Understanding Sarcasm Through Dataset-Level Linguistic and Semantic Profiling: A Comparative Study of iSarcasm and MMSD2.0

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Abstract. With the widespread use of social media, Natural Language Processing systems often struggle to detect the true sentiment of sarcastic text. While previous studies primarily focused on model architecture design, less emphasis has been placed on internal dataset profiling. To address this gap, we propose a framework to analyze sarcasm datasets across five dimensions: Lexical Diversity and Complexity, Sentiment Conflict Intensity, Syntactic Marker Frequency, Contextual Incongruity Density, and Pragmatic Cue Disparity. Analyzing 2,000 samples across iSarcasm and MMSD2.0 reveals distinct differences in lexical richness (0.342 vs. 0.381), positive sentiment rates (0.151 vs. 0.262), readability (0.5081 vs. 0.5586), and explicit cues (0.043 vs. 0.091). These findings demonstrate that textual and multimodal datasets represent fundamentally different styles of sarcasm, requiring tailored modeling strategies for reliable detection.

Keywords: Dataset Profiling, Lexical Diversity, Linguistic Analysis, Multimodal Analysis, Natural Language Processing, Sarcasm Detection

1 Introduction

Sarcasm is a rhetoric prevalent in social media communication, which expresses a meaning opposed to the literal words used in the message, usually with an intent to convey irony, mockery, and criticism [1],[2]. Natural Language Processing (NLP) tackles the challenge of teaching computers to understand and generate human language. To do this well, it needs to look at language from several angles. Lexical features focus on which words people choose. Syntactic features deal with how those words fit together in sentences. Pragmatic features dig into what the speaker actually means, which often goes beyond the words themselves. In order to develop, train, test, and improve the NLP models, researchers have formulated several critical datasets [1]. There is a persistent gap which needs to be filled: to quantify and analyse the linguistic divergence in the datasets. Then there's the multimodal side: not just words, but images too. These signals, when paired together, can line up neatly or clash completely. That clash say, cheerful words next to a gloomy image often signals sarcasm. For NLP systems, picking up on this kind of mismatch isn't just important; it's one of the biggest hurdles in detecting sarcasm.

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The primary aim of this paper is to profile structural properties of the chosen datasets: iSarcasm and MMSD2.0. The first metric is Lexical Diversity and Complexity (LDC) [10] to measure the richness in vocabulary, grammar, etc, of sarcastic vs non-sarcastic data. The second metric is Sentiment Conflict Intensity (SCI) [10], which measures the degree of polarity between the literal and implied meaning of a text. The third metric is Syntactic Marker Frequency (SMF) [16] to calculate the usage of parts of speech such as interjections, adverbs, that associate with the sarcastic tone of the text. To analyze the multimodal property of the dataset, the fourth metric, Contextual Incongruity Density (CID) [8], measures the concentration and co-occurrence of contradictory cues within text and between text-image pairs. The fifth metric, Pragmatic Cue Disparity (PCD) [13], focuses on divergent structure and conversational or pragmatic markers such as shared context or cultural differences, which are integral to decode intended meaning. By systematic quantification of these linguistic and multimodal attributes, the study aims to highlight the overlooked disparities which significantly impact the performance of sarcasm detection. These insights can guide the development of improvised NLP models that have the ability to interpret nuanced human communication with great reliability.

2 Related Work

The automation sarcasm detection literature has progressed from simple lexicon-based rules to deep learning models that capture context, structure and multimodal information. To support our profiling framework, we consider the previous work in two key areas that fall under our metrics LDC, SCI, SMF, CID and PCD. This overview also demonstrates how dataset characteristic can affect the model behaviour and cause bias, a problem that this comparative analysis aims at eliminating.

2.1 The Linguistic Structure and Surface Markers (LDC, SMF, and Lexical PCD) Role

Preliminary studies on sarcasm detection had concentrated on surface level signs of linguistic cues including intensifiers, punctuation, and typical patterns of POS that most often indicated ironic intent [4]. We base our measurements, namely LDC, SMF and the text-based elements of PCD, on these types of observations since they are able to reflect differences in vocabulary richness, structural use, and explicit stylistic cues. The old methods used a significant portion of feature engineering in which hand-chosen indicators frequently discriminated sarcastic text [9]. Surface level NLP techniques like noun/verb phrase extraction were also able to confirm the worth of such structural markers [9]. Once the notion of deep learning was introduced, learners in the form of CNNs, RNNs, and attention-based BiLSTMs started learning these patterns itself, in both local and long-range textual relationships [6]. Other articles investigated co-occurring word forms and observed that sarcasm frequently contains lexical opposite or semantically remote words as has been done in the TCSD technique [14]. This is in line with our language data LDC and SMF to examine such variation in lexical and structural variation. Research also indicate that state-of-the-art models have a more difficult time predicting iSarcasm, implying that, the prior datasets disproportionately modeled less subtle and surface-level sarcasm indicators [11]. This shows the necessity to quantify linguistic complexity and the use of cues when comparing data. The study of pragmatics can also demonstrate that sarcasm may be based on signals at discourse level, such as idioms or rhetorical questions, which violate norms of conversation [4]. The more recent graph-based and affect-sensitive models implicitly

represent these relationships, and act like sophisticated extractors of SMF and PCD related cues [17].

2.2 Modelling Sentiment Incongruity and Explicit Conflict (SCI and Text-Internal CID)

An essential feature of sarcasm is that there are contrasts between the literal feeling and the intention of the speaker. Earlier schemes modeled this by use of sentiment lexicons and heuristics of polarity that reported the conflicting emotional signals [3]. Subsequent techniques adopted embeddings and sentiment-conscious models to better model such delicate conflicts, exactly matching our Sentiment-Conflict Intensity (SCI) measure [7]. This contrast was further designed in Dual-channel and multi-task learning structures by dissociating literal sentiment and contextual intent, to better identify polarity reversals [18]. Emotion-sensitive and knowledge-enhanced models illustrate the role of external commonsense in solving low intensity conflict, and indicate why subtle sarcasm datasets are more difficult to generalize by models [17]. Our SCI and CID measures fill in this gap by measuring the polarity contrasts and context difference on database level and showing us structural differences that explain the cross dataset performance variations.

3 Dataset Description

For a comparative analysis, the study uses two datasets, iSarcasm [11] for textual sarcasm and MMSD2.0 [12] for multimodal sarcasm detection. The datasets are an improvement over the previous biased corpora work, focusing on more serious and thoughtfully compiled benchmarks. iSarcasm overcomes the major limitation of previous research that labelling in this case is based on perceived sarcasm and not intended sarcasm. The dataset offers superior labels to subtle, context dependent sarcastic expressions based on author-annotated tweets. The fact that it proves especially challenging to traditional models implies the existence of a greater number of conflict of low intensity sentiment and a greater degree of lexical complexity, rendering the sarcasm rather covert [11]. MMSD2.0, in its turn, is a finer multimodal dataset comprising of text image pairs. It is better than its predecessor since it disregards spurious visual signs and remakes incongruent samples. This architecture inhibits shortcut as well as forcing models to use actual cross-modal inconsistency as compared to non-sarcastic visual patterns to identify sarcasm [12].

4 Methodology

In this paper, we compare the linguistic and semantic properties of two datasets: iSarcasm and MMSD2.0. We analyze the datasets using the following metrics: Lexical Diversity and Complexity (LDC), Sentiment-Conflict Intensity (SCI), Syntactic Marker Frequency (SMF), Contextual Incongruity Density (CID), and Pragmatic Cue Disparity (PCD). For this research, we used a combined dataset consisting of 2,000 selected sarcastic samples.

4.1 Data Acquisition and Pre-processing

A total of 2,000 sarcastic samples were selected, equally distributed across both datasets (NiSarcasm = 1,000, NMMSD2.0 = 1,000). In MMSD2.0, each sample includes an associated image, whereas iSarcasm consists only of text-based tweets [11]. Real-world data was pre-processed carefully using the following steps:

- Tokenization: Each sentence was tokenized using a tokenizer optimized for social media text (e.g., Twitter-specific or BERT WordPiece tokenizer) [15] to handle informal language and irregular structure.
- Normalization: Text was converted to lowercase, and placeholders were introduced for user mentions, URLs, and HTML entities (e.g., <user>, <url>).
- Punctuation and Contraction Handling: Repeated punctuation marks (e.g., "!!!") were reduced to a single mark ("!"), and common contractions were expanded (e.g., "don't" → "do not") to improve POS tagging and sentiment accuracy.

The resulting datasets were then used as input for calculating LDC, SCI, SMF, and the textual portions of CID and PCD.

5 Metric Calculation

5.1 Lexical Diversity and Complexity (LDC)

The LDC metric measures both the richness and structural difficulty of the language. It combines multiple sub-metrics into a normalized score between 0 and 1:

- Lexical Diversity (LD): Measured using the Root Type-Token Ratio (RTTR), which corrects the standard TTR's bias toward shorter texts:

$$RTTR = \sqrt{\frac{\text{Number of Unique Tokens}}{\text{Total Number of Tokens}}} \quad (1)\ [10]$$

- Mean Word Length (MWL): Average number of characters per word, representing vocabulary sophistication.
- Sentence Complexity (SC): Computed using the Gunning Fog Index (GFI):

$$\text{GFI}=0.4\times\left(\frac{\text{TotalWords}}{\text{Total Sentences}}+100\times\frac{\text{ComplexWords}}{\text{Total Words}}\right) \quad (2)[10]$$

Each sub-metric was normalized using min–max scaling across samples, and their weighted average was taken to obtain the final LDC score (0–1).

5.2 Sentiment-Conflict Intensity (SCI)

SCI quantifies how much the literal meaning of a sentence differs from its intended sentiment. Given that all samples are sarcastic, the actual intent is typically opposite the literal sentiment. The literal sentiment (Scomp(T)) was calculated using the VADER model, producing a compound score between −1.0 and +1.0. SCI is defined as:

$$SCI = |Scomp(T)| \quad (3)[10]$$

A higher SCI value indicates stronger surface sentiment polarity and higher potential for sarcastic reversal [10].

5.3 Syntactic Marker Frequency (SMF)

SMF measures the presence of grammatical and stylistic cues typically associated with sarcasm [5]. Part-of-speech tagging was performed using the spaCy transformer-based model (en core web trf). Three groups of markers were extracted and normalized per 100 tokens:

- SMF-Adj/Adv (Intensifiers): Degree adverbs (e.g., so, very) and comparative/superlative adjectives (e.g., better, best).
- SMF-Punctuation (Exaggeration): Hyperbolic punctuation such as "??", "!!", or quotation marks for irony.
- SMF-Lexical (Rhetoric): Interjections and idiomatic expressions (e.g., "oh wow", "my god") used sarcastically.

The final SMF score was computed as a weighted mean of these features. Higher SMF values denote the use of more explicit sarcasm cues.

5.4 Contextual Incongruity Density (CID)

CID captures semantic mismatch, a core mechanism of sarcasm. The computation differs for text-only and multimodal datasets.

CID for iSarcasm (Textual Incongruity — CIDtext) The semantic distance between a literal phrase (Tlit) and its context (Tctx) was computed using Sentence-BERT embeddings. CID was defined using cosine distance:

$$CIDtext = 1 - \text{Cosine Similarity}(Elit, Ectx) \quad (4)$$

CID for MMSD2.0 (Cross-Modal Incongruity — CIDCM)

For multimodal samples, incongruity was measured across modalities using CLIP embedding:

$$CIDCM = 1 - \text{Cosine Similarity}(Etext, Eimage) \quad (5)$$

Higher CID values indicate greater semantic distance either across modalities or between literal and contextual meaning.

5.5 Pragmatic Cue Disparity (PCD)

PCD quantifies how much sarcasm understanding depends on external or contextual knowledge rather than surface features [13].

- Baseline Model A logistic regression classifier trained on TF–IDF features from a general sentiment corpus was used as a minimal context-agnostic model.
- Prediction Confidence For each sample S with ground-truth label LGT ∈ {Sarcastic, Non-sarcastic}, the model produced a confidence score P (LGT | S).
- PCD Score: The disparity score was defined as the inverse of the model's confidence:

$$PCD = 1 - P(LGT \mid S) \quad (6)$$

This follows confidence-based classification methods. For example, a 55% confidence prediction (P = 0.55) yields PCD = 0.45, indicating high reliance on contextual cues, whereas a 95% confident prediction (P = 0.95) yields PCD = 0.05, meaning basic textual features were sufficient. Each of the five metrics was computed and normalized to a [0,1] range, enabling quantitative comparison between iSarcasm and MMSD2.0.

6 Results and Comparative Analysis

The quantitative analysis derived using above mentioned methodology, results into a significant difference in linguistic and semantic profiles of the two datasets. These differences establish a quantitative explanation for the existing gap in the performance significant in the models trained and tested using these datasets.

6.1 Mean Metric Analysis

The mean values for the 5 metrics (scaled to 0 – 1) demonstrate the clustering and separation between the two datasets. Table 1 shows that MMSD2.0 scores higher than iSarcasm on sentiment conflict, syntactic markers, and contextual incongruity, while iSarcasm exhibits greater lexical complexity and pragmatic cue disparity, highlighting clear differences in how each dataset encodes sarcasm.

Table 1. Mean Metric Comparison between iSarcasm and MMSD2.0

Metric (Normalized Mean)	iSarcasm (Textual)	MMSD2.0 (Multimodal)
LDC (Lexical Complexity)	0.68	0.49
SCI (Sentiment Conflict Intensity)	0.35	0.57
SMF (Syntactic Marker Frequency)	0.22	0.41
CID (Contextual Incongruity Density)	0.55	0.88

PCD (Pragmatic Cue Disparity)	0.79	0.40

Table 1 shows the mean metric comparison between iSarcasm and MMSD2.0 through various metrics explained above.

7 Comparative Analysis

7.1 Linguistic Complexity (LDC and SMF)

- Lexical Complexity (LDC): iSarcasm has a higher mean LDC (0.68 VS 0.49) which indicates that the text has a richer , nuanced and vocabulary that is less likely to be predictable [10]. It aligns with subtle and author-intended sarcasm.
- Syntactic Marker Frequency (SMF): The SMF is double as high in MMSD2.0 dataset (0.41 vs 0.22). This establishes that the multimodal text more often consists of specially mentioned amplifications, such as intense adverbs and exaggerated punctuation, to identify the literal meaning of the text, which is then contradicted by the associated image. The lower LDC and higher SMF values in the MMSD2.0 dataset also imply a complementary relationship: the text can be simple and explicit when the sarcastic cue is combined with the visual modality [5].

7.2 Conflict and Incongruity (SCI and CID)

- Sentiment Conflict Intensity (SCI): The SCI is higher in the MMSD2.0 dataset (0.57 vs 0.35). This establishes that the literal meaning of the sentiment in MMSD2.0 dataset is very opposite, creating an intense textual-internal polarity that is later contradicted by the visual modality [8]. The lower SCI in iSarcasm(0.35) proposes that author–labelled sarcasm frequently has low-intensity conflicting sentiment that may appear neutral or ambiguous.
- Contextual Incongruity Density (CID): MMSD2.0 dataset showed significant divergence , maximum cross-modal incongruity (0.88). This score highlights a stark semantic difference between the image and the text by removing spurious cues. The CID for iSarcasm (0.55) is moderate, showing that the textual-internal conflict is prevalent yet not a primary cue in the multimodal setting.

7.3 Pragmatic Difficulty (PCD)

- Pragmatic Cue Disparity (PCD): iSarcasm demonstrates a significant PCD (0.79), a sharp contrast to MMSD2.0 (0.40).
- The high PCD in iSarcasm (0.79) validates the assertion that it presents high-context sarcasm; the context-agnostic model, confirming the necessity of external knowledge, user history, required for the interpretation of sarcasm [13].
- The low PCD in MMSD2.0 (0.40) validates that sarcasm here is low context as compared to iSarcasm dataset due to the contextual information that is the associated

contradictory image is available in the input hence now the model's primary task can focus on resolving the multimodal conflict [12].

8 Supporting Comparative Linguistic Feature Analysis

The comparative analysis highlights the further details in the linguistic and stylist divergence between datasets:

Table 2. Comparative Linguistic Feature Analysis

Feature	Dataset	Mean	Key Finding / Implication
Sentiment Polarity (VADER Compound)	MMSD2.0	0.262	73% higher average positive sentiment in MMSD2.0.
	iSarcasm	0.151	
Readability (Flesch Reading Ease)	MMSD2.0	55.86	Texts in MMSD2.0 are simpler and more easily understood.
	iSarcasm	50.81	
Sarcasm Cue Frequency	MMSD2.0	0.091	More than double the frequency of explicit cues in MMSD2.0.
	iSarcasm	0.043	

Table 2 shows that the MMSD2.0 dataset uses more positive literal language (high sentiment polarity), simpler text (high readability), and more explicit cues (high sarcasm cue frequency), supporting the observation that text is simplified to maximize semantic conflict with the visual modality.

Table 3. Part-of-Speech Tag Comparison between MMSD2.0 and iSarcasm

Part-of-Speech Tag	MMSD2.0 (Relative Frequency %)	iSarcasm (Relative Frequency %)	Key Finding/Implication
NN (Singular Noun)	41.00	38.01	Focus on entities/concepts in both datasets.
VBP (Verb, non-3rd person singular present)	4.64	0.00	Appears only in MMSD2.0 – direct, conversational action.

VBG (Verb, gerund/present participle)	0.00	5.64	Appears only in iSarcasm – continuous/complex phrasing.

Table 3 shows the variance in the verbal forms (VBP in MMSD2.0 vs VBG in iSarcasm) is a notable distinction. The prevalence of VBP in MMSD2.0 is direct, first-person form, whereas the use of VBG in iSarcasm hints at a more complex and descriptive sentence structure.

9 Discussion

The result from the analysis of the dataset provides key insights into the evolving landscape of sarcasm detection. The quantified data across all metrics: LDC, SCI, SMF, CID, and PCD validate the argument that there is significant divergence in the results when one model developed for a particular dataset is tested on other dataset.

9.1 The Contrast in Sarcasm: Context vs Conflict

9.1.1 The High-Context Sarcasm (iSarcasm Dataset)

- High PCD (0.79): This key finding confirms that iSarcasm since only provided with text struggles to classify the instances with confidence. The high PCD supports that the intended sarcasm is reliant on pragmatic cues like the author's history, topic knowledge, conversational context remains absent from the sample. To observe significant results on iSarcasm dataset it becomes necessary to use advanced models that integrates external resources of knowledge such as knowledge graphs or user profile embeddings.
- High LDC (0.68) and Low SMF (0.22): The complex language and low use of explicit syntactic markers show authors of iSarcasm rely on sophisticated linguistic constructions instead of obvious signaling. This points out the necessity that robust and large-scale language models like BERT - based systems are capable enough to conduct deep semantic parsing as opposed to models that primarily look for patterns and superficial sentiment cues.

9.1.2 The Cross-Modal Conflict (MMSD2.0 Dataset)

- Maximal CID (0.88): The cross-modal incongruity score validates the use of MMSD2.0 that forces models to genuinely perform cross-modal reasoning and detection of conflict between the text and image instead of relying on text-only shortcuts and spurious correlations. Models based on CLIP excel in aligning as well as contrasting features in multimodal embedded space.
- High SCI (0.57) and Moderate SMF (0.41): These scores are an indicative that textual components specify a clear objective: to categorize a sentiment as explicitly

positive or negative (High SCI) using amplification markers (High SMF). The explicit textual signal is intentionally contrasted by the associated image. The mechanism here is centered to resolve the multimodal contraction rather than just finding the linguistic cues.

- Low PCD (0.40): The low pragmatic disparity testifies that the Sarcasm is self-contained. The contextual information (the associating image) is present in the input therefore the models need not extract external knowledge to resolve the present ambiguity hence focuses on the task of multimodal fusion quality.
- The MMSD2.0 dataset resolves the challenge of high congruity within the input.

10 Recommendations for Model Development

The quantitative profiling of the two datasets (iSarcasm and MMSD2.0) specifies the architectural requirements to design the models to excel in the unimodal as well as multimodal domain.

10.1 For iSarcasm-like data (High Context)

Models need to prioritize integration of external knowledge. This implies designs beyond standard text encoders, systems that can dynamically extract external resources like commonsense knowledge or conversational history to fill the pragmatic gaps posed by high PCD. The difficulty thus shifts from linguistic understanding to contextual inference.

10.2 For MMSD2.0-like data (High Incongruity)

Model must be developed focusing on robust multimodal fusion and conflict modelling. The high CID requires attention mechanisms that can measure and use the inconsistency between the modalities to successfully detect the sarcasm. Recent advancements like context-aware routing or knowledge enhanced incongruity perception can be directly validated using these quantitative results since they address the need for conflicting signal management effectively.

The difference between the performance of models on iSarcasm and MMSD2.0 is not random rather a direct consequence of the encoding of datasets, fundamentally different types of sarcastic expression. iSarcasm dataset aims to challenge and analyze the model's ability to extract and integrate external context. Whereas the MMSD2.0 dataset aims to challenge and analyze the model's ability to perceive and resolve cross-modal contradiction. This quantitative difference is required to design targeted models and accurate evaluation of proposed sarcasm detection systems.

11 Conclusion

The quantitative analysis developed using five key linguistic and semantic measurements (LDF, SCI, SMF, CID and PCD) clearly showcases that iSarcasm (text-only) and MMSD2.0 (multimodal) represent two different computational problems. 1. iSarcasm is the Pragmatic Inference Benchmark with Lexical Complexity (LDC=0.68) and Pragmatic Cue Disparity

(PCD=0.79): iSarcasm is highcontext subtle sarcasm. The sarcasm is concealed in subtle language, not on the surface of confrontation, and it is generally impossible to resolve by simple models. The models need to do a deep linguistic comprehension and combine external and commonsense knowledge to bridge the context gap to succeed on this particular dataset. 2. MMSD2.0 Multimodal Conflict resolution: Maximal Contextual Incongruity Density (CID=0.88) and High Sentiment-Conflict Intensity (SCI=0.57): The Benchmark of Multimodal Conflict Resolution is a capture of low-context, explicit-conflict sarcasm. This contradiction is encapsulated and purposefully increased in the given text-image couple, and the main task is to overcome the major and core obstacle of strong cross-modal fusion to gauge and overcome this utmost antagonism of meanings.

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