Aposteriori Unimodality: Attributing polarization to sociodemographic groups

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1 Introduction

Annotations are essential for a wide range of tasks, especially in fields such as content moderation and toxicity and racism detection. These tasks are especially essential for training systems that protect vulnerable and minority groups in online spaces, where they are often targeted [22, 7]. However, these annotations are usually based on majority-group annotators, which may limit their usefulness; if a comment targets marginalized groups, there can be cases where most annotators overlook it, while the few marginalized annotators vehemently disagree in vain. This issue exists even in representative samples. An example of such cases would be racist comments that are presented with coded language (usually referred to as "dog-whistles" [17]), which are not picked up by most annotators, but only by ones belonging in the targeted minority.

Inter-annotator agreement is often used to detect such cases [12]. Metrics based on agreement mostly measure annotation variance, which may not be an optimal problem formulation for detecting such cases. Polarization is a better instrument in this regard, since it formulates it as a cluster identification problem[15, 16] —specifically whether two or more annotation clusters are present in the annotations. Figure 1 displays how the two methods handle four common cases of annotation distributions for a hypothetical toxicity annotation task.

While we can detect polarization [16], there is currently no work on how to detect whether it is actually caused by marginalized groups. Pavlopoulos and Likas [16] propose a mechanism which only works in

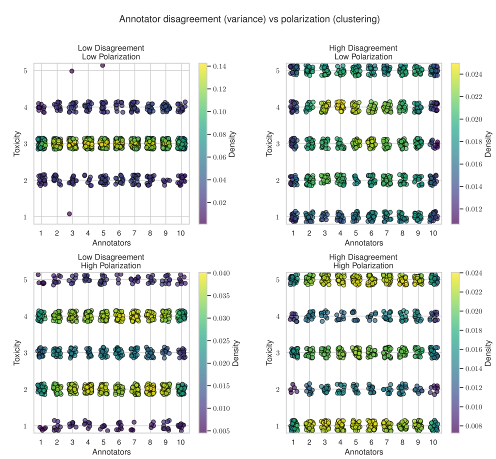

Figure 1: Disagreement is similar to variance; thus it overlooks cases where annotators may be "split down the middle". Polarization on the other hand, is able to identify multiple clusters, even if they are close together.

the extreme case where polarization is zero; in this work we demonstrate that this case is not frequent in real-world data. We instead propose the "Apunim Metric", which attributes polarization to individual annotator sociodemographic groups. We provide a formulation which avoids inherent statistical limitations. We discover issues not yet acknowledged in literature, such as the presence of inherent polarization and conflicting polarization directions, which our formulation successfully biases. We apply our test to four datasets; two with human comments and annotations [19, 13] as well as two generated and annotated by Large Language Model (LLM) agents [21]. Finally, we find interesting patterns in polarization in the human datasets, and verify current findings in literature w.r.t. LLM SocioDemographic Background (SDB) prompts.

2 Methodology

In this section, we provide a formal mathematical formulation for the problem of attributing polarization to specific annotator characteristics (§2.1), and offer an intuitive rationale for how established polarization metrics can be leveraged (§2.2). We then introduce a data-point-level statistic that attributes polarization to individual SDB groups (§2.3), and subsequently develop a statistic that generalizes this mechanism to an entire dataset.

2.1 Problem Formulation

SocioDemographic Backgrounds Since our goal is to pinpoint which specific characteristics contribute to polarization, we need to isolate individual groups within a SDB. Let Θ be one of multiple "dimensions" the set of all annotator SDB groups for a single dimension (e.g. "male", "female" and "non-binary" if we are investigating annotator gender).

Annotations Now let $d = \{c_1, c_2, \ldots\}$ be a dataset composed of multiple annotated data-points. We assume that annotating a data-point depends on three variables: its contents, the annotator's SDB, and uncontrolled factors such as mood and personal experiences. Assuming that each data-point c is assigned multiple annotators, we can define the annotation multi-set $A(c) = \{(a, \theta)\}$, where a is a single annotation. As an example, the annotations for a comment in a sentiment analysis task would be formulated as:

$$A(\text{"}\textit{Could be better, could be worse}\text{"}) = \{(\textit{positive}, \textit{female}), (\textit{positive}, \textit{male}), (\textit{negative}, \textit{female}), \ldots\} \quad (1)$$

Polarization Each set of annotations features a certain degree of *polarization*. Unpolarized annotations are usually unimodal, which makes intuitive sense; there is a difference between the annotators disagreeing on the details (which would be shown roughly as a bell curve around the median annotation), and them fundamentally disagreeing with each other (which would likely be shown as a multimodal distribution). Pavlopoulos and Likas [16] create a polarization metric, the "normalized Distance From Unimodality (nDFU)", which measures whether an annotation set shows no polarization (unimodal distribution — $nDFU \to 0$), up to complete polarization (multimodal distribution — $nDFU \to 1$). Thus, we will define a test that, given that annotation polarization exists, tests whether the nDFU of a data-point's annotations can be partially explained by θ.

2.2 Quantifying changes in polarization

Data-point polarization Intuitively, θ partially explains the polarization of a data-point c when the annotations grouped by θ are more polarized compared to the full set of annotations. Figure 2 exhibits a hypothetical example where a misogynistic comment is annotated for toxicity by male and female annotators.[1] The annotations are generally polarized ($nDFU_{all} = 0.625$). The annotations by female annotators exhibit low polarization between themselves ($nDFU_{women} = 0.1$), since most agree the data-point

[1] The use of only two predominant genders is made only for the purposes of demonstration.

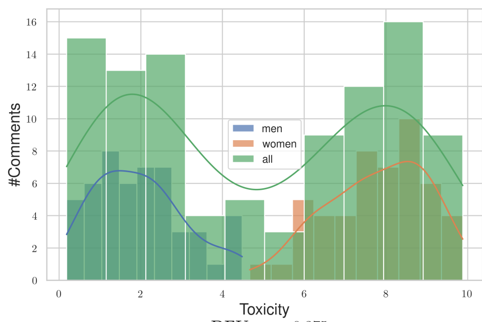

Figure 2: Hypothetical example of a polarizing comment, where male and female annotators agree between themselves, but disagree with the opposite gender. Overall polarization ($nDFU_{all} = 0.625$) is much greater than the polarization exhibited by the annotations grouped by gender ($nDFU_{men} = 0.3725$, $nDFU_{women} = 0.1$).

is toxic. The set of male annotations, also shows low polarization ($nDFU_{men} = 0.3725$), but for the opposite reason—most men agree that it is *not* toxic. This suggests that the overall polarization is driven by disagreements between male and female annotators.

Dataset polarization Given this observation, we would be tempted to aggregate all annotations in the dataset and compare the polarization of each θ with the full set of annotations $A(c)$. However, this formulation would not work well. Figure 3 illustrates a hypothetical discussion with two comments, both of which are toxic, but where male and female annotators disagree on *which* comment is the toxic one. If we aggregate the annotations to a single discussion, the opposing polarization effects might balance each other out, leading to a false negative. In simpler terms, polarization has a *direction*, and care must be taken to not combine polarization effects of opposite directions.

In our example, while it is obvious that gender partly explains the polarization found in each of the individual comments ($nDFU_{all} \gg nDFU_{men}$, $nDFU_{all} \gg nDFU_{women}$), this observation is much harder to make when aggregating the two comments. This is graphically shown as the presence of three bimodal distributions instead of two unimodal distributions, and one bimodal (aggregated) distribution. To avoid this, we apply our statistic only on annotations that reference the same data-point.

2.3 The pol-statistic

As demonstrated above, it is necessary to define a statistic for each individual data-point. We thus introduce the *"pol-statistic"*, which quantifies the change in nDFU when annotations are grouped by $\theta \in \Theta$.

In order to define this statistic, we need to measure (1) the polarization of a data-point when grouped by θ, and (2) the "inherent" polarization present in the annotations, which is driven by either the contents of the data-point, or by the uncontrolled factors mentioned in §2.1. Note that we can not directly compare the θ-subset of annotations with the full set of annotations, since any statistical comparison between them violates the assumption of independent samples.

The observed polarization of a data-point on the group of annotations θ can be directly computed as:

$$pol(c, \theta) = nDFU(P(A(c), \theta) \tag{2}$$

where $P(A(c), \theta_i) = \{a(c; \theta) \in A(c) | \theta = \theta_i\}$ is the partition of A for a data-point c, for which its annotators belong to the SDB group θ_i.

We can estimate the inherent polarization in data-point c by bootstrapping. We randomly partition the data-point's annotations in $|\Theta|$ groups, with matching group sizes (e.g., if we have 100 annotations, 80 of which are made by male annotators and 20 by female annotators, we will create random partitions of sizes 80 and 20). The randomly partitioned annotations are then sampled t times. Formally, the expected inherent polarization will be given by:

$$\frac{1}{t} \sum_{i=1}^{t} nDFU(\tilde{P}_i(A(c))) \tag{3}$$

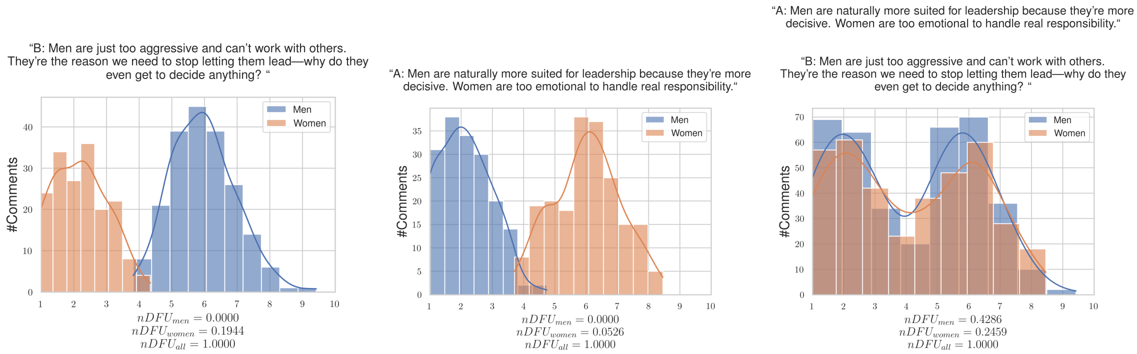

Figure 3: Hypothetical example of a polarizing discussion with two comments, for which the annotators disagree on which is the toxic one. If we aggregate the two comments, the polarization scores for both men and women significantly rise, obscuring whether the exhibited polarization can be partially attributed to gender.

where $\tilde{P}_i$ is the random partition operator with matching group sizes.

2.4 Aposteriori Unimodality

By obtaining the pol-statistics for all data-points in a dataset d for SDB θ, we can get the mean observed polarization for the dataset:

$$pol_O(d, \theta) = \frac{1}{|d|} \sum_{c \in d} pol(c, \theta) \tag{4}$$

and similarly the mean apriori dataset polarization:

$$pol_E(d) = \frac{1}{|d|} \sum_{c \in d} \frac{1}{t} \sum_{i=1}^{t} nDFU(\tilde{P}_i(A(c))) \tag{5}$$

We can then define the Aposteriori Unimodality Statistic (κ) with a formulation inspired by Cohen’s Kappa [6], as:

$$\kappa = apunim(d, \theta) = \frac{pol_O(d, \theta) - pol_E(d)}{1 - pol_E(d)} \tag{6}$$

If $\kappa \approx 0$, the exhibited polarization among annotators of group θ does not surpass what would be expected by chance. If $\kappa > 0$, then the group partially explains a rise in polarization. Unlike Cohen’s Kappa, the case of $\kappa < 0$ does have meaning; the group actually exhibits lower polarization compared to the whole. The scope of the statistic and its relationship with the previously presented statistics are demonstrated in Figure 4.

Like most metrics, we also include a p-value alongside the κ value. This can be computed either non-parametrically, by repeatedly shuffling annotations and computing a null distribution of *apunim*, or parametrically, by assuming a normal distribution (which is generally a safe assumption if $t \geq 30$). In the latter case, we compute:

$$z = \frac{\hat{\kappa} - \mathbb{E}[\kappa]}{SE(\hat{\kappa})}, \; p = 1 - \Phi(z) \tag{7}$$

2.5 Technical Details

Since we are simultaneously considering $|\Theta|$ hypotheses, we apply a multiple comparison correction to the resulting p-values. We choose the Holms method [10]. The test is parameterized by the Family-Wise Error Rate (FWER), which is used to tune the strength of the correction; we can increase this value to make our test more conservative towards multiple hypotheses [5]). In general, it is safe to set FWER equal to the significance level of our test (e.g., $FWER = 0.95$ if we are looking for $p < 0.05$).

SDB dimensions can partially explain polarization in the toxicity/racism annotations.

The results for the Kumar et al. [13] and Sap et al. [19] datasets can be found in Tables ??, ?? respectively.

Table 1: Aposteriori Unimodality kappa and pvalue results for the Sap et al. 2022 dataset

SDB Feature		kappa	pvalue
Age	(-0.001, 20.0]	0.000000	1.000000
	(20.0, 40.0]	-0.032111	0.819964
	(40.0, 60.0]	0.036419	0.819964
	(60.0, 80.0]	0.082569	0.819964
Ethnicity	black	-0.415255	1.000000
	hisp	0.000000	1.000000
	other	0.000000	1.000000
	white	0.147577	1.000000
Gender	man	0.151223	1.000000
	nonBinary	0.000000	1.000000
	woman	-0.350066	1.000000

Table 2: Aposteriori Unimodality kappa and pvalue results for the Kumar et al. 2021 dataset

SDB Feature		kappa	pvalue
Age	18 - 24	-0.030070	0.682607
	25 - 34	0.041895	0.682607
	35 - 44	-0.010272	0.682607
	45 - 54	0.017935	0.682607
	55 - 64	0.006664	0.682607
	65 or older	0.020481	0.682607
	Prefer not to say	0.000000	1.000000
Education	Associate degree	-0.050788	0.747020
	Bachelor's degree	0.097889	0.747020
	College, no degree	-0.104898	0.747020
	Doctoral degree	0.005425	0.340136
	High School graduate	-0.038466	0.747020
	Master's degree	0.052035	0.747020

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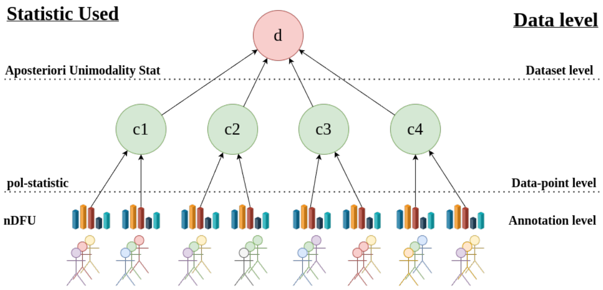

Figure 4: An overview of the Aposteriori Unimodality Test. We gather statistical information from the annotations (different SDBs are denoted by different colors) via the nDFU measure, which is aggregated on the data-point-level by the pol-statistic. The Aposteriori Unimodality Test is applied on the discussion level, operating on the pol-statistics of the individual data-points.

3 Results

We apply our test on four datasets; two human-annotated datasets, and two with comments and annotations generated by LLMs.

3.1 Human Datasets

We use the datasets provided by Kumar et al. [13] and Sap et al. [19]. The datasets feature various online comments, each annotated by a number of human annotators (5 and $4-6$ annotators per comment respectively). The Sap et al. [19] dataset includes racism annotations for 626 Twitter/X comments, and standard SDB information (age, race, education, gender). The Kumar et al. [13] dataset measures toxicity on various online comments, and the provided SDBs include mostly annotator experiences (e.g., whether they have been personally targeted online) as well as standard SDB information such as sexual orientation, age and education. Since the dataset is extensive ($XXXX$ tweets), we only select a sample of 5000 comments. This is due both to computational constraints, as well as statistical tests being unreliable on large enough samples [20]. Assuming a confidence level of $\alpha = 0.05$ we test whether any of the provided

Table 2: Aposteriori Unimodality kappa and pvalue results f
Kumar et al. 2021 dataset

SDB Feature		kap
	No high school	-0.0073
	Other	0.0000
	Prefer not to say	0.0000
	Professional degree	0.0015
Has Been Targeted	False	-0.0929
	True	0.1135
Is Parent	No	-0.1385
	Prefer not to say	-0.0045
	Yes	0.0931
Is Transgender	No	-0.1678
	Prefer not to say	0.5002
	Yes	0.0497
Political Affiliation	Conservative	0.0660
	Independent	-0.0155
	Liberal	-0.0391
	Other	-0.0230
	Prefer not to say	-0.0007
Seen Toxicity	False	0.1465
	True	-0.1144
Sexual Orientation	Bisexual	0.1763
	Heterosexual	-0.1410
	Homosexual	-0.0526
	Other	0.0042
	Prefer not to say	-0.0315
	NaN	0.0689
Thinks Religion Is Important	Not important	-0.1665
	Not too important	-0.0264
	Prefer not to say	0.0035
	Somewhat important	0.0349
	Very important	0.0906
Thinks Toxicity Is Problem	Frequently a problem	-0.0586
	Not a problem	0.0396
	Occasionally a problem	-0.0075
	Rarely a problem	0.0413
	Very frequently a problem	-0.0561

3.2 Synthetic Datasets

We use two synthetic datasets; one is the Virtual Moderation Dataset (VMD) presented in Tsirmpas, Androutsopoulos, and Pavlopoulos [21]. This dataset features 140 discussions, each having 14 comments (and usually up to 14 facilitator comments), each comment annotated by 10 LLM annotators, each supplied with a different SDB. The second dataset, is an extension of VMD, where we select four random unmoderated discussions, and employ 100 distinct LLM annotators.

We find no statistically significant results in any of the SDB dimensions, in any of the datasets (annotator age, gender, sexual orientation, education, employment and political alignment). While polarization does exist in the dataset, it can not be attributed to any of the synthetic SDB groups. This suggests that SDB prompting can not be used to simulate annotations for human groups, which is consistent with relevant literature on the topic [2, 9, 18, 11, 3, 14].

The results for the VMD and 100-annotator datasets can be found in Tables **??**, **??** respectively.

Table 3: Aposteriori Unimodality kappa and pvalue results for the 100 Annotator Synthetic dataset

SDB Feature		kappa	pvalue
Age	(14.927, 33.25]	-0.020288	0.388889
	(33.25, 51.5]	-0.002660	0.370370
	(51.5, 69.75]	0.022487	0.370370
	(69.75, 88.0]	0.018017	0.370370
Education	high-school	-0.036330	0.388889
	none	0.033416	0.388889
	university	-0.013384	0.388889
Employment	blue-collar	0.002831	0.388889
	unemployed	-0.026926	0.388889
	white-collar	0.016706	0.388889
Ethnicity	asian	-0.037780	0.500000
	black	-0.025178	0.500000
	other	0.070790	0.500000
	white	-0.040028	0.500000
Gender	female	-0.001871	0.416667
	male	0.030700	0.416667
	non-binary	-0.091121	0.500000
Political Affiliation	apolitical	0.067363	0.416667

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Table 3: Aposteriori Unimodality kappa and pvalue results for the 100 Annotator Synthetic dataset

SDB Feature		kappa	pvalue
	left-wing liberal	-0.030723	0.444444
	right-wing conservative	-0.011642	0.416667
Sexual Orientation	bisexual	-0.066358	0.500000
	homosexual	0.002492	0.500000
	other	0.101821	0.500000
	straight	-0.012399	0.500000

Table 4: Aposteriori Unimodality kappa and pvalue results for the Virtual Moderation Dataset dataset

SDB Feature		kappa	pvalue
Age	(20.956, 32.0]	-0.012182	0.588462
	(32.0, 43.0]	-0.034860	0.588462
	(43.0, 54.0]	-0.005863	0.588462
	(54.0, 65.0]	0.019657	0.588462
Education	Bachelor's	-0.004826	0.724038
	Master's	0.013366	0.724038
	No formal education	0.000000	1.000000
	PhD	0.026923	0.724038
	Some College	-0.031871	0.724038
Employment	Botanist	0.000000	1.000000
	Cybersecurity Expert	0.000000	1.000000
	Farmer	0.000000	1.000000
	Game Developer	0.000000	1.000000
	Historian	0.000000	1.000000
	Poet	0.000000	1.000000
	Registered Nurse	0.000000	1.000000
	Research Scientist	0.000000	1.000000
	Retired Philosopher	0.000000	1.000000
	Stock Trader	0.000000	1.000000
	Travel Blogger	0.000000	1.000000
Gender	female	-0.026100	0.835385
	male	-0.000932	0.835385
	non-binary	0.000000	1.000000
Sexual Orientation	Asexual	0.000000	1.000000
	Bisexual	0.000000	1.000000

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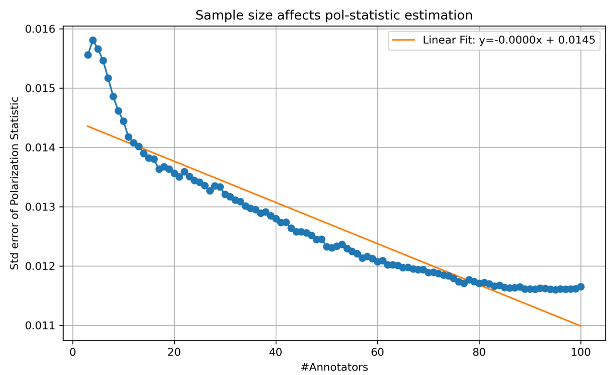

Figure 5: Standard error of the *pol-statistic* when sampled with replacement from the 100-annotator synthetic dataset for various number of annotators.

Table 4: Aposteriori Unimodality kappa and pvalue results for the Virtual Moderation Dataset dataset

SDB Feature	kappa	pvalue
Heterosexual	0.014899	1.000000
Homosexual	0.000000	1.000000
Lesbian	0.000000	1.000000
Pansexual	0.000000	1.000000

3.3 Effect of number of annotators

In §2.4 we mentioned that the test relies on enough annotations for each SDB group and data-point. This can be an issue, given the cost required to utilize multiple human annotators for each data-point [18]. Figure 5 demonstrates the effect of the number of annotators to the *pol-statistic* estimation. We use the 100-annotator synthetic dataset and sample progressively $3 - 100$ annotators with replacement, then calculate the standard error with the mean *pol-statistic*. As expected, the standard error is inversely proportional to the number of annotators, although the difference is not great, even for a low number of annotators.

4 Conclusion

We introduced the "Aposteriori Unimodality Test", a statistical test that detects whether certain sociodemographic groups partly cause polarization in annotations. Our test is resistant to low samples of annotations, bypasses common statistical issues such as sample dependence, and avoids newly-discovered issues such as the presence of inherent polarization and polarization direction. We apply our test two human-generated and two LLM-generated datasets and find interesting patterns on the former, and verify current literature on LLM SDB prompting on the latter.

5 Limitations

Since there are no other established tests that attribute polarization to sociodemographic characteristics, there is no way to verify that the results presented in §3 are accurate. Similarly, there is no qualitative way of evaluating our test, other than observations on the (non-) efficacy of LLM SDB prompting and our own intuition. Lastly, while our test seems to work sufficiently well with a small number of annotators per data-point, we still encourage researchers using this test to have at least a few annotators of each sociodemographic group that is being tested, in their dataset.

6 Ethical Considerations

While our works aims to help protect marginalized and disadvantaged groups by attributing polarization to certain subgroups, it can be taken advantage of by malicious actors. Given a dataset with fine-grained SDB information, these actors can use our test to target specific vulnerable groups. We thus urge researchers to keep datasets including such information protected, and provided to others only under explicit permission.

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A Appendix

A.1 Acronyms

VMD Virtual Moderation Dataset

LLM Large Language Model

SDB SocioDemographic Background

nDFU normalized Distance From Unimodality

FWER Family-Wise Error Rate

A.2 Demonstrative examples

Our paper uses synthetic examples to demonstrate the intuition behind the Aposteriori Unimodality test. These examples use random sampling of manually selected distributions. Table 5 summarizes the synthetic annotation distributions used to demonstrate the Aposteriori Unimodality test. In each scenario, annotations for men and women were sampled independently from Gaussian distributions with distinct parameters.

Figure	**Group**	**Distribution**	**Size**
Figure 2	A_{men}	$\mathcal{N}(2, 1.3)$	50
	A_{women}	$\mathcal{N}(8, 1.3)$	50
Figure 3 (1st comment)	A_{men}	$\mathcal{N}(6, 1)$	200
	A_{women}	$\mathcal{N}(2, 1)$	200
Figure 3 (2nd comment)	A_{men}	$\mathcal{N}(2, 1)$	200
	A_{women}	$\mathcal{N}(6, 1)$	200

Table 5: Synthetic annotation sets used to illustrate the Aposteriori Unimodality test. Each group corresponds to samples drawn from a Gaussian distribution with specified mean and standard deviation.