_i (from up to J annotators; annotations may be missing when not completed by an annotator or excluded in post-review, e.g. based on self-reports), the model yields a posterior

$$\Pr\{z_i = k \mid \mathbf{y}_i\} \propto \pi_k \prod_{j \in \mathcal{J}_i} \theta_{jk, y_{ij}},$$

where $\mathcal{J}_i$ indexes the annotators who labelled i .

The distinction from voting is easiest to see when two items receive the same number of positive annotations. A voting rule treats them alike when their total annotation counts also match, but the evidence may differ: one positive annotation may come from someone who frequently (over)flags that foundation, while another comes from someone who rarely does. The confusion matrices capture these response patterns across items. Bayesian consensus therefore uses both the labels and who supplied them, producing a probability rather than forcing every item into an equally certain positive or negative category.

Reliability is specific to the foundation being annotated; an annotator may frequently assign Care where others see only Fairness, yet provide informative judgments of Loyalty. We therefore estimate response patterns separately for each foundation, rather than assigning one overall reliability score to each person. In Figure 1, this distinction allows the recurring Care flags to receive less weight without discounting that annotator’s other

judgments. Both positive and negative annotations contribute to the inferred consensus. The resulting soft label reflects the combined evidence, rather than simply counting how many annotators selected the foundation.

The corresponding generative model is shown formally in plate notation in Figure 2.

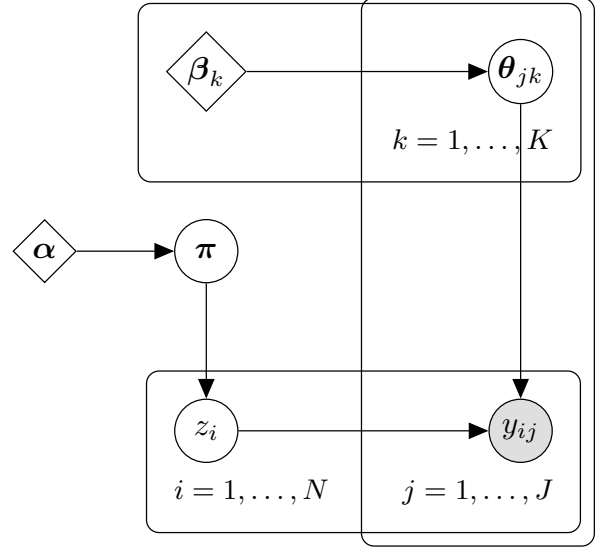


Figure 2: Plate diagram of the Bayesian Dawid–Skene model. The prior parameters β_k are shared across annotators. Conditional on $z_i = k$, the annotation is drawn as $y_{ij} \mid z_i = k, \Theta_j \sim \text{Categorical}(\theta_{jk})$. Only observed annotations ($j \in \mathcal{J}_i$) contribute to the likelihood.

We first fit the model by the maximum a posteriori (MAP) estimation via gradient ascent on the log-posterior (Adam, log-domain computation for numerical stability); then, to move from a point estimate to full posterior uncertainty, we approximate the posterior with a Laplace approximation — a Gaussian centered at the MAP estimate with covariance given by the inverse negative Hessian of the log-posterior. We take this route because exact sampling via NUTS proved fairly slow; reassuringly, our epistemic–aleatoric entropy decomposition (Section 4.3) shows epistemic uncertainty to be small relative to aleatoric, confirming post hoc that the MAP estimate was already a good approximation to the full posterior.

We refer to the resulting per-item probability as $p_i = \Pr\{z_i = 1 \mid \mathbf{y}_i\}$, the *Bayesian consensus*; the core part of the implementation, optimized for GPU in PyTorch, is shared in Listing 1.

```
import numpy as np
import torch
import torch.nn as nn
import torch.nn.functional as F
from torch.distributions import Dirichlet
```

```

from tqdm import tqdm

def annotations_to_bag(annotations, K):
    """(N,J) array with NaN for missing -> flat_ids,
    offsets for embedding_bag."""
    N, J = annotations.shape
    valid_mask = ~np.isnan(annotations)
    n_coors, j_coors = np.where(valid_mask)
    order = np.argsort(n_coors, kind='stable') #
    # group by item
    n_coors, j_coors = n_coors[order], j_coors[order]
    labels = annotations[valid_mask].astype(int)[order]

    flat_ids = torch.as_tensor(j_coors * K + labels, dtype=
    =torch.long)
    counts = np.bincount(n_coors, minlength=N)
    offsets = torch.as_tensor(np.concatenate([[0], np.
    cumsum(counts)[-1]]], dtype=torch.long)
    return flat_ids, offsets

class MoralConsensus(nn.Module):
    def __init__(self, J, K, alpha):
        super().__init__()
        self.J, self.K = J, K
        self.pi_logits = nn.Parameter(torch.randn(K) * 0.1)
        init_theta = (0.6 * torch.eye(K) + 0.4 / K).expand(
            J, K, K).clone()
        self.theta_logits = nn.Parameter(torch.log(
            init_theta + 1e-8))

        self.register_buffer('alpha', torch.as_tensor(alpha
            , dtype=torch.float32))
        conf_alpha = torch.full((J, K, K), 0.4)
        conf_alpha.diagonal(dim1=-2, dim2=-1).fill_(0.6)
        self.register_buffer('conf_alpha', 3 * conf_alpha)

    @classmethod
    def from_annotations(cls, annotations, alpha, device='
    cpu'):
        K = int(np.nanmax(annotations)) + 1
        N, J = annotations.shape
        model = cls(J, K, alpha).to(device)
        flat_ids, offsets = annotations_to_bag(annotations,
            K)
        return model, flat_ids.to(device), offsets.to(
            device)

    def forward(self, flat_ids, offsets):
        """Returns unnormalized per-item log-scores over
        true class, shape (N, K)."""
        log_pi = F.log_softmax(self.pi_logits, dim=-1)
        log_theta = F.log_softmax(self.theta_logits, dim
            =-1)

        lt = log_theta.transpose(1, 2).reshape(self.J *
            self.K, self.K)
        lp = F.embedding_bag(flat_ids, lt, offsets, mode='
            sum')
        logits = lp + log_pi[None, :]
        return logits # (N, K)

    def log_p(self, logits):
        """Marginal log-likelihood + log-prior, given
        logits from forward()."""
        log_pi = F.log_softmax(self.pi_logits, dim=-1)
        log_theta = F.log_softmax(self.theta_logits, dim
            =-1)
        pi, theta = log_pi.exp(), log_theta.exp()

        ll = torch.logsumexp(logits, dim=1).sum()
        ll = ll + Dirichlet(self.alpha).log_prob(pi)
        ll = ll + Dirichlet(self.conf_alpha).log_prob(theta
            ).sum()
        return ll

    def posterior(self, logits):
        return F.softmax(logits, dim=-1)

    def fit(self, flat_ids, offsets, max_iter=1000, lr=5e
        -3):
        opt = torch.optim.Adam(self.parameters(), lr=lr)
        pbar = tqdm(range(max_iter))
        for _ in pbar:
            opt.zero_grad()
            logits = self(flat_ids, offsets)
            loss = -self.log_p(logits)
            loss.backward()
            opt.step()
            pbar.set_postfix(loss=loss.item())
        return self

```

Listing 1: PyTorch implementation of the Moral Consensus model. The method forward returns per-item log-scores via a batched embedding_bag recombination over ragged annotator sets; log_p adds Dirichlet priors for MAP training.

2.2 Moral Entropy: Total, Aleatoric, and Epistemic

For a binary foundation label, the total predictive uncertainty of item i is the entropy of the consensus probability (the posterior mean over draws),

$$H_{\text{tot}}(i) = -p_i \log p_i - (1 - p_i) \log(1 - p_i),$$

which we call the item's *Moral Entropy*. For each parameter draw from the approximate posterior, we recompute the item's label probability. The average entropy across draws gives the aleatoric component; subtracting it from the entropy of the average probability gives the epistemic component. Given posterior draws $p_i^{(1)}, \dots, p_i^{(S)}$ — here obtained by sampling from the Laplace approximation to the posterior (Section 2.1) — H_{tot} decomposes as

$$H_{\text{tot}}(i) = \underbrace{\frac{1}{S} \sum_s H(p_i^{(s)})}_{\text{aleatoric}} + \underbrace{H_{\text{tot}}(i) - \frac{1}{S} \sum_s H(p_i^{(s)})}_{\text{epistemic}},$$

following the mutual-information decomposition standard in Bayesian deep learning. The aleatoric term is the uncertainty a fully informed model would still report — true, irreducible moral ambiguity. The epistemic term, non-negative by Jensen's inequality, reflects disagreement *among* plausible models, e.g. from too few or too noisy annotators on an item — uncertainty that more annotation could reduce. Section 4.3 reports this split empirically and finds epistemic uncertainty consistently negligible, so H_{tot} is effectively aleatoric throughout.

2.3 Grading Common Consensus Rules

The Moral Entropy $H_{\text{tot}}(i)$ is maximized exactly at $p_i = 1/2$ — the point of maximal ambiguity — and thresholding there is also the Bayes-optimal decision under 0/1 loss, minimizing balanced error. We treat this Bayesian consensus as the ground truth: from p_i we obtain a reference label $z_i^* = \mathbf{1}[p_i \geq 1/2]$, against which we grade the discrete consensus/decision rules popular in prior work on moral inference — the any-annotator rule $g_i^{\text{any}} = \mathbf{1}[\sum_j y_{ij} \geq 1]$, majority vote $g_i^{\text{maj}} = \mathbf{1}[\bar{y}_i \geq 1/2]$, and the absolute two-vote rule $g_i^{2v} = \mathbf{1}[\sum_j y_{ij} \geq 2]$. Writing g_i for the consensus rule under study, we report the simplest hard-label comparison with the Bayes-optimal gold label:

$$\text{FPR} = \Pr[g_i=1 \mid z_i^*=0],$$

$$\text{FNR} = \Pr[g_i=0 \mid z_i^*=1].$$

The false-positive rate (FPR) is the fraction of reference-negative items that a rule labels positive; the false-negative rate (FNR) is the fraction of reference-positive items it misses. Thus, $1 - \text{FPR}$ is specificity and $1 - \text{FNR}$ is sensitivity (recall).

The rule can also be compared with the *continuous consensus* p_i via cross-entropy/KL, the Brier score’s reliability–resolution–uncertainty decomposition, and Expected Calibration Error. These measures arise as Bregman divergences under different convex generators and aggregation norms, and are discussed in the supplementary material¹.

3 Data

We evaluate on three MFT-annotated corpora, summarized in Table 2. **MFTC** (Hoover et al., 2020) provides roughly 125,000 annotations from 23 trained annotators across 33,858 tweets spanning seven discourse domains (#BlackLivesMatter, 2016 U.S. Election, #MeToo, Hurricane Sandy, Baltimore protests, #AllLivesMatter, and Davidson’s hate-speech corpus). **MFRC** (Trager et al., 2022) provides 17,886 Reddit posts across three subcorpora — Everyday Morality (r/AmItheAsshole), U.S. politics, and French politics — capturing more colloquial, informally structured moral reasoning than MFTC’s tweets. **eMFD** (Hopp et al., 2021) is by far the largest of the three (54,883 items here) but topically narrower, drawn entirely from GDELT-indexed news-article paragraphs; we ourselves group these into subcorpora by GDELT theme tags (Physical Violence, Asymmetric Threats, Internal Unrest, Civil Liberties, plus an “Untagged” residual category) for this study, to enable cross-domain comparison to the social-media corpora.

4 Results

We fit the Bayesian consensus model per foundation and per corpus (MFTC, MFRC, eMFD), compute p_i (Bayesian consensus) alongside heuristic consensus schemes g_i (any-annotator, two-vote, and majority) for every item, then study uncertainty and biases with entropy per discourse domain.

4.1 Audit of Moral Consensus Rules

The heatmaps should be read by comparing voting rules within each foundation and domain: higher

¹Repository: <https://github.com/maciejksorski/moral-entropy/>. An eprint of this work is available as Skorski (2026a).

Corpus	Subcorpus	Au%	Ca%	Fa%	Lo%	Sa%	#Ann.	N
MFRC	Everyday Morality	10.4	37.4	25.5	11.7	13.5	3.00	5,366
	US Politics	19.7	29.6	38.3	7.7	8.4	2.99	5,351
	French Politics	25.4	16.0	26.0	13.1	8.0	3.00	7,169
	<i>MFRC total</i>							17,886
MFTC	ALM	20.9	61.6	49.8	26.3	16.9	3.03	4,326
	BLM	21.3	56.6	49.5	27.2	20.8	4.92	5,117
	Baltimore	31.8	27.1	31.4	42.3	9.0	3.32	5,190
	Davidson	33.0	11.5	11.2	11.6	12.3	3.78	4,873
	Election	17.5	38.0	34.4	22.8	30.4	3.88	5,050
	MeToo	65.7	33.3	43.9	41.0	52.8	3.65	4,711
	Sandy	45.6	60.9	30.3	42.7	15.0	3.03	4,591
	<i>MFTC total</i>							33,858
eMFD	Physical Violence	24.3	24.5	21.1	22.4	18.3	1.20	30,261
	Asymmetric Threats	26.1	22.2	24.1	26.8	18.0	1.44	6,622
	Internal Unrest	25.0	26.7	29.4	26.6	23.1	1.83	5,758
	Civil Liberties	26.0	23.6	26.1	22.2	18.3	1.40	10,334
	Untagged	21.6	30.3	19.4	17.8	18.7	1.11	1,908
	<i>eMFD total</i>							54,883

Table 2: Corpora, subcorpora, and per-foundation prevalence (% of total texts flagged at least once). Au=authority, Ca=care, Fa=fairness, Lo=loyalty, Sa=sanctity. #Ann.=mean number of annotations / text.

FPR indicates more positive assignments among reference-negative items, whereas higher FNR indicates more missed reference-positive items.

Pooling across corpora, the any-annotator rule shows $\text{FPR} = 30.6\%$ against the Bayesian consensus and $\text{FNR} = 0.0\%$: since $g_i=0$ requires every annotator to vote negative, and the confusion-matrix prior is diagonal-dominant, an all-negative vote pattern almost never yields a posterior above 0.5 — the asymmetry is close to structurally guaranteed by the OR-rule, not an empirical coincidence. The 30.6% false-positive rate, in contrast, is genuine and substantial: **roughly a third of items flagged positive by the naive rule are not supported by the calibrated Bayesian consensus**. It also varies sharply across discourse domains — per-foundation FPR ranges from 12.8% (Election) to 30.4% (MeToo) and FNR from 20.2% (Sandy) to 83.8% (Davidson); MeToo and Sandy are in fact the only two domains where FPR still exceeds FNR, preserving the pooled false-positive-dominant pattern, while the other five domains (ALM, BLM, Baltimore, Davidson, Election) invert it, with FNR the larger error — so **item-level moral ambiguity and aggregation-rule bias are independent axes** (Figure 3).

No common vote-count rule is well calibrated. Breaking FPR/FNR out by the five MFT foundations, and adding two stricter rules — an absolute two-vote threshold and a per-item ma-

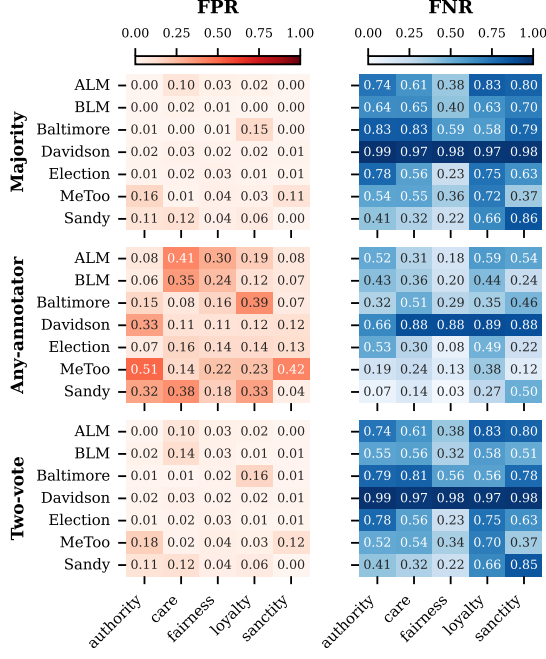


Figure 3: MFTC: per-foundation FPR/FNR of the majority, any-annotator, and two-vote rules against the Bayesian consensus, across the seven discourse domains and five MFT foundations.

majority vote — shows any-annotator’s near-zero pooled FNR does not survive at the foundation level (mean FPR/FNR: 19.9%/38.9% on MFTC, 10.2%/54.8% on the three MFRC domains), while majority and two-vote invert the failure — nearly eliminating false positives (3.5% and 4.2% on MFTC, under 1% on MFRC) but missing most true positives instead (mean FNR 63–65% on MFTC, $\approx$ 83% on MFRC). The two strict rules are near-identical only where annotation is thin — on MFRC 13 of 15 FNR cells coincide, since at 3.00 annotations per item a majority *is* two votes — and separate where items carry more annotators (BLM, 4.92 per item: FNR 0.64 vs. 0.55) (Figure 4).

An independent check against eMFD’s expert gold labels, rather than our own posterior, confirms the pattern and exposes one rule’s failure outright: two-vote becomes nearly degenerate (mean FPR = 1.5%, FNR = 96.6%), since most eMFD items never reach two votes at all. **The same absolute threshold that looked comparatively clean on MFTC is nearly useless on eMFD (Figure 5)** — no fixed vote-count rule generalizes across annotation designs, and which rule looks “safe” is itself dataset-dependent.

The number of annotations per item helps explain these differences. For three binary annota-

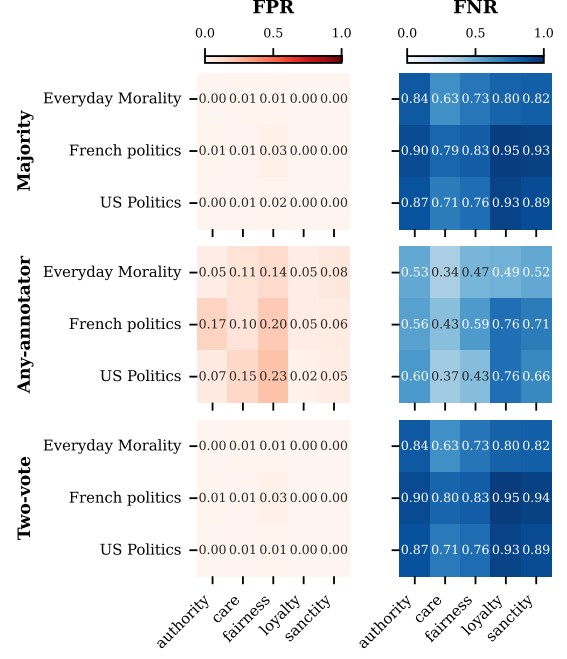


Figure 4: MFRC: per-foundation FPR/FNR of the three rules against the Bayesian consensus, across Everyday Morality, French Politics, and US Politics.

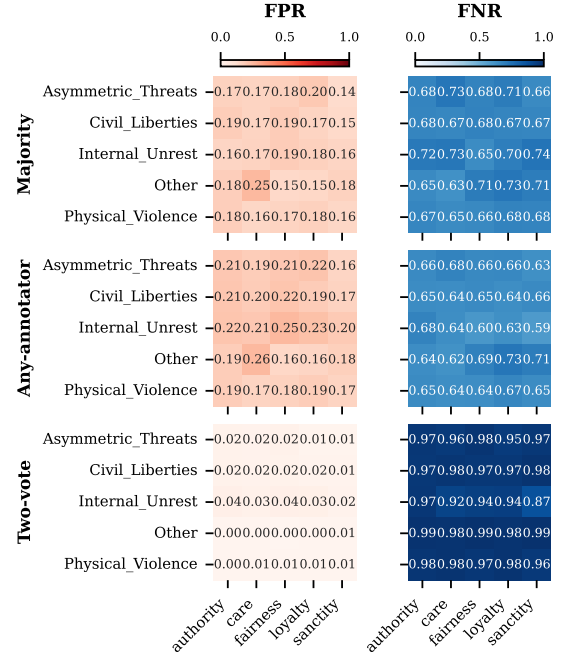


Figure 5: eMFD: per-foundation FPR/FNR of the three voting rules compared against the Bayesian consensus, across the five topic categories.

tions, majority voting and a two-vote threshold coincide. Among five annotations, however, two positive votes satisfy the two-vote rule but fall short of a majority. If an item has only one annotation,

the two-vote rule cannot return a positive label at all. An unchanged voting rule can therefore behave very differently across datasets. The audit makes this dependence visible and shows why aggregation choices should be considered together with the annotation design.

4.2 Soft-Label Fine-Tuning

Instead of a collapsed hard label, we fine-tune classifiers on MFTC directly on the calibrated posterior p_i as a soft target; in this experiment mDeBERTa-v3, achieving strong results on MFT classification (Skorski and Landowska, 2025b), was trained with a learning rate of 5×10^{-5} for 5 epochs. Soft-label models beat identical architectures trained on aggregated voting labels by 2–3% accuracy, consistently across foundations. The gain tracks the argument above: p_i never forces false confidence onto an ambiguous item, so the model isn’t trained to be certain where the annotators weren’t. Training is stable and fast — Table 3 reports final ROC-AUC against the hard label, plateauing within the first epoch; Care converges highest at 0.955.

Foundation	ROC-AUC vs. Hard
Sanctity	0.950
Authority	0.944
Loyalty	0.934
Care	0.955
Fairness	0.949

Table 3: Soft-label fine-tuning on MFTC: final ROC-AUC of the soft-label model against the hard (aggregated-vote) label on test data, per foundation. Reported as an agreement check; the details of 2–3% accuracy comparison are provided in the project repository.

4.3 Entropy Decomposition

Table 4 shows that total posterior entropy is **almost entirely aleatoric**. In every corpus/foundation cell the epistemic term is one to three orders of magnitude smaller than the aleatoric term: it contributes **under 1%** of total entropy in MFTC (mean 0.3%) and MFRC (mean 0.3%), and **never exceeds 6%** even in eMFD, the corpus with the fewest annotators per item. Under the fitted posterior approximation, most label uncertainty remains conditional on the model parameters, with comparatively little contribution from parameter uncertainty.

Entropy and the voting-rule audit answer different questions. Entropy asks how certain the model is about an item’s label; the audit asks whether a voting rule agrees with the inferred consensus. A rule may agree with the consensus on an item

whose posterior remains close to one half, or disagree on an item whose posterior strongly favors one label. Reporting both therefore distinguishes uncertain decisions from clear differences between aggregation methods. This distinction is lost when a dataset provides only a single binary label.

4.4 Outliers in Moral Judgment

Moral Entropy can also localize specific items and annotators worth closer inspection. Among the 100 highest-entropy Care items in BLM, disagreement concentrates on **hostile political rhetoric** (“*terrorists*,” “*TERRORISM*,” “*shoot tyrants*”) rather than on compassion-laden content. Disagreement rates against the BLM majority range from 7.6% (A04) to 31.3% (A02) — some annotators are simply more discordant than others.

Table 5 shows five representative items. **Almost no annotator plays a fixed role**: A00 agrees with the majority on all five and A03 flags Care on all five, while A04 and A01 each dissent twice — but on different items, so neither is a consistent outlier. Most tellingly, A02, the most discordant annotator corpus-wide (31.3%), agrees with the majority on four of these five items and dissents alone only on the least ambiguous one — a wish for someone’s death.

This tracks a known difficulty in moral psychology: violent, dehumanizing rhetoric resists clean foundation assignment. Kennedy et al. (2023) find that hateful language mostly invokes Purity and Loyalty/Authority, implicating Care only when an explicit harmful act is described. The items in Table 5 sit exactly on that boundary — harm-adjacent language, no concrete act — which is precisely where annotators diverge. **Moral Entropy recognizes the uncertainty of this class accurately, instead of silently burying it in a majority vote.**

These examples complement the aggregate audit by showing how response patterns play out on individual texts. The audit measures how often aggregation rules change foundation assignments; the examples show why a fixed description of an annotator as permissive or strict can miss important variation. A recurring tendency across items and a dissenting judgment on one particular item are different observations. The confusion matrices summarize the former, while item-level posterior probabilities retain uncertainty about the latter. Examining both makes the analysis useful at two levels: identifying systematic effects of aggregation and locating passages whose moral interpretation

Corpus	Authority		Care		Fairness		Loyalty		Sanctity	
	Ale	Epi	Ale	Epi	Ale	Epi	Ale	Epi	Ale	Epi
<i>MFRC</i>										
Everyday Morality	0.0670	0.0002	0.0542	0.0002	0.0760	0.0002	0.0661	0.0002	0.0587	0.0002
French politics	0.1385	0.0003	0.0348	0.0001	0.0856	0.0002	0.1420	0.0003	0.0520	0.0002
US Politics	0.1126	0.0002	0.0531	0.0002	0.0902	0.0002	0.0928	0.0002	0.0588	0.0002
<i>MFTC</i>										
ALM	0.0771	0.0001	0.0799	0.0001	0.1015	0.0001	0.0790	0.0001	0.0485	0.0001
BLM	0.1066	0.0002	0.0824	0.0002	0.0944	0.0002	0.0917	0.0002	0.0307	0.0001
Baltimore	0.0969	0.0004	0.0586	0.0002	0.0843	0.0003	0.0643	0.0002	0.0226	0.0002
Davidson	0.0349	0.0002	0.0729	0.0002	0.0203	0.0001	0.0713	0.0002	0.1321	0.0002
Election	0.0773	0.0001	0.0551	0.0001	0.0384	0.0001	0.0663	0.0001	0.0414	0.0002
MeToo	0.1257	0.0006	0.0421	0.0003	0.0617	0.0004	0.0953	0.0003	0.0473	0.0003
Sandy	0.0697	0.0002	0.0667	0.0002	0.0333	0.0002	0.0734	0.0002	0.0552	0.0002
<i>eMFD</i>										
Asymmetric Threats	0.1168	0.0031	0.0517	0.0015	0.0609	0.0039	0.1097	0.0026	0.0387	0.0018
Civil Liberties	0.1088	0.0035	0.0428	0.0011	0.0670	0.0025	0.0860	0.0025	0.0334	0.0013
Internal Unrest	0.1063	0.0036	0.0503	0.0015	0.0680	0.0034	0.1012	0.0046	0.0620	0.0030
Physical Violence	0.1055	0.0026	0.0446	0.0010	0.0511	0.0018	0.0921	0.0020	0.0352	0.0015
Untagged	0.0821	0.0020	0.0504	0.0012	0.0527	0.0012	0.0798	0.0017	0.0327	0.0011

Table 4: Aleatoric and epistemic components of posterior entropy (nats) by corpus and moral foundation.

Text	A00	A01	A02	A03	A04	Maj.
“Sick of obama & his leftist sycophant propagandists @washingtonpost supporting #blacklivesmatter terrorists.”	0	0	0	1	1	0
“#I94ShutDown ignorant idiots promoting ANARCHY over the death of CRIMINALS. #BLM is TERRORISM”	0	0	0	1	1	0
“#AllLivesMatter sick of the racism bullshit. Stop keeping it alive by putting a certain race in the spotlight.”	1	0	1	1	1	1
“#RightWingLogic u need guns to shoot tyrants, but always obey the police!”	0	1	0	1	0	0
“i hope this nigger suffers as he dies he deserves to suffer and die in pain”	1	1	0	1	1	1

Table 5: Annotator votes on Care for five representative high-entropy BLM items. No annotator occupies a fixed “permissive” or “conservative” role: the same annotators switch sides depending on item wording. **Content warning:** racial slur in the final item is quoted verbatim.

merits closer attention.

5 Discussion

These results motivate three changes to moral inference pipelines.

- **Report entropy.** Entropy should accompany any consensus label, decomposed into

aleatoric and epistemic components (Section 4.3), so a “hard” corpus can be diagnosed as genuinely contested versus under-annotated — and so any heuristic consensus rule already in use can be audited against it, since a rule can look reasonable in isolation while hiding a large, systematic, corpus-dependent bias.

- **Train on entropic (soft) labels.** Training directly on the posterior probability — an entropic, uncertainty-aware label — in place of a collapsed hard one, yields consistent 2–3% accuracy gains (Table 3), driven by the greater consistency of a calibrated soft target relative to a heuristic that lacks uncertainty.
- **Approximate posterior entropy is affordable.** Epistemic uncertainty is a small, near-negligible share of total entropy across corpora (Table 4), meaning the confusion-matrix parameters are tightly identified by the data. A Laplace approximation around the MAP fit suffices in place of costly full MCMC — making Bayesian consensus scalable.

In practice, a dataset could retain its familiar binary labels while also releasing consensus probabilities and entropy scores. Users could then select the representation appropriate to their task: binary

labels when a discrete decision is needed, and probabilities for training or analysis that can use uncertainty. High-entropy items could be prioritized for further annotation or examination of the codebook. Reviewing these items would help investigate whether uncertainty reflects unclear wording, overlapping foundations, or differing interpretations among annotators.

Two aspects of soft-label training are worth distinguishing. A consensus probability describes the evidence for a foundation, whereas entropy describes how concentrated that evidence is. Probabilities of 0.1 and 0.9 have the same entropy but favor opposite labels. Entropy alone is therefore insufficient as a training target: the probability retains both the direction and the uncertainty of the judgment. For binary cross-entropy, a target near one half encourages a moderate prediction, while a target near zero or one encourages a more decisive prediction. This gives uncertain examples a different role from examples that the annotation model resolves confidently.

The same distinction suggests a practical evaluation strategy. A classifier can be assessed both on its foundation predictions and on whether its confidence reflects variation in human judgments. These questions require different comparisons: agreement with a hard reference label assesses a discrete decision, while comparison with held-out annotations can test whether predicted probabilities match observed responses. A useful next experiment would hold the architecture and data split fixed while varying only the training targets: hard votes, raw vote proportions, and Bayesian consensus probabilities. This would help separate the benefit of retaining uncertainty from the benefit of modeling annotator response patterns. Together, these evaluations would clarify when the richer annotation representation improves prediction and when it is most useful for identifying cases that deserve human review.

Together, these three points reframe annotator disagreement as a resource rather than a nuisance to vote away: cheap to model, informative to report, and directly exploitable at training time, with no accuracy cost — soft labels beat the hard labels they were built from. None of this machinery is specific to Moral Foundations Theory; entropy audit can be applied to any values- or judgment-annotation pipeline before a hard-label dataset ships.

6 Conclusions and Future Work

Main findings. Moral labels depend on how annotator judgments are combined. Across three corpora, we show that common voting rules can produce markedly different labels while hiding uncertainty. Moral Entropy makes these differences visible by accounting for annotator reliability and retaining uncertainty in the labels. The practical contribution is to make aggregation itself open to examination: which foundations a rule adds or misses, how this changes with annotation density, and where uncertainty remains after accounting for annotator response patterns. Reporting consensus probabilities alongside entropy gives users more information than a single hard label and supports both closer inspection of contested items and learning from soft targets.

Practical implications. For moral-foundation research, aggregation is part of how the phenomenon is measured. A change in the consensus rule can change which texts count as expressing Care, Fairness, or Loyalty, even when the underlying annotations remain the same. Making this choice explicit helps researchers compare findings across corpora and distinguish differences in moral language from differences introduced by the labeling procedure.

Models trained on heuristic moral labels may inherit systematic false-positive and false-negative biases. Posterior consensus probabilities preserve uncertainty that hard labels discard, while high-entropy items can be prioritized for additional annotation or human review. These practices support oversight, but do not remove cultural or ideological bias in the annotator pool.

Future work. Inspired by research on disagreement-aware learning (Falk and Lapesa, 2025; Preniqi et al., 2024), future work will investigate training models for moral foundations that retain annotator disagreement. We plan to compare posterior soft labels with raw vote proportions under the same training setup, test high-entropy items with independent reannotation, and evaluate predictive calibration and entropy-based abstention. These studies will test where reliability modeling adds value beyond retaining soft labels and whether entropy helps identify judgments that benefit from further human review.

Limitations

Aleatoric/epistemic decomposition. The decomposition reported in Table 4 rests on a Laplace approximation around the MAP fit, not on full posterior draws. We attempted a direct validation via NUTS sampling, but it suffered from slow mixing (effective sample size as low as 5 out of 300 draws even after tuning burn-in and trajectory depth, likely due to strong correlations in the high-dimensional confusion-matrix parameter space); on the small number of items where MCMC did yield usable draws, the resulting decomposition matched the Laplace approximation, which is why we report the latter as our primary uncertainty decomposition. A systematic validation, via a reparameterized sampler or an ensemble of independently seeded MAP fits, is a natural extension we leave to future work.

The decomposition characterizes uncertainty under the assumed annotation model: its aleatoric component captures residual label uncertainty, which may reflect ambiguity, differences in perspective, or annotation noise. The small estimated epistemic component indicates limited variation in label predictions within the posterior approximation, rather than independently establishing the accuracy of that approximation. Independent re-annotation of high-entropy items would provide a useful further test.

Cultural and annotator-pool bias. Our consensus model treats disagreement as informative rather than as noise to be voted away, but the annotator pool itself remains a source of unmodeled bias: annotators for MFTC (and MFRC, eMFD) were not sampled to represent diverse cultural or ideological perspectives, so even a well-calibrated consensus over this pool could still encode a comparatively narrow (plausibly WEIRD — Western, Educated, Industrialized, Rich, Democratic) view of which cues count as morally salient. This risk is partly mitigated by the fact that annotators were trained against a shared codebook rather than left to apply unconstrained personal judgment: training standardizes what counts as a flag-worthy cue across annotators, which is exactly the regularity the consensus model relies on to be meaningful in the first place — though it cannot correct for a codebook, or an annotator pool, that is itself culturally narrow. A second, complementary mitigation comes from recent translation research: Skorski (2026b) shows that moral semantics are largely preserved under careful LLM-based translation (EN→PL, AUROC

gaps of 0.01–0.02 across foundations), pointing to a practical route for testing — and eventually correcting — this bias without new from-scratch annotation: translate an existing English corpus and re-run the Moral Entropy audit on it directly. We leave this cross-lingual test to future work.

A further distinction is between annotator error and systematic differences in perspective. Because Dawid–Skene assumes a shared latent label, its confusion matrices may assign lower reliability to annotators whose interpretations consistently differ from the inferred consensus. Models that explicitly represent annotator groups or multiple perspectives offer a complementary extension for studying such disagreement.

Scope of the fine-tuning result. The soft-label accuracy gains reported above are demonstrated on a subset of corpora/foundations and a single classifier architecture; generalization across architectures and the full label set is untested and left to future work.

The comparison with hard-label training demonstrates the practical value of the proposed soft targets. A direct comparison with raw positive-vote proportions would further establish how much of this benefit comes from modeling annotator reliability rather than retaining soft labels alone. Comparisons with point-estimate aggregation, downstream calibration assessment, and entropy-based abstention are additional directions for evaluation.

Ethical Considerations

This study uses existing annotated corpora and recruits no new participants. Moral-foundation labels and estimated annotator reliability describe interpretations and response patterns within the annotation framework, not a person’s moral character or competence. Offensive examples are only shown to illustrate annotation disagreement.

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