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ALG-Sent:Dataset Creation for Sentiment Detection in Algerian Dialect

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We conclude with a sincere thanks to our family for their encouragement and moral support.

Dedication

This work is dedicated to my family, whose unwavering support and encouragement have been my foundation. To my friends, who have provided companionship and motivation throughout this journey, thank you for always believing in me. I would also like to express my gratitude to my teachers and mentors, whose guidance and knowledge have profoundly shaped my understanding and passion for this field. Your contributions have been invaluable, and I am truly grateful.

Abstract

Social media platforms have become major spaces for expression and interaction. However, they have also become fertile ground for the spread of hate speech and antisocial behavior, including various forms of negative sentiment. In light of this reality, there is an urgent need to develop tools and methods to detect and analyze such harmful content, especially in underrepresented languages and dialects within linguistic research and natural language processing technologies. Algerian dialect is a prime example of these low-resource dialects. In this context, our work aims to build a dataset of YouTube comments to analyze sentiment, with a specific focus on the Algerian dialect. We collected thousands of comments from various Algerian YouTube channels in areas such as cooking, entertainment, and news. We manually annotated the text into categories reflecting different sentiments, including positive, negative, and neutral. The resulting dataset serves as a foundation for training machine learning models capable of detecting sentiment in under-resourced dialects, thereby supporting a deeper understanding of social interactions in digital environments. We validate our dataset by proposing and evaluating several machine learning classification models. These models demonstrate the dataset's effectiveness in accurately identifying sentiment, confirming its potential as a valuable resource for future research and applications aimed at enhancing sentiment analysis in low-resource dialects like Algerian Arabic.

Keywords: Sentiment Analysis, machine learning, Algerian dialect, Social media, YouTube, Dataset annotation.

Résumé

Les plateformes de médias sociaux sont devenues des espaces majeurs d'expression et d'interaction. Cependant, elles sont également devenues un terrain fertile pour la propagation de discours de haine et de comportements antisociaux, y compris diverses formes de sentiments négatifs. Dans ce contexte, il est urgent de développer des outils et des méthodes pour détecter et analyser ce contenu nuisible, en particulier dans les langues et dialectes sous-représentés au sein de la recherche linguistique et des technologies de traitement du langage naturel. Le dialecte algérien est un exemple de ces dialectes à faibles ressources. Dans ce contexte, notre travail vise à construire un ensemble de données de commentaires YouTube pour analyser les sentiments, en mettant spécifiquement l'accent sur le dialecte algérien. Nous avons collecté des milliers de commentaires provenant de diverses chaînes YouTube algériennes dans des domaines tels que la cuisine, le divertissement et les actualités. Nous avons annoté manuellement le texte en catégories reflétant différents sentiments, y compris positif, négatif et neutre. L'ensemble de données résultant sert de base pour former des modèles d'apprentissage automatique capables de détecter les sentiments dans des dialectes sous-resources, soutenant ainsi une compréhension plus profonde des interactions sociales dans les environnements numériques. Nous validons notre ensemble de données en proposant et en évaluant plusieurs modèles de classification d'apprentissage automatique. Ces modèles démontrent l'efficacité de l'ensemble de données à identifier avec précision les sentiments, confirmant son potentiel en tant que ressource précieuse pour de futures recherches et applications visant à améliorer l'analyse des sentiments dans des dialectes à faibles ressources comme l'arabe algérien.

Mots-clés: Analyse des sentiments, apprentissage automatique, dialecte algérien, médias sociaux, YouTube, annotation d'ensemble de données.

ملخص

أصبحت منصات وسائل التواصل الاجتماعي مساحات رئيسية للتعبير والتفاعل. ومع ذلك، أصبحت أيضًا أرضًا خصبة لانتشار خطاب الكراهية والسلوكيات المضادة للمجتمع، بما في ذلك أشكال مختلفة من المشاعر السلبية. في ضوء هذه الحقيقة، هناك حاجة ملحة لتطوير أدوات وطرق للكشف عن هذا المحتوى الضار وتحليله، خاصةً في اللغات واللهجات غير الممثلة بشكل كافٍ في أبحاث اللغة وتقنيات معالجة اللغة الطبيعية. يُعدّ اللهجة الجزائرية مثالاً على هذه اللهجات منخفضة الموارد.

في هذا السياق، يهدف عملنا إلى بناء مجموعة بيانات من تعليقات يوتيوب لتحليل المشاعر، مع التركيز بشكل خاص على اللهجة الجزائرية. جمعنا آلاف التعليقات من قنوات يوتيوب الجزائرية في مجالات مثل الطهي والترفيه والأخبار. قمنا بتعليق النص يدويًا إلى فئات تعكس مشاعر مختلفة، بما في ذلك إيجابية وسلبية ومحايدة. تُعد مجموعة البيانات الناتجة أساسًا لتدريب نماذج التعلم الآلي القادرة على الكشف عن المشاعر في اللهجات منخفضة الموارد، مما يدعم فهمًا أعمق للتفاعلات الاجتماعية في البيئات الرقمية.

نقوم بالتحقق من مجموعة بياناتنا من خلال اقتراح وتقييم عدة نماذج تصنيف للتعلم الآلي. تُظهر هذه النماذج فعالية مجموعة البيانات في تحديد المشاعر بدقة، مؤكدةً على إمكانياتها كموارد قيمة لأبحاث مستقبلية وتطبيقات تهدف إلى تحسين تحليل المشاعر في اللهجات منخفضة الموارد مثل العربية الجزائرية.

الكلمات المفتاحية: تحليل المشاعر، التعلم الآلي، اللهجة الجزائرية، وسائل التواصل الاجتماعي، يوتيوب، تعليق مجموعة البيانات.

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MSA Modern Standard Arabic. 39

General Introduction

The rapid advancement in data analysis techniques has fundamentally transformed how we understand and interpret emotions in texts. Sentiment analysis has become a crucial tool used across various fields, such as marketing and market research, to monitor customer feedback and understand trends. This domain involves evaluating texts to determine whether they express positive, negative, or neutral emotions, thereby aiding informed decision-making.

Despite its significance, sentiment analysis faces numerous challenges, particularly when it comes to different dialects such as Algerian Arabic. This dialect, characterized by unique linguistic features, requires specialized techniques to accurately grasp expressions and emotions. Consequently, many existing tools struggle to perform well when applied to non-standard dialects.

This thesis aims to address this gap by developing a manually annotated dataset focused on sentiment analysis in Algerian Arabic, based on user comments on platforms like YouTube. The construction process will involve the careful collection and annotation of data, considering the linguistic and cultural diversity present in the texts. Through these efforts, we seek to support the development of machine learning models capable of accurately identifying sentiments in varied cultural and linguistic contexts.

The importance of this research lies in the growing need for analytical tools that reflect linguistic diversity, which will enhance the performance of sentiment-related applications in low-resource languages. By creating a high-quality annotated dataset, we aim to advance research in this field and promote digital safety for diverse communities.

Chapter One: Sentiment Analysis This chapter discusses the concepts and applications of sentiment analysis, focusing on the levels of analysis (sentence, document, aspect) and its types (binary, fine-grained, sentiment-detecting, etc.). It reviews the challenges in analyzing dialects, particularly the Algerian dialect, and compares lexical, machine learning, and mixed approaches. It also discusses analysis on social media and challenges such as sarcasm and informal language.

Chapter Two: Building a Dataset This chapter defines the concept of a dataset, its types (structured, semi-structured, unstructured), and its characteristics, such as size, language, and accuracy. It explains the steps involved in creating a dataset: data collection, preparation, transformation, quality control, and preservation. It also discusses the importance of hand coding, its tools, challenges, and data acquisition sources, such as Kaggle and Google Dataset Search.

Chapter 3: Techniques and Experiments Applied This chapter presents the objectives of the experiment, the stages of data segmentation into training, validation, and testing, and the tools and languages used. The ALG-Sent project is described, from collecting YouTube comments in the Algerian dialect to manual coding and processing. Finally, multiple classification models were tested to evaluate the accuracy of the model and the efficiency of the proposed dataset.

Chapter 1

Sentiment Analysis

1.1 Introduction

Sentiment analysis is one of the key fields in artificial intelligence and natural language processing. It focuses on extracting and identifying emotional tones within written texts, categorizing them as positive, negative, or neutral. With the rise of social media and digital platforms, the need for tools that can accurately interpret user sentiment has become essential. In this chapter, we will explore this topic. We will present Sentiment analysis

1.2 Sentiment Analysis

Sentiment Analysis, also known as opinion mining, is a subfield of Natural Language Processing (NLP) and a key research area in computer science, particularly within artificial intelligence and data analytics. It involves the computational study of people's opinions, sentiments, and emotions expressed in written text. The primary goal is to automatically detect the sentiment conveyed in a piece of text—whether it is positive, negative, or neutral—though more fine-grained classifications are also possible.

In the context of computer science and informatics, sentiment analysis combines various technical components, including text preprocessing (tokenization, stemming, lemmatization), feature extraction (TF-IDF, word embeddings), and classification algorithms. Traditional machine learning techniques such as Naive Bayes, Logistic Regression, and Support Vector Machines have been widely used. More recently, deep learning approaches have become dominant, especially with the adoption of Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM) networks, and Transformer-based architectures like BERT, RoBERTa, and GPT, which provide improved context understanding and semantic analysis.

These models are often trained on large datasets and require substantial computational resources, making the integration of cloud computing and GPU acceleration increasingly important. Applications of sentiment analysis include social media monitoring, recommender systems, financial market prediction, healthcare sentiment tracking, and political forecasting.

Despite its advantages, sentiment analysis still faces limitations in handling sarcasm, idiomatic expressions, cultural context, and domain-specific language. Addressing these challenges is a key focus in current research, which aims to improve accuracy and gener-

alization across languages and domains.[1]

1.3 levels of sentiment analysis

1.3.1 Aspect-level sentiment analysis

Aspect-level sentiment analysis (ALSA) has gained significant attention in recent years within the field of natural language processing. Unlike document- or sentence-level sentiment analysis, ALSA focuses on identifying the sentiment polarity associated with specific aspects or entities mentioned in a text. A single sentence can express different opinions about various aspects; for instance, "The service in this restaurant is great, but the taste is really not good." Here, "service" has a positive sentiment, while "taste" carries a negative one.

ALSA involves two main tasks: aspect entity extraction and aspect sentiment classification. Based on how the aspect is presented in the sentence, ALSA is divided into two types:

* Aspect-Term Sentiment Analysis (ATSA) : where aspects are explicitly mentioned in the text. Models like MemNet and TNet-ATT use memory networks and attention mechanisms to learn context-aware aspect representations and determine sentiment polarity.

* Aspect-Category Sentiment Analysis (ACSA): where aspects are implicitly present, requiring predefined aspect categories and techniques like recurrent neural networks (RNNs) with attention to infer sentiment. The corresponding extraction tasks are: - Aspect-Term Extraction (ATE): Often treated as a sequence labeling task. - Aspect-Category Extraction (ACE): Typically framed as a classification task. In the studied model, the authors propose CPA-SA, a context-aware sentiment model that incorporates aspect-specific positional information. By applying asymmetric positional weighting functions, the model enhances the impact of nearby sentiment words and reduces the influence of word distribution around aspect terms. Additionally, a multi-sentence Bi-GRU captures contextual dependencies across sentences to refine sentiment judgment. To tackle class imbalance, a custom loss function is introduced by focusing on samples in hard-to-separate regions, converting the imbalance problem into a more manageable form. This approach significantly improves the precision of sentiment analysis at the aspect level, particularly in real-world scenarios involving multiple sentiments and unbalanced datasets.[2]

1.3.2 Sentence-level sentiment analysis

Sentence-level sentiment analysis is a subtask of sentiment analysis that focuses on identifying the sentiment polarity—positive, negative, or neutral—of an individual sentence. Unlike document-level analysis, which provides a general sentiment overview of an entire text, sentence-level analysis aims to determine the sentiment conveyed in a single, self-contained unit of meaning. This level of analysis is particularly useful when dealing with user-generated content such as reviews, tweets, or comments, where each sentence may express a distinct sentiment.

Various techniques are applied to achieve sentence-level sentiment classification, ranging from rule-based systems to machine learning and deep learning models. Traditional approaches often use bag-of-words and syntactic features with classifiers like Support Vector Machines (SVM) or Naive Bayes. More advanced models employ Recurrent Neural

Networks (RNN), Long Short-Term Memory networks (LSTM), and Transformer-based architectures (e.g., BERT), which capture contextual and semantic nuances in sentences. Sentence-level sentiment analysis plays a critical role in applications such as opinion mining, recommendation systems, and social media monitoring. [3]

1.3.3 Document-level sentiment analysis

Document-level sentiment analysis is a task in natural language processing that aims to determine the overall sentiment polarity—positive, negative, or neutral—of an entire document. This level of sentiment analysis assumes that each document expresses a single, unified opinion or sentiment towards a particular subject, product, or topic. It is especially effective in analyzing structured reviews, blog posts, or news articles, where a consistent tone is typically maintained throughout the text.

At this level, the analysis aggregates the sentiment conveyed by all sentences or paragraphs within the document to form a global judgment. Traditional approaches use features such as term frequency, sentiment lexicons, and syntactic cues combined with machine learning algorithms like Naive Bayes, SVM, or Logistic Regression. In recent years, deep learning models—such as CNNs, RNNs, and Transformers—have improved the ability to capture long-range dependencies and semantic consistency across the document. While document-level sentiment analysis offers scalability and efficiency, it may overlook nuanced or conflicting sentiments that exist within individual sentences or aspects. [4]

1.4 Application of sentiment analysis

Sentiment analysis has become a core component in numerous real-world applications across diverse domains. Its ability to extract subjective information from textual data enables organizations and researchers to gain insights into public opinion, customer satisfaction, and emotional tone. Key applications include:

- Customer Feedback Analysis: Companies use sentiment analysis to automatically evaluate product reviews, support tickets, and survey responses to understand customer satisfaction and identify areas for improvement.
- Brand and Reputation Monitoring: Businesses and public figures monitor social media platforms and online content to assess public perception and manage reputation in real time.
- Market Research: Sentiment data from forums, blogs, and news articles help researchers and marketers track consumer trends, preferences, and reactions to product launches or advertisements.
- Political and Social Opinion Mining: Analysts use sentiment analysis during election campaigns, policy discussions, and public debates to understand voter sentiment or public attitudes toward societal issues.
- Financial Market Prediction: In financial sectors, sentiment from news or social media can be correlated with stock movements, helping in predictive analytics and algorithmic trading.

- Healthcare and Wellbeing: Sentiment analysis of patient reviews, health forums, or mental health chatbots provides insights into emotional states and potential public health concerns.
- Recommender Systems: By incorporating sentiment information from user reviews, recommendation engines can provide more accurate and personalized suggestions.
- Human-Computer Interaction (HCI): Sentiment-aware systems improve user experience by adapting responses based on detected emotions, especially in virtual assistants and chatbots.

Despite its widespread utility, challenges such as sarcasm detection, context ambiguity, multilingual analysis, and domain adaptation still limit sentiment analysis performance in some applications.[3]

1.5 Sentiment Analysis online

In recent years, sentiment analysis of online textual content—such as news articles, blogs, and microblogs—has become an increasingly important area of research due to the growing availability of user-generated content on the internet. Understanding the emotional undertones within such texts is essential for a variety of applications, including public opinion monitoring, media analysis, brand perception tracking, and social behavior research. In response to this need, a novel algorithm has been proposed for automatically constructing a word-level emotional dictionary tailored specifically for social emotion detection. This dictionary is unique in that it associates each word with a distribution over a set of human emotions, enabling a more nuanced and fine-grained interpretation of language than traditional sentiment lexicons, which often classify words into only basic categories like positive, negative, or neutral. To improve the quality and precision of the dictionary, the authors introduce three pruning strategies that filter out irrelevant or less emotionally significant terms. Additionally, the study presents a topic modeling-based method for constructing a topic-level emotional dictionary, where each topic is linked to a particular emotional profile. The effectiveness and reliability of these methods were validated using real-world datasets, showing promising results in both accuracy and applicability. One of the major strengths of the proposed approach is that the resulting dictionary is language-independent, fine-grained in its emotion categorization, and scalable to any volume of data. This makes it a highly versatile tool for various applications, such as predicting the emotional tone of news stories, identifying emotional reactions toward specific events or public figures, and analyzing social dynamics on a broader scale. Ultimately, the work contributes significantly to the field of sentiment analysis by offering a more sophisticated and adaptable way to interpret emotions in large-scale online textual data.[5]

1.6 Types of Sentiment Analysis

Online profanity encompasses a wide range of expressions that vary in form, intensity, and function. Scholars such as Jay (2000), Dynel (2015), and Lapidot-Lefler & Barak (2012) have analyzed how profanity manifests online in different communicative settings. Below is a classification of the most common types of online profanity:

1.6.1 Fine-Grained Sentiment Analysis

is a detailed approach to sentiment classification that goes beyond the basic positive, negative, or neutral categories. Instead, it breaks down sentiment into more nuanced levels such as "very positive," "positive," "neutral," "negative," and "very negative." This type of analysis is particularly useful in contexts like customer reviews, where users often express varying degrees of satisfaction or dissatisfaction. For example, a 5-star rating system on platforms like Amazon or Yelp can be mapped directly to fine-grained sentiment labels, allowing models to predict sentiment with greater precision.

Fine-grained sentiment analysis typically uses machine learning and natural language processing (NLP) techniques to classify texts. Traditional models like Naive Bayes, Support Vector Machines (SVM), or more recent deep learning approaches such as BERT (Bidirectional Encoder Representations from Transformers) are employed to identify the subtle differences in emotional tone. This approach is especially valuable for businesses aiming to extract actionable insights from customer feedback, identify specific pain points, and improve product or service offerings accordingly. Additionally, sexual profanity reflects broader societal attitudes toward sex and gender. The use of such language can be seen as a way to assert power and establish hierarchy within online communities. It often feeds into toxic masculinity, reinforcing stereotypes that associate aggression with male identity while objectifying female bodies. The impact of sexual profanity extends beyond individual interactions. It contributes to a culture where misogyny and sexual objectification are normalized, shaping the way people communicate online. Victims of such language may experience significant psychological effects, including anxiety, depression, and feelings of exclusion or vulnerability. This reinforces the need for platforms to implement effective moderation policies to combat sexual harassment and create safer online spaces. Overall, the complexities of sexual profanity reflect deep-seated cultural taboos and the ongoing struggles for gender equality and respect in digital communication. Addressing these issues requires a multifaceted approach that includes education, community guidelines, and active intervention from platform moderators.[6]

1.6.2 Binary Sentiment Analysis (Paragraph Explanation)

Binary Sentiment Analysis is a fundamental technique in the field of Natural Language Processing (NLP) that involves categorizing textual data into one of two distinct sentiment classes: positive or negative. This method simplifies sentiment classification by focusing solely on polar emotions, excluding neutral or ambiguous sentiments. The binary model is particularly effective in scenarios where a straightforward interpretation of sentiment is sufficient, such as identifying whether a customer review expresses satisfaction or dissatisfaction, or gauging public opinion about a political statement, product launch, or brand event. The process of binary sentiment analysis usually begins with data preprocessing steps such as tokenization, stop word removal, and stemming or lemmatization. After preparing the data, a classification model is trained using labeled datasets—texts that are already annotated as positive or negative. Commonly used algorithms in binary sentiment analysis include Logistic Regression, Naive Bayes, Support Vector Machines (SVMs), and more recently, deep learning models like Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and transformer-based models such as BERT. These models learn to identify patterns in word usage, sentence structure, and contextual meaning that are indicative of sentiment polarity. Although binary sentiment analysis is straightforward and computationally efficient, it has notable

limitations. It cannot capture subtle emotional variations, such as neutrality, sarcasm, or mixed sentiments within a single sentence or document. As a result, this method may oversimplify complex opinions, especially in nuanced domains like political discourse or mental health narratives. Nevertheless, its simplicity makes it a reliable and scalable tool for sentiment detection in large datasets, and it is often used as a baseline or starting point for more advanced sentiment analysis systems.[6]

1.6.3 Aspect-Based Sentiment Analysis (ABSA)

Aspect-Based Sentiment Analysis (ABSA) is an advanced form of sentiment analysis that goes beyond identifying the overall sentiment of a text. Instead, ABSA aims to detect sentiment expressed toward specific aspects or features of an entity mentioned within the text. This technique is particularly valuable in domains like product and service reviews, where a single document may contain multiple sentiments directed at different attributes. For instance, in the review "The phone's screen is brilliant, but the battery life is disappointing," ABSA would identify "screen" as an aspect associated with a positive sentiment and "battery life" as an aspect linked to a negative sentiment. This level of granularity provides more actionable insights than general sentiment analysis, allowing organizations to pinpoint areas of strength and weakness in their offerings. The ABSA process generally involves three key tasks: aspect extraction, opinion term extraction, and sentiment polarity classification. First, the system identifies relevant aspects mentioned in the text (e.g., "screen", "battery"). Then, it extracts the associated opinion expressions (e.g., "brilliant", "disappointing"). Finally, the system determines the polarity (positive, negative, or neutral) of the sentiment toward each aspect. This requires sophisticated Natural Language Processing (NLP) techniques, including dependency parsing, part-of-speech tagging, and semantic role labeling. In recent years, deep learning models such as Long Short-Term Memory (LSTM) networks, attention mechanisms, and transformer-based architectures like BERT and RoBERTa have significantly improved ABSA accuracy by capturing contextual relationships between aspects and opinions. ABSA has a wide range of practical applications, including product development, competitive analysis, and customer experience management. By providing detailed sentiment insights at the feature level, businesses can better understand customer priorities and adapt their strategies accordingly. However, ABSA also presents several challenges, such as dealing with implicit aspects (e.g., "It heats up too quickly" implies a problem with the thermal design) and interpreting domain-specific language. Despite these challenges, ABSA represents a significant advancement in sentiment analysis, moving closer to a truly human-like understanding of opinions in text.[6]

1.6.4 Emotion Detection in Sentiment Analysis

Emotion Detection is a specialized branch of sentiment analysis that aims to identify and classify a wide range of human emotions expressed in textual data. Unlike binary or fine-grained sentiment analysis, which typically focuses on polarity (positive vs. negative) or sentiment intensity, emotion detection targets specific emotional states such as joy, anger, sadness, fear, surprise, disgust, and sometimes more complex emotions like trust, anticipation, or frustration. This form of analysis plays a crucial role in understanding human behavior, enhancing human-computer interaction, and improving applications such as customer service, social media monitoring, mental health assessments, and per-

sonalized content recommendation systems. Emotion detection relies heavily on Natural Language Processing (NLP) and often incorporates resources like emotion lexicons (e.g., NRC Emotion Lexicon, WordNet-Affect) to map words and phrases to emotional categories. In addition to rule-based approaches, modern emotion detection systems utilize machine learning and deep learning techniques, including Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) models, and transformer-based architectures like BERT and GPT, which are fine-tuned to recognize emotion-laden patterns in text. These models are trained on emotion-labeled datasets such as ISEAR (International Survey on Emotion Antecedents and Reactions) or Emotion-Stimulus datasets, which provide context-specific examples of emotional expression. One of the key challenges in emotion detection is the subjectivity and ambiguity of human language. People often express emotions implicitly, through sarcasm, metaphor, or understatement. Furthermore, the same word may convey different emotions depending on context—"cry" could indicate sadness, joy, or even relief. [6]

1.6.5 Intent Analysis in Sentiment Processing

Intent Analysis, also known as intent detection, is a specialized area within natural language understanding (NLU) that focuses on identifying the underlying intention or purpose behind a user's textual input. Unlike traditional sentiment analysis, which seeks to determine emotional tone (positive, negative, neutral), intent analysis classifies text based on what the user wants to achieve, such as making a request, asking a question, lodging a complaint, giving feedback, or expressing a desire or command. This is particularly vital in applications like chatbots, voice assistants, customer support systems, and conversational AI, where systems must interpret and respond to user input accurately and efficiently. The process of intent analysis typically involves training supervised machine learning or deep learning models on labeled datasets where each user utterance is annotated with a specific intent label (e.g., "order-pizza", "track-package", "cancel-reservation"). Classical approaches include Naive Bayes, Support Vector Machines (SVM), and decision trees, but the current state-of-the-art relies on neural network architectures, especially transformers such as BERT, RoBERTa, or DistilBERT, which can understand semantic meaning and context. These models are often integrated into NLU pipelines within larger conversational frameworks like Rasa, Dialogflow, or Microsoft LUIS. Intent analysis faces several challenges. One of the primary difficulties is disambiguation, as a single phrase may correspond to multiple intents depending on context. For instance, "I need help" could be a general request for assistance, a complaint, or an inquiry. Moreover, users may combine multiple intents in one sentence ("I want to cancel my order and get a refund"), requiring multi-intent classification capabilities. Despite these complexities, intent analysis is essential for enabling machines to understand and act on user goals, providing the foundation for effective human-computer interaction. As digital services and conversational interfaces proliferate, intent analysis continues to evolve, playing a pivotal role in personalization, automation, and customer experience optimization across industries such as e-commerce, healthcare, banking, and smart home technologies.[6]

1.6.6 Multilingual Sentiment Analysis

Expletives are standalone words or short phrases used to convey sudden emotions such as anger, surprise, frustration, or excitement without directing their impact toward a specific

individual or group. Common examples include terms like ”damn,” ”shit,” and ”fuck.” These expressions often arise in reaction to various situations, particularly in high-stress environments such as gaming, competitive sports, or when encountering unexpected challenges. The use of expletives serves several functions in communication. Primarily, they act as emotional release valves, allowing individuals to express feelings that might otherwise be difficult to articulate. In contexts where traditional language may fall short, expletives provide a means to convey intense emotions succinctly. For instance, a gamer might exclaim ”shit!” after a frustrating loss, using the term to encapsulate disappointment and anger in a moment. Moreover, expletives can foster a sense of camaraderie among individuals who share similar experiences. In gaming communities, for example, the use of shared expletives can create bonds among players, as these expressions often signify a common understanding of the frustrations and joys inherent in the gaming experience. This shared language can enhance group identity and reinforce social connections. Interestingly, research suggests that the use of expletives may also have physiological benefits. Some studies indicate that swearing can help individuals cope with pain and stress, potentially due to its ability to trigger a fight-or-flight response. This cathartic effect can provide a sense of relief, making expletives a useful tool in managing emotional responses in challenging situations. However, the context in which expletives are used is crucial. While they can serve as harmless expressions of emotion among friends or in informal settings, their use in professional or public contexts may be viewed as inappropriate or offensive. This duality highlights the importance of understanding audience and context when employing expletives in communication. In online environments, the prevalence of expletives can vary significantly. In some communities, they may be embraced as part of the culture, contributing to a relaxed and informal atmosphere. In others, particularly those with stricter moderation policies, their use may be discouraged or penalized, reflecting differing standards of acceptable behavior. Ultimately, while expletives and interjections may seem trivial at first glance, they play a significant role in emotional expression and social interaction. By providing an outlet for feelings and facilitating connections among individuals, these expressions contribute to the richness of human communication, particularly in the fast-paced and often unpredictable online landscape.[6]

1.6.7 Sarcasm and Irony Detection in Sentiment Analysis

Sarcasm and Irony Detection is a highly challenging and nuanced subfield of sentiment analysis that aims to identify expressions in text where the literal meaning diverges from the intended sentiment. In sarcastic or ironic statements, the surface-level sentiment may appear positive while the actual emotional intent is negative (or vice versa). For example, in the sentence ”Oh great, another Monday!”, the word ”great” typically indicates positivity, but in this context, it’s likely expressing frustration or annoyance. Traditional sentiment analysis systems often fail to detect this reversal of meaning, making sarcasm and irony detection essential for improving the accuracy of sentiment classification, particularly in social media analysis, review mining, and conversational AI. Detecting sarcasm requires a deep understanding of pragmatics, tone, context, and sometimes even world knowledge or cultural references. Rule-based systems and lexicon-based approaches struggle with sarcasm due to their reliance on literal word meanings. Therefore, modern approaches use machine learning and deep learning techniques, such as Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, attention

mechanisms, and transformer-based models like BERT or RoBERTa, often fine-tuned on sarcasm-labeled datasets. Some models also incorporate contextual clues, such as user history, punctuation (e.g., excessive exclamation marks), emoticons, and hashtags (e.g., sarcasm) to improve performance. Datasets like the Twitter Sarcasm Corpus, Reddit Irony Dataset, and SARC (from Reddit comments) are widely used to train and evaluate sarcasm detection models. Researchers are also exploring multi-modal sarcasm detection, which includes textual data along with visual or audio cues, such as voice tone or facial expression, especially in spoken or video content. Sarcasm and irony detection remains an open problem in NLP due to the subjectivity and context-dependence of sarcastic language. However, advancements in this area are critical for building emotionally intelligent systems that can truly understand user sentiment, thereby enhancing applications like chatbots, virtual assistants, automated content moderation, and opinion mining. [7]

1.7 Effects of Sentiment Analysis

Sentiment analysis has profound effects across various domains, transforming how organizations, researchers, and technology interact with human emotions and opinions. One of the primary effects is the enhancement of decision-making processes. By systematically analyzing public sentiment, businesses and policymakers can make informed decisions based on real-time feedback, improving strategies related to marketing, product development, and public relations. Another significant effect is the improvement in customer experience and engagement. Sentiment analysis helps companies identify customer satisfaction levels, detect dissatisfaction early, and tailor responses to individual needs. This leads to increased customer loyalty and better brand reputation management. In the field of social media monitoring and public opinion analysis, sentiment analysis enables large-scale tracking of trends, societal moods, and reactions to events. This allows governments, NGOs, and media outlets to understand public concerns and sentiments, facilitating better communication and policy-making. Technologically, sentiment analysis drives advancements in natural language processing (NLP) and artificial intelligence (AI) by pushing the development of more nuanced and context-aware algorithms that can understand subtle emotional cues, sarcasm, and cultural differences in language. Furthermore, sentiment analysis has contributed to the growth of automated systems, such as chatbots and virtual assistants, making them more empathetic and responsive to user emotions. This leads to enhanced human-computer interaction and more personalized user experiences. However, there are challenges as well, including risks of bias and misinterpretation, which may lead to incorrect conclusions if the sentiment models fail to understand context or cultural nuances. Despite this, the overall impact of sentiment analysis remains highly positive, enabling more emotionally intelligent technologies and data-driven decision-making.

1.8 Causes of Sentiment Analysis

Sentiment analysis has become a crucial technology in many fields due to several key reasons that drive its widespread adoption:

- Massive User-Generated Content : With the explosion of social media platforms, online review sites, blogs, and forums, people continuously share their opinions, experiences, and emotions about products, services, and events. This massive volume

of unstructured textual data is impossible to analyze manually, creating a strong need for automated sentiment analysis tools that can efficiently process and extract meaningful insights from such content.

- Real-Time Feedback and Monitoring : In today's fast-paced world, businesses and organizations require instant access to customer feedback to react quickly to changing sentiments. Sentiment analysis enables real-time monitoring of public opinion during important events such as product launches, political campaigns, or crisis management, allowing for swift responses that can protect brand reputation and improve customer satisfaction.

- Market Research and Competitive Intelligence : Companies use sentiment analysis to understand how consumers perceive their products and services compared to competitors. This information helps identify strengths and weaknesses, tailor marketing strategies, and innovate based on customer preferences, ultimately providing a competitive advantage in the market.

- Advances in NLP and AI Technologies : The development of advanced natural language processing, machine learning, and deep learning techniques has made sentiment analysis more accurate, scalable, and accessible. These technological improvements have enabled deeper understanding of sentiment nuances, such as sarcasm, emotions, and context, broadening the scope and effectiveness of sentiment analysis applications.

- Enhancement of Human-Computer Interaction : Sentiment analysis plays a vital role in making interactive systems, like chatbots and virtual assistants, more responsive and empathetic. By understanding user emotions and intents, these systems can provide more personalized and meaningful interactions, enhancing user experience and satisfaction.

1.9 Social media

Social media refers to online platforms where users can share information and connect with virtual communities through text, video, photos, and other content. In 2024, social networks had more than five billion global users, which is equal to more than 62 percent of the world's population. This includes apps or websites designed for messaging and chat, social platforms (like Facebook, Instagram, and TikTok), and community forums, such as Reddit and Discord.

Types of Social Media Platforms

I knew that platforms, sites Social media are of many types, including

- **Facebook** – a social networking platform for connecting with friends, sharing content, and engaging with communities.

- **Instagram** – a visual-based platform focused on sharing images, stories, and short videos.

- **TikTok** – a short-form video platform known for entertainment, challenges, and viral trends.
- **YouTube** – a video-sharing platform where users upload, watch, and engage with video content.

1.10 Sentiment Analysis on Social Media

Sentiment Analysis on Social Media refers to the process of extracting and interpreting opinions, emotions, and attitudes expressed by users through platforms like Twitter, Facebook, Instagram, Reddit, and others. Social media is a rich source of real-time, user-generated content, where people freely share their thoughts on products, brands, political events, social issues, and personal experiences. Due to the vast scale and diversity of social media data, sentiment analysis in this context plays a crucial role in understanding public mood and trends across different populations and regions.

One of the main challenges in social media sentiment analysis is handling the informal, noisy, and highly variable nature of the data. Posts often contain slang, abbreviations, emojis, hashtags, and misspellings, which complicate natural language processing tasks. Additionally, social media language is often context-dependent and may include sarcasm, irony, or mixed sentiments within a single post.

To address these challenges, researchers and practitioners use specialized techniques such as preprocessing methods to normalize text, lexicon-based approaches tailored for social media language, and deep learning models that can capture context and sentiment nuances more effectively. Popular models like BERT and its social-media-tuned variants have significantly improved accuracy.

Sentiment analysis on social media is widely used in areas such as brand monitoring, customer feedback analysis, political campaign tracking, and public health surveillance. For instance, companies monitor social media sentiment to gauge customer reactions to new product launches or advertising campaigns, enabling real-time marketing adjustments. Governments and organizations analyze public sentiment to detect emerging social issues, misinformation spread, or public responses to policy changes.

In summary, sentiment analysis on social media provides invaluable insights into collective human emotions and opinions, empowering decision-makers to act swiftly and appropriately in a dynamic and interconnected digital world. [8]

1.11 Challenges in Dialectal Sentiment Analysis

With the rise of interactions on social networking sites in recent years, these platforms have become a rich source for gathering opinions through comments. However, these comments present numerous challenges, particularly in the preprocessing stage. The language used on social media is often unstructured, lacking capitalization that typically helps identify features. Additionally, it frequently includes spelling errors, slang, and abbreviations, along with a tendency for users to repeat letters in words for emphasis [9].

Another significant challenge is the absence of an open-source dataset for the Algerian dialect. This gap has compelled many researchers to collect and annotate data independently to further their studies. TWIFIL is one of the available open-source datasets for

the Algerian dialect, comprising 9,000 annotated tweets collected between 2015 and 2019 from various geographic locations in Algeria, with the assistance of 26 annotators [**?**].

1.12 Techniques for Dialectal Sentiment Analysis

Based on numerous previous studies, there are three primary approaches to sentiment analysis that we will discuss below: Lexicon-Based Approaches, Machine Learning Approaches, and Hybrid Approaches [10] [11].

1.12.1 Lexicon-Based Approaches

Lexicon-based approaches rely on predefined lists of words (lexicons) associated with positive or negative sentiments. The sentiment of a text is determined by calculating the score based on the occurrences of these words. For example, if a tweet contains words like ”happy” or ”great,” it may be classified as positive, while words like ”bad” or ”sad” would indicate a negative sentiment. One well-known lexicon used in this approach is SentiWordNet, which assigns sentiment scores to words based on their meanings. This technique is straightforward and interpretable but may struggle with context and sarcasm, as it does not consider the arrangement of words [12].

1.12.2 Hybrid Approaches

Hybrid methods combine both lexicon-based and machine learning techniques to improve sentiment analysis accuracy. For example, a system might first use a lexicon to identify sentiment-bearing words and then apply a machine learning model to consider context and nuances in the text. This approach allows for better handling of sarcasm or mixed sentiments in dialectal expressions. By leveraging the strengths of both methods, hybrid approaches can achieve higher accuracy and robustness in sentiment classification [13].

1.13 Conclusion

In conclusion, sentiment analysis emerges as a powerful tool for understanding emotions and opinions in digital text. By analyzing data extracted from social media platforms, we can uncover prevailing patterns in emotional expression, helping us understand how digital discourse impacts individuals and communities. Sentiment analysis provides valuable insights into general trends and emotional tendencies, guiding efforts to enhance digital safety by raising awareness of communication practices. Moreover, combining sentiment analysis techniques with other technological innovations can contribute to developing effective strategies to address negative behaviors, leading to safer and more inclusive digital environments. Therefore, investing in research and development in the field of sentiment analysis is a vital step toward understanding and improving human interactions in the digital age.

Chapter 2

Dataset Construction

2.1 Introduction

A dataset is a structured collection of data that serves as a cornerstone for analysis, research, or machine learning tasks. These datasets can manifest in various formats—including text, images, audio, and numerical values—and are typically organized in rows and columns when dealing with tabular data. In the realm of artificial intelligence and data science, datasets play an instrumental role in training and evaluating models, providing the examples from which systems learn to recognize patterns, make informed decisions, and generate accurate predictions.

In this chapter, we will delve into the fundamental aspects of datasets, beginning with a clear definition and exploring the diverse types of datasets that exist. We will also discuss the intricacies of dataset construction, highlighting the methodologies and best practices for creating robust datasets. Lastly, we will examine the key characteristics that define effective datasets, emphasizing their relevance to the success of machine learning applications

2.2 Definitions of dataset

The concept of a dataset is fundamental across nearly all scientific disciplines, as data provide the empirical foundation for research activities. Despite its widespread use in scholarly articles, reports, and informal scientific discourse, the term lacks a precisely defined and universally accepted definition. Nonetheless, its common usage suggests a broadly shared understanding, as our review of the literature reveals a set of recurring themes associated with the concept. At the same time, this review highlights considerable variation in how the term is employed across different fields, raising questions about whether a single, precise definition is achievable. This variability is unsurprising, as demanding exact precision in definitions is often impractical. Instead, relying on the informal, general understanding shared within disciplinary communities tends to be more efficient, with more specific distinctions negotiated as needed. Such flexibility not only facilitates intra-disciplinary communication but also aids cross-disciplinary dialogue through loosely defined concepts. However, the absence of a precise, common definition across disciplines can present challenges for multi-disciplinary digital data repositories. These repositories aim to integrate diverse data sources to address complex real-world problems and must present their collections within a consistent and coherent framework. The following sum-

marizes preliminary findings from a project examining definitions of datasets in scientific literature, technical documentation, and information processing standards (Sacchi, 2010). This work has identified a core set of common characteristics and serves as a foundational step toward developing a normative, formal framework of clearly defined and interrelated concepts that both maintains internal coherence and meets the needs of scientists and institutions engaged in data-intensive research. This research is part of the Data Conservancy initiative, a multi-institutional project funded by the NSF and hosted at Johns Hopkins University Sheridan Libraries. The Data Conservancy builds infrastructure for digital research data management. Its Data Concepts team, based at the Center for Research in Science and Scholarship at the University of Illinois Urbana-Champaign, is developing a formal framework of fundamental data concepts to standardize how Data Conservancy datasets are identified, described, related, and organized. [14]

2.3 Types of dataset

Types of datasets refer to the various forms in which data can be organized and utilized in machine learning and data analysis. Each type plays a specific role in the data processing pipeline. Below are the main types of datasets:

2.3.1 Structured Data

Structured data refers to data that adheres to a well-defined schema or format, where each data point is organized into rows and columns, typically within tabular formats such as relational databases or spreadsheets. Each column (or field) has a defined data type (e.g., integer, string, date), and each row represents a unique record or entity. This type of data is highly organized and easily searchable and queryable using structured query languages (e.g., SQL). Structured data is the most traditional and widely used form of data in enterprise systems, where data integrity, consistency, and normalization are essential. Due to its clear schema, structured data is generally easier to process, analyze, and visualize using classical machine learning algorithms and statistical techniques. In the context of machine learning, structured data typically consists of feature vectors, where each row is an observation and each column is a feature. Algorithms such as logistic regression, decision trees, support vector machines, and gradient boosting are commonly applied to structured data for tasks like classification and regression.

- Structured data is often contrasted with unstructured data, which lacks a predefined format. Sources of structured data include:

- Relational database management systems (e.g., MySQL, PostgreSQL) - Spreadsheets (e.g., Microsoft Excel)

- CSV files

Sensor data with consistent fields

The advantages of structured data include ease of storage, querying, integration, and analysis. However, it may not be suitable for handling more complex information such as images, videos, or free text.[15]

2.3.2 Unstructured Data

Unstructured data refers to information that does not have a predefined data model or schema. Unlike structured data, which is organized in rows and columns, unstructured

data is typically stored in its native format and lacks a consistent structure, making it more complex to process and analyze.

This type of data includes a wide variety of formats such as text documents, emails, social media posts, audio, video, images, PDF files, and more. Unstructured data is ubiquitous in the digital world, accounting for an estimated 80

In the context of machine learning and data science, unstructured data poses significant challenges but also offers substantial value. For instance, text mining can be used to extract sentiment, topics, or named entities from documents or social media, while deep learning models can extract features from images or classify audio signals.

- Common sources of unstructured data include:
- Social networks (e.g., Twitter, Facebook)
- Audio and video recordings
- Customer service transcripts and chat logs
- News articles and blog posts
- Sensor logs with free-form text

The advantages of unstructured data lie in its richness and potential to provide deeper insights. However, its disadvantages include higher storage and processing requirements, data cleaning complexity, and the need for advanced algorithms to interpret it meaningfully.[16]

2.3.3 Semi-Structured Data

Semi-structured data refers to a type of data that does not conform strictly to the formal structure of traditional relational databases (as in structured data), yet still contains organizational properties that make it easier to analyze than unstructured data. This data type includes elements such as tags, markers, or key-value pairs that provide semantic meaning and structure, though not in a rigid table-like format.

Unlike structured data, which is stored in relational tables with fixed schemas, semi-structured data allows for flexibility in representation, making it suitable for data that evolves or varies over time. It typically includes formats such as:

- XML (eXtensible Markup Language)
- JSON (JavaScript Object Notation)
- YAML
- NoSQL database formats (e.g., MongoDB, CouchDB)
- Email headers, log files, and metadata-enriched documents

Semi-structured data is common in web technologies, application logs, API outputs, and big data ecosystems. It plays a crucial role in modern data science and machine learning pipelines, especially in data ingestion and integration processes, where heterogeneity of data sources is the norm.

From a machine learning perspective, semi-structured data can be converted into structured format using parsing techniques, feature extraction, or schema inference algorithms to enable predictive modeling. Its flexibility provides a trade-off between the rigid schema of structured data and the complete lack of organization in unstructured data.[17]

2.3.4 Numerical Data

Numerical data refers to data that is represented in the form of numbers, which can be measured and quantified. It is one of the primary types of quantitative data and is

essential for statistical analysis, machine learning, and mathematical modeling. Numerical data can be further classified into two main types:

Discrete data: Data that take on countable values, often integers, such as the number of students in a class or the number of cars in a parking lot.

Continuous data: Data that can take any value within a given range or interval, such as height, weight, temperature, or time.

Numerical data is characterized by its measurability and orderability, allowing for operations such as addition, subtraction, multiplication, and division. This makes numerical data particularly suitable for mathematical modeling, regression analysis, hypothesis testing, and various machine learning algorithms.

The quality and distribution of numerical data greatly affect the performance and interpretation of statistical and predictive models. Proper preprocessing, such as normalization, standardization, and handling missing values, is often necessary to prepare numerical data for analysis.

In many datasets, numerical features serve as key predictors and are crucial for uncovering underlying trends, patterns, and relationships in the data. [18]

2.3.5 Categorical Data

Categorical data refers to variables that represent discrete groups or categories rather than numerical values. These data types classify observations into distinct categories, which may or may not have an inherent order. Categorical data plays a fundamental role in statistical analysis, data mining, and machine learning, particularly in classification problems and descriptive statistics.

Categorical data can be subdivided into two main types:

- Nominal data: Categories without any intrinsic order or ranking. Examples include gender (male, female), blood type (A, B, AB, O), or types of animals (dog, cat, bird). In nominal data, the categories serve solely as labels.

- Ordinal data: Categories with a natural, meaningful order or ranking but without a fixed numerical difference between them. Examples include educational levels (high school, bachelor, master, PhD), customer satisfaction ratings (poor, fair, good, excellent), or stages of cancer (stage I, II, III, IV). Though these categories have an order, the intervals between them are not necessarily uniform or measurable.

Categorical variables are typically encoded using techniques such as one-hot encoding, label encoding, or binary encoding to convert categories into numerical format suitable for machine learning algorithms. Proper encoding ensures that models do not infer misleading relationships (e.g., implying ordinal relationships where none exist).

Handling categorical data requires careful consideration of the cardinality (number of unique categories) and imbalance in category frequencies, as these can affect model performance. High-cardinality categorical features may require dimensionality reduction or grouping strategies.

In statistics and machine learning, categorical data is essential for tasks such as segmentation, clustering, and classification. Models such as decision trees, random forests, and naive Bayes classifiers naturally handle categorical variables, while others like linear regression require prior data transformation.

Furthermore, the interpretation of categorical data often involves the use of contingency tables, chi-square tests, and frequency distributions to assess relationships and dependencies between categorical variables. [19]

2.4 Characteristics of the Dataset

2.4.1 Data Type and Nature

The type or nature of data in a dataset refers to the intrinsic form of the values it contains. Common types include:

- **Numerical**: Quantitative values such as age, temperature, or price.
- **Categorical**: Discrete, often qualitative values representing distinct groups, such as gender or color.
- **Textual**: Language-based data including sentences, documents, and other linguistic constructs.
- **Multimedia**: Includes non-text data such as images, audio recordings, or video files.
- **Other**: May include embedding vectors, log files, or machine-generated outputs.

Identifying the data type is essential for selecting appropriate preprocessing and analysis techniques [20].

2.4.2 Structure

The structure of a dataset describes how the data is organized:

- **Structured**: Well-organized in rows and columns, typically stored in spreadsheets or relational databases.
- **Semi-structured**: Partially organized data, such as JSON or XML, where the schema is implicit.
- **Unstructured**: Data with no predefined format, like raw text, images, or audio recordings.

Understanding structure guides how data should be parsed and transformed for analysis [21].

2.4.3 Records and Examples and Instances

Each row or instance in a dataset represents a single observation or data point. For example, one tweet, image, or sensor reading can be a single instance. These units are essential for training and evaluating machine learning models [22].

2.4.4 Variables / Attributes / Features

Variables or features are the measurable properties or characteristics of the data. They often appear as columns in a structured dataset. Attributes provide descriptive aspects assigned to each record. These elements form the basis for modeling and inference in data-driven tasks [23].

2.4.5 Statistical Properties

These refer to the mathematical characteristics of data distribution:

- **Distribution**: e.g., normal, uniform, or skewed.
- **Summary statistics**: Mean, median, standard deviation, skewness, kurtosis.
- **Correlation**: Measures the relationships between variables.

Analyzing statistical properties aids in feature engineering and anomaly detection [20].

2.4.6 Quality Attributes

Dataset quality is determined by several attributes:

- **Accuracy**: Data correctly reflects the real-world phenomena.
- **Completeness**: All required fields and values are available.
- **Consistency**: Data is uniform across entries and formats.
- **Relevance**: Data is pertinent to the intended analytical goals.
- **Timeliness**: Data is up-to-date and reflects the current context.
- **Accessibility and Usability**: Data is easy to retrieve, interpret, and use effectively.

High-quality data enables more reliable insights and model performance [20].

2.4.7 Schema and Metadata

The schema defines the structural blueprint of the dataset, including variable names, types, and constraints. Metadata provides additional contextual information such as data source, creation date, and collection method. Together, they support data interoperability and governance [24]

2.4.8 Size and Quantity

This characteristic includes the number of records (rows) and features (columns) in the dataset. It affects memory usage, processing time, and model scalability [25].

2.4.9 Language

For textual datasets, the language (e.g., English, French, Algerian dialect) plays a crucial role in Natural Language Processing (NLP) tasks. Language determines preprocessing needs, available tools, and model applicability [21].

2.5 How to construct a dataset

To construct a dataset, there is a set of key steps to follow, which we cite:

2.5.1 Data Collection

Data collection constitutes the initial and most critical phase in the process of dataset construction. It entails a systematic approach to acquiring and quantifying information from a variety of sources, with the objective of enabling the development, training, validation, and testing of reliable machine learning (ML) models. The effectiveness of an ML system is highly contingent upon the quality, relevance, and volume of the collected data. Inadequate or poor-quality data can severely undermine the performance of even the most advanced learning algorithms, leading to inaccurate predictions and limited generalizability [26, 27].

Importance of Effective Data Collection

The importance of conducting data collection in a structured and deliberate manner is multifaceted and directly impacts the success of ML-driven applications:

- **Model Performance:** The availability of clean, representative, and diverse data significantly enhances a model's ability to capture underlying patterns and generate accurate, robust predictions.
- **Bias Mitigation:** Thoughtful data collection helps uncover and mitigate biases that may be embedded in the data, thereby promoting the development of more equitable and socially responsible AI systems.
- **Generalizability:** Comprehensive datasets drawn from varied conditions and populations enable models to perform effectively on previously unseen data, ensuring broader applicability and resilience.
- **Reproducibility and Transparency:** Documenting the data acquisition process, including sources, collection techniques, and conditions, enhances reproducibility in research and contributes to greater transparency in the ML lifecycle.
- **Problem Definition:** The process of data gathering often leads to a deeper and more refined understanding of the underlying problem, shaping the direction of subsequent analytical and modeling efforts.

Key Steps in Data Collection

A well-structured data collection process involves a sequence of essential steps that ensure the acquisition of high-quality, relevant, and usable data for machine learning systems [27]:

1. **Define Project Goals and Data Requirements:**
    - Begin by articulating clear and measurable objectives for the AI/ML project. This includes identifying the core problem to be addressed and the desired predictive or classification outcomes.
    - Determine the nature of the data required (e.g., numerical, categorical, textual, visual, auditory, or time-series) based on the problem domain.
    - Specify the key variables and features that are expected to influence model performance.

- Estimate the volume of data necessary to achieve reliable results, keeping in mind that while larger datasets can improve model learning, data quality remains the top priority.

2. **Identify Data Sources:**

   - Identify where the necessary data can be sourced, whether from internal repositories, external public datasets, online platforms, sensor networks, or user-generated inputs.
   - Consider both primary data sources (original, directly collected data) and secondary sources (existing, preprocessed datasets).
   - Evaluate the credibility, accessibility, and licensing restrictions of each data source.

3. **Extract Data Using Appropriate Tools:** After identifying the sources, the data must be extracted using suitable tools and techniques tailored to the structure and format of the target datasets:

   - **SQL Queries:** For extracting data from structured relational databases such as MySQL, PostgreSQL, or Oracle. SQL enables efficient querying, joining, and aggregation of large datasets through structured commands.
   - **APIs (Application Programming Interfaces):** Many digital platforms offer APIs that facilitate standardized, programmatic access to data. APIs ensure consistent data retrieval and often include usage limits and authentication layers. Common examples include the Twitter API, Google Maps API, and financial market APIs.
   - **Web Scraping:** In cases where APIs are unavailable, web scraping tools (e.g., BeautifulSoup, Scrapy) can be used to programmatically extract content from HTML pages. This approach requires adherence to ethical guidelines and legal terms of service, including respect for ‘robots.txt‘ restrictions and site-specific usage policies.
   - **Manual Methods:** When dealing with small-scale datasets, complex data formats, or contexts requiring human interpretation, manual data collection may be necessary. This includes tasks such as annotating images, transcribing speech, or extracting text from physical documents. Although time-consuming, manual methods can yield high-quality, domain-specific data.

Automating Collection: Where feasible, automating the data collection process is highly advantageous. Automation enhances operational efficiency, minimizes human error, and facilitates the continuous and scalable acquisition of data. This can be achieved by deploying scheduled tasks such as cron jobs, cloud-based functions, or orchestrated data pipelines using tools like Apache Airflow or Prefect.

Data Ingestion and Storage:

- Once collected, data must be ingested into appropriate storage infrastructures such as data lakes, data warehouses, or cloud-based storage platforms.
- Effective data management practices—encompassing version control, access permissions, and data security—are essential to ensure long-term usability and governance.

Initial Data Validation and Quality Assurance:

- Perform preliminary checks to identify evident data quality issues, such as missing values, outliers, or format inconsistencies.
- This early-stage validation is critical before proceeding to advanced data cleaning and preprocessing steps.

Document Data Collection Process:

- Maintain comprehensive documentation detailing the data collection procedures, including the timeline, tools used, data sources, and methods employed.
- Record assumptions, limitations, and any biases observed during the process. Transparent documentation ensures reproducibility and provides essential context for future analysis and audits.

Best Practices in Data Collection

To maximize the success and reliability of machine learning projects, the following best practices should be observed [28]:

- **Data Quality Over Quantity:** Prioritize the collection of data that is accurate, consistent, complete, and relevant to the task at hand. A smaller, high-quality dataset often outperforms a large, noisy one.
- **Diversity and Representativeness:** Strive to include diverse samples that reflect the real-world scenarios and populations the model will interact with. This improves generalization and reduces model bias.
- **Ethical Considerations and Privacy:** Adhere strictly to ethical standards and data protection regulations (e.g., GDPR, CCPA). Obtain informed consent where required and anonymize personally identifiable information (PII). Actively address and mitigate biases present in the data sources.
- **Regular Monitoring and Maintenance:** Data sources can evolve over time. Establish monitoring mechanisms to track data drift, refresh outdated datasets, and adapt the collection strategy accordingly.
- **Version Control for Datasets:** Manage datasets using version control systems to maintain historical records, enable reproducibility, and ensure traceability of changes over time.
- **Collaboration:** Involve domain experts early in the data collection process to validate that the data collected is contextually appropriate and captures the nuances necessary for the problem domain.

Sources of Datasets

Dataset sources can be categorized into two broad classes: (1) primary or raw data collected directly from real-world settings, and (2) secondary data from publicly available repositories [29].

Primary Data Sources

Primary sources refer to unprocessed, original data collected for specific research or operational purposes:

- **Social Media Platforms:** Platforms such as YouTube, Twitter, Facebook, and TikTok serve as rich sources of multimedia and text-based user-generated content.
- **User-Generated Content:** This includes forums, product reviews, comments, and blogs, which offer authentic insights into public opinion and behavior.
- **Surveys and Interviews:** Widely used in disciplines such as sociology, linguistics, and psychology to collect structured responses directly from participants.
- **Governmental or Institutional Reports:** Public records and datasets released by governmental bodies or academic institutions often provide reliable and validated information.
- **Experimental and Sensor Data:** Generated from scientific experiments or industrial setups involving sensors, logs, or telemetry. These sources are particularly common in fields such as IoT, healthcare, and physics [29].

2.5.2 Data Annotation

Manual Annotation:

Manual annotation refers to the process by which human experts or trained annotators label raw data manually. This annotation process varies depending on the data type task, and may include assigning class labels to images, identifying named entities or sentiments in textual content, transcribing and segmenting speech, or categorizing video footage. Unlike automated annotation methods, manual annotation leverages human cognitive abilities to interpret context, manage ambiguity, and recognize subtle nuances—capabilities where current artificial intelligence often falls short.

Due to its reliance on human intelligence, manual annotation tends to yield high-quality, precise labels, making it particularly valuable in supervised learning applications where data quality directly affects model performance. However, manual annotation presents several limitations: it is highly labor-intensive, time-consuming, and costly, especially when large-scale datasets or domain-specific expertise (such as in medical, legal, or psychological domains) are required.

Another significant challenge is ensuring label consistency among annotators. Inter-annotator agreement must often be managed through detailed labeling guidelines, annotator training, and multi-phase quality control reviews. Despite these challenges, manual annotation remains indispensable in tasks that demand deep understanding and ethical judgment.

A notable example is its use in hate speech detection, where annotators manually label social media posts to indicate whether they contain abusive, misogynistic, or toxic content. These labeled datasets then serve as the foundation for training machine learning models capable of identifying harmful speech automatically at scale.

In summary, while manual annotation is resource-intensive, it remains a cornerstone for developing accurate and trustworthy datasets, particularly for complex and sensitive AI applications. [30]

Automatic Annotation:

Automatic annotation is the process of labeling datasets using machine-driven techniques rather than relying solely on human input. This process typically utilizes algorithms, heuristics, rule-based systems, or pre-trained machine learning models to generate annotations at scale. It is particularly useful in scenarios where manually labeling large datasets would be prohibitively time-consuming, expensive, or impractical.

Automatic annotation can be implemented using a variety of methods, including:

- Supervised machine learning models: Previously trained models are used to infer labels for new, unlabeled data. For example, a sentiment analysis classifier trained on a labeled corpus can be used to automatically label new text reviews as positive, negative, or neutral.
- Unsupervised or semi-supervised learning: Clustering or probabilistic models assign labels or groupings based on inherent data structures. These methods may help uncover hidden patterns or structure without explicit human labeling.
- Rule-based systems: Expert-designed rules or pattern-matching algorithms are used to identify specific features in the data and assign labels accordingly. This is common in information extraction and natural language processing tasks.
- Heuristic approaches: These involve leveraging domain knowledge or external metadata (such as tags, timestamps, or user feedback) to infer plausible labels.
- Transfer learning and weak supervision: Pretrained models are adapted to new domains with minimal additional labeling, or noisy labels are generated from indirect sources (e.g., web labels, hashtags).

Despite its scalability and efficiency, automatic annotation comes with several trade-offs. Most notably, it can introduce label noise, systematic bias, or contextual misunderstandings, especially in complex or ambiguous cases. For this reason, automatic annotation is often followed by human validation or correction to ensure label quality. In practice, a hybrid annotation strategy—where automatic annotation is used to pre-label data followed by human review—is commonly adopted in industrial and research settings. A common use case includes pre-labeling large volumes of product reviews or social media posts using sentiment classification models. These annotations may then be refined by human annotators or used directly if confidence levels are high. Automatic annotation is a powerful tool for scaling dataset creation in machine learning pipelines. When combined with proper quality control mechanisms, it significantly accelerates the development of labeled corpora for training robust AI systems.[31]

Hybrid Annotation:

automatic and manual annotation approaches. In this method, machine learning models or algorithmic systems are first used to generate initial labels for the data. These machine-generated annotations are then carefully reviewed, verified, and refined by human annotators. This dual-stage process is designed to achieve an optimal balance between annotation speed and data quality. By delegating routine or high-confidence labeling tasks to automated systems, hybrid annotation significantly reduces the human labor required, allowing annotators to focus on complex, ambiguous, or context-sensitive cases

where human expertise is essential. For example, in sentiment analysis or hate speech detection on social media, pre-trained classifiers may automatically tag thousands of posts, while human reviewers examine uncertain or low-confidence predictions to ensure the accuracy and fairness of the final dataset. Hybrid annotation not only accelerates the data preparation process but also improves label consistency and reliability, making it especially effective in natural language processing (NLP), named entity recognition (NER), and other AI domains that demand both scale and nuance. Ultimately, this method leverages the computational efficiency of machines and the critical thinking capabilities of humans to create high-quality labeled datasets suitable for advanced machine learning applications.

[32]

Crowdsourcing-Based Construction:

Crowdsourcing-based dataset construction is a data annotation approach that leverages the collective efforts of a large number of non-expert contributors, often recruited through online platforms, to label, verify, or generate data for machine learning tasks. This method offers a scalable and cost-effective alternative to traditional manual annotation performed by domain experts. Crowdsourcing platforms such as Amazon Mechanical Turk, Figure Eight (formerly CrowdFlower), and Prolific provide access to a broad and diverse workforce capable of performing a wide range of annotation tasks—from image classification and sentiment labeling to entity recognition and data validation.

One of the main advantages of crowdsourcing is its high throughput: large datasets can be annotated in parallel by distributing small micro-tasks to many workers simultaneously. This parallelism dramatically reduces the time required for dataset construction. Additionally, by collecting multiple annotations for the same data point from different individuals (a technique known as redundancy), researchers can use statistical methods like majority voting or weighted consensus to improve label reliability and detect outliers or inconsistencies.

However, crowdsourcing is not without its challenges. Because contributors are typically non-experts, the quality of annotations can vary significantly. To mitigate this, researchers often implement quality control measures, such as gold standard questions, performance tracking, and real-time validation checks. Furthermore, clear task instructions and user-friendly interfaces are essential to ensure worker understanding and consistency.

Crowd-sourcing has been successfully used in numerous large-scale machine learning projects, including sentiment analysis corpora, named entity recognition datasets, hate speech detection, and even medical image labeling (when guided by expert-designed workflows). By tapping into distributed human intelligence, crowd-sourcing has become a cornerstone of modern dataset development, especially in scenarios where labeled data is scarce or expensive to obtain through expert annotation alone.[33]

2.5.3 Data Preparation

After data has been collected, it must undergo a comprehensive preparation process before being utilized effectively in analytical tasks or machine learning (ML) model training. This phase is critical, as raw data is often incomplete, inconsistent, or contaminated with noise. Data preparation ensures that the dataset is not only clean but also structured in a way

that aligns with the objectives of the analysis or the assumptions of the algorithms being applied [34].

Stages of Data Preparation

Data preprocessing is a foundational step within the broader data preparation pipeline. It encompasses a variety of techniques aimed at enhancing data quality and transforming it into a usable format. Poor data quality can significantly degrade the performance of analytical models, making this step indispensable.

- **Duplicate Removal:** Eliminating redundant entries ensures the uniqueness of records and prevents bias in training data. Duplicate data can distort statistical properties and lead to overfitting in ML models [28, 27].
- **Missing Value Handling:** Datasets frequently suffer from incomplete records due to various factors such as human error or data corruption. Handling missing data involves techniques like deletion, imputation (mean, median, mode), or model-based methods to fill in the gaps based on available patterns.
- **Error and Inconsistency Correction:** Real-world data often contains anomalies such as typos, misclassifications, and inconsistent label formats. For instance, variations like "NYC", "New York", and "new york city" may refer to the same entity but need standardization for accurate analysis.
- **Data Standardization and Formatting:** Ensuring consistent formats across variables (e.g., dates in ISO 8601 format, categorical values in lowercase) improves interoperability between tools and models. Uniform data structure facilitates easier parsing and feature extraction [28, 27].

Modern data preprocessing tasks are often performed using tools such as Python's `pandas` library, which offers flexible and efficient data manipulation capabilities. In more complex or enterprise-level environments, platforms like OpenRefine or Trifacta provide interactive interfaces and automation for advanced data wrangling operations.

2.5.4 Data Transformation and Integration

Following data preprocessing, transformation and integration steps are essential to adapt the dataset into a format that aligns with the requirements of downstream analysis or machine learning models. These processes enhance the quality and utility of the data, especially in sentiment analysis tasks where feature representation and consistency across sources are crucial.

- **Transforming data into a suitable analytical format:** This includes several operations aimed at standardizing and enriching the dataset:
  - **Normalization and Scaling:** Numerical attributes may vary significantly in range. Scaling techniques such as min-max normalization (scaling to [0, 1]) or z-score standardization (centering to mean 0 and standard deviation 1) ensure that no single feature dominates the learning process, which is particularly important in distance-based models.

  - **Aggregation:** Aggregating data—such as computing average sentiment scores over time or by category—helps extract macro-level patterns and trends, which can support more robust insights or modeling.

  - **Feature Engineering:** Creating new variables derived from existing ones (e.g., word counts, sentiment polarity scores, or syntactic patterns) enhances the feature space. These engineered features often capture domain-specific nuances that improve model performance in sentiment classification tasks [35].

- **Data Integration from Multiple Sources:** When datasets are collected from heterogeneous platforms (e.g., Twitter, Reddit, review websites), it becomes necessary to merge them using shared identifiers (e.g., timestamps, user IDs, text fields). Integration also involves resolving inconsistencies such as differing sentiment labels, text encodings, or schema structures [28, 27]. Harmonizing these aspects ensures coherence and improves the generalizability of the resulting model.

2.5.5 Data Balancing

Data balancing is a vital preprocessing step in sentiment analysis, particularly when working with **imbalanced datasets**—a common occurrence where certain sentiment classes (e.g., positive, negative, or neutral) dominate the distribution. Such imbalance can skew the training process, leading machine learning models to develop a bias toward the majority sentiment class and consequently misclassify underrepresented sentiments [36].

RandomOversampling/Undersampling

To address this issue, several **resampling techniques** have been developed. These methods aim to either reduce the number of majority class samples (*undersampling*) or increase the representation of the minority class (*oversampling*). Among oversampling strategies, the Synthetic Minority Over-sampling Technique (**SMOTE**) is widely adopted. SMOTE generates synthetic instances of the minority class by interpolating between existing examples, thereby enriching the dataset with more representative training data without simply duplicating original samples.

Data augmentation:

Data augmentation refers to the process of artificially increasing the size and diversity of a dataset by applying various transformations to existing data samples. This technique is widely used in machine learning and deep learning to enhance model generalization, mitigate overfitting, and compensate for limited or imbalanced training data. By systematically modifying the original data while preserving its label or semantic meaning, data augmentation helps models become more robust to variability in real-world inputs. In the context of computer vision, data augmentation includes geometric transformations (e.g., rotation, flipping, cropping, scaling), color space adjustments (e.g., brightness, contrast, saturation), noise injection, and even advanced methods such as CutMix, MixUp, and adversarial perturbations. For natural language processing (NLP) tasks, augmentation techniques involve synonym replacement, back-translation, random word insertion/deletion, paraphrasing, or language model–based text generation (e.g., using BERT

or GPT to rephrase sentences). In audio and speech processing, augmentation may involve pitch shifting, speed variation, background noise injection, and time-stretching. Data augmentation is particularly beneficial in low-resource settings or domains where collecting new labeled data is costly or time-consuming, such as in medical imaging or legal document analysis. Furthermore, augmentation improves the robustness and transferability of models by exposing them to a broader range of variations and edge cases during training. In recent years, automated data augmentation techniques have emerged, using reinforcement learning or Bayesian optimization to discover optimal augmentation policies (e.g., AutoAugment, RandAugment). These approaches learn which transformations contribute most effectively to model performance, without requiring manual design or domain-specific tuning. In summary, data augmentation plays a vital role in modern AI pipelines by enriching datasets, promoting model robustness, and ultimately enhancing prediction accuracy, particularly when data is limited, noisy, or imbalanced. [37]

2.5.6 Data Validation

Data validation is a critical quality assurance process that verifies the integrity, accuracy, and consistency of a dataset prior to its use in model training or analysis. In the context of sentiment analysis, ensuring the correctness and representativeness of labeled data is particularly important, as even minor inconsistencies can significantly degrade model performance.

- **Assessing Accuracy, Completeness, and Reliability:** Several techniques can be employed to evaluate data quality:
  - **Cross-Referencing with External Sources:** Key attributes (such as sentiment labels or metadata) may be compared with known reliable datasets or benchmark corpora to verify correctness.
  - **Manual Spot Checks:** Reviewing random samples manually can help identify mislabeling, noise, or formatting issues that automated tools might miss—especially important when sentiment labels are generated using rule-based or crowdsourced approaches.
  - **Statistical Validation:** Descriptive statistics and distribution plots (e.g., class balance, text length, sentiment score distribution) can help identify outliers, anomalies, or unbalanced label distributions that may affect model generalization [38].
- **Validation Tools and Manual Review:** Depending on dataset size and complexity, a combination of automated validation tools (e.g., data profiling libraries) and manual review may be used. Tools such as Pandas Profiling, Great Expectations, or custom validation scripts can facilitate the detection of formatting errors, missing values, or inconsistent encodings.
- **Ensuring Usability for Modeling:** Ultimately, the goal of validation is to ensure the dataset is not only clean but also logically and statistically consistent with the assumptions of the analysis or machine learning algorithm being applied. This step plays a vital role in enhancing model robustness and reproducibility.

2.5.7 Storing and Sharing the Dataset

The final step in dataset preparation involves secure storage and appropriate dissemination strategies. Proper data management not only preserves the dataset but also ensures its responsible use and facilitates reproducibility in sentiment analysis experiments.

- **File Format and Storage:** Datasets should be stored in widely supported, portable formats such as CSV, JSON, or Parquet. For larger datasets, databases (e.g., PostgreSQL, MongoDB) or cloud-based storage platforms (e.g., Amazon S3, Google Cloud Storage) are recommended for efficient access and scalability [28, 27].
- **Access Control and Security:** It is essential to enforce strict access controls to safeguard the dataset, particularly if it contains user-generated content or sensitive information. Role-based access and encryption are commonly used for this purpose.
- **Data Sharing and Collaboration:** When appropriate, datasets may be shared with external collaborators or the research community. Public sharing (e.g., via repositories such as Kaggle, Hugging Face, or Zenodo) can enhance the visibility and impact of the project, provided proper licensing and ethical guidelines are followed.

2.6 Manual Annotation

Manual annotation is the process of labeling datasets by human annotators. This method plays a critical role in supervised learning, where accurate, labeled data is essential for training models that learn mappings between inputs and outputs. Manual annotation is especially important in complex tasks such as natural language processing (NLP), computer vision, speech recognition, and medical image analysis, where nuanced human understanding is required to interpret context, ambiguity, or specialized domain knowledge[32] [39]

2.6.1 Importance of Manual Annotation:

Manual annotation provides high-quality ground truth data, which is foundational for building robust and accurate machine learning models. Unlike automated methods, human annotators can understand cultural, contextual, and emotional subtleties in data, making them ideal for subjective or ambiguous tasks such as detecting sarcasm, hate speech, or sentiment in text. For instance, annotating online comments for misogyny or hate often demands cultural and linguistic awareness that automated tools may lack. Additionally, in fields like medical imaging, manual annotation ensures that the data reflects expert-level insight, often crucial for diagnostic model performance[32]

2.6.2 Types of Manual Annotation Tasks:

Manual annotation includes a wide variety of task types across different modalities:

- Text Classification: Assigning a text to a predefined category, such as spam detection or sentiment polarity (positive, neutral, negative).
- Named Entity Recognition (NER): Identifying and labeling entities like people, organizations, locations, and dates within a text.

- Image Labeling: Drawing bounding boxes around objects or tagging image regions based on their content.
- Speech Transcription: Converting spoken language into written text, often with speaker identification
- Sentiment Annotation: Assigning emotional tone or attitude to textual inputs

2.6.3 Annotation Guidelines:

Consistency and reproducibility in manual annotation are achieved through detailed annotation guidelines. These documents define label sets, offer examples (including ambiguous or borderline cases), and describe standard operating procedures for handling disagreement between annotators. Guidelines ensure that all annotators apply labels uniformly, reducing subjectivity and improving inter-annotator agreement [39]

2.6.4 Tools for Manual Annotation:

Various tools have been developed to support efficient and collaborative manual annotation:

- Labelbox, Prodigy, and Doccano: Provide intuitive interfaces for text and image annotation
- CVAT (Computer Vision Annotation Tool): Designed for complex video and image labeling
- LightTag: Focused on NLP annotation with team-based workflows

These tools typically support features like project management, review workflows, quality assurance checks, and integration with machine learning pipelines.

2.6.5 Challenges in Manual Annotation:

Manual annotation is resource-intensive and presents several challenges:

- Cost and Time: It is slow and expensive, especially for large datasets
- Subjectivity: Human interpretations can vary, particularly for emotional or moral content
- Fatigue and Inconsistency: Annotators may make mistakes over long periods of work
- Domain Expertise Requirements: Some tasks require professional expertise (e.g., legal, medical)

These challenges necessitate careful project planning, annotator training, and quality monitoring systems.[32]

2.6.6 Quality Assurance Techniques:

To ensure reliability and accuracy in manual annotations, several quality control mechanisms are commonly employed:

- Inter-Annotator Agreement (IAA) Measured using metrics like Cohen's Kappa or Fleiss' Kappa to evaluate consistency between annotators.
- Double Annotation: Having multiple annotators label the same data with a reconciliation step to resolve disagreements.
- Spot-Checking and Expert Review: Random or targeted review by senior annotators or domain experts

These measures help maintain high data integrity, especially in high-stakes domains.

2.6.7 Use Cases Requiring Manual Annotation:

Manual annotation remains indispensable in several critical application areas:

- Hate Speech Detection: Requires contextual understanding and cultural sensitivity
- Medical Imaging: Demands input from trained clinicians or radiologists
- Legal Document Analysis: Involves understanding complex and archaic language
- Low-Resource Languages: Where labeled datasets or pretrained models are scarce or nonexistent

In these scenarios, human annotation ensures that labeled data reflect accurate, ethical, and culturally relevant judgments.

2.7 Where find Dataset

In the field of artificial intelligence and machine learning, data plays a central role in training, validating, and evaluating models. The quality, diversity, and relevance of datasets are critical to achieving robust and generalizable AI systems. Data can originate from a wide range of sources, each offering unique advantages depending on the task at hand. Common dataset sources include open-access repositories, dataset search engines, web scraping methods, synthetic data generation, and community-driven platforms. These sources provide a foundation for academic research, industrial applications, and the development of benchmark models.[40][41]

2.7.1 UCI Machine Learning Repository:

The UCI Machine Learning Repository is one of the oldest and most respected resources in the machine learning community. Hosted by the University of California, Irvine, it offers a curated collection of datasets covering a wide range of domains and tasks, such as classification, regression, and clustering. It is widely used for academic instruction, algorithm testing, and benchmarking. The datasets are formatted for ease of use and typically include metadata and references. https://archive.ics.uci.edu/ml/index.php

2.7.2 Google Dataset Search:

Google Dataset Search[1] is a specialized search engine designed to help researchers and data practitioners discover datasets stored across the internet. It indexes metadata from thousands of data repositories, making it easier to locate structured data across domains such as health, environment, finance, and machine learning. Its interface is user-friendly, and it provides direct access to dataset hosting pages.

2.7.3 Kaggle Datasets:

Kaggle, a prominent platform for data science and machine learning competitions, also hosts a large and dynamic repository of public datasets. These datasets come from both user contributions and real-world challenges presented by companies and institutions. Features include:

- **T**housands of datasets across domains like natural language processing, computer vision, healthcare, and finance.
- **B**uilt-in tools for interactive analysis using Python or R directly within the browser.
- **C**ommunity-driven collaboration and discussion to explore and improve datasets.
- **F**requent updates and quality controls to ensure relevance and usability. Kaggle datasets are widely used for experimentation, rapid prototyping, and educational purposes in both academia and industry.[42]

Conclusion

In this chapter, we presented the practical implementation of our sentiment analysis project focused on the Algerian dialect. The methodology included the systematic collection, annotation, and preparation of YouTube comments to create the ALG-Sent dataset. We then applied various preprocessing steps and experimented with multiple machine learning models, evaluating their performance using standard metrics. The results demonstrated the effectiveness of our dataset and highlighted the challenges posed by data imbalance and dialectal variation.

Overall, the experimentation validated our approach and confirmed the feasibility of sentiment classification in low-resource dialects. The ALG-Sent dataset proved to be a valuable asset for training and testing models designed for sentiment analysis in Algerian Arabic. This lays the foundation for future work in improving model accuracy and expanding coverage to additional domains and dialectal variations.

[1] https://datasetsearch.research.google.com

Chapter 3

Applied Techniques and Results

3.1 Introduction

This chapter presents the operational methods used for constructing the ALG-Sen dataset and its experimental application with deep learning models. We detail the practical steps involved in dataset creation, annotation, and model implementation, followed by an in-depth analysis of the results obtained.

3.2 Goal and reasons

This thesis investigates the problem of sentiment analysis in online content, with focus on YouTube comments written in Algerian dialects and multilingual contexts. In recent years, online platforms have become key arenas for the expression of varied sentiments, including both positive and negative interactions. YouTube, in particular, serves as a highly interactive space where comments reflect not only individual opinions but also broader societal attitudes, including diverse emotional responses. However, due to the informal and multilingual nature of user-generated content—especially in regions like Algeria where code-switching between Algerian Arabic, French, and Arabizi is common—automatically identifying sentiment remains a complex and underexplored challenge [43]. The primary objective of this work is to construct a high-quality, manually annotated dataset that captures various forms of sentiment, ranging from explicit expressions of joy or anger to more implicit, culturally embedded emotional nuances. Each comment is carefully labeled based on well-defined annotation guidelines, taking into account linguistic diversity, tone, and context. Manual annotation is chosen as the core method because existing automatic tools often fail to recognize indirect or sarcastic expressions, especially in dialectal or non-standard language [44]. This annotated dataset will serve as the foundation for developing and evaluating machine learning models aimed at automatic sentiment detection. By doing so, the study not only addresses a gap in current natural language processing (NLP) resources for underrepresented languages and dialects but also contributes to the broader goal of improving online interactions and promoting inclusive digital spaces [45]. Ultimately, this research aspires to support future efforts in automated analysis by offering a robust and context-aware resource that reflects the linguistic realities of online discourse in the Algerian context [46].

3.3 Related Works

Sentiment analysis in the Algerian dialect is a rapidly evolving field within natural language processing (NLP), driven by the unique linguistic features of the dialect and the limited availability of annotated datasets. Pioneering work in this area was conducted by Guellil et al. [47], who created the first comprehensive corpus aimed at sentiment analysis in the Algerian dialect. This dataset consists of 373,984 YouTube comments, meticulously collected through targeted keywords related to social issues, making it the most extensive resource available for this task [47, 48]. The corpus is characterized by significant code-switching among Arabic, French, and English, accurately reflecting the linguistic landscape of Algerian social media interactions [47].

The annotation process was rigorous, involving three native Arabic speakers who manually reviewed and classified 5,000 comments into positive, negative, and neutral sentiments [48]. Their approach utilized Convolutional Neural Networks (CNN), achieving an impressive 86

Subsequent contributions in this domain include the work of Mazari & Kheddar, who developed an Algerian Sentiment Corpus in 2023, comprising nearly 14,000 social media comments sourced from platforms such as Facebook, YouTube, and Twitter [49]. This dataset addresses the complexities inherent in Algerian Arabic, including code-switching and variability in script (Arabic script vs. Arabizi/Latin script). It features multi-label annotations across three sentiment categories: positive, negative, and neutral, encompassing a broad spectrum of emotional expressions. While not solely focused on negativity, their corpus provides a robust foundation for various sentiment classification tasks.

The annotation strategy employed a combination of automatic keyword filtering alongside manual validation by native speakers, ensuring that cultural and regional nuances were preserved. This careful curation has resulted in a dataset that supports advanced models like DzaraShield, a transformer-based architecture built on DziriBERT, which was pre-trained on Algerian dialect data. This model achieved 87% accuracy and a 0.87 F1-score in sentiment classification tasks [50]. These advancements highlight the importance of developing resources tailored to low-resource languages, ultimately paving the way for more nuanced and effective sentiment analysis in diverse linguistic contexts.

Table 3.1: Algerian Dialect Sentiment Analysis Datasets

Dataset/ Study	**Focus**	**Size**	**Scripts**	**Annotation Approach**	**Availability**
Guellil et al. (2021)	Sentiment Analysis (code-switch)	373,984	Arabic, French, English	3 annotators, ML validation	Published, request
Mazari & Kheddar (2023)	Sentiment analysis	∼14K comments	Arabic, Latin	Multi-label, manual	Accessible
Lanasri et al. (2023)	Sentiment classification	Not specified	Arabic, Latin	Pre-trained model, fine-tuning	Public (HuggingFace)

3.4 Dataset Splits in Machine Learning

3.4.1 Training Set

The training set represents the largest and most critical portion of the overall dataset used in machine learning and artificial intelligence models. Its primary role is to serve as the foundation for teaching the model how to understand and learn from data [51].

During the training phase, the model is exposed to input data along with the corresponding correct outputs, often referred to as labels or target values. By processing this data, the model attempts to predict the output and compares it with the actual expected result. Based on the difference between the predicted and actual outcomes, the model adjusts its internal parameters—such as weights and biases in neural networks—to minimize error and improve prediction accuracy [52].

This process of learning from the training data is repeated multiple times over several iterations, known as epochs. With each epoch, the model refines its internal structure and becomes better at recognizing patterns and relationships within the data [53].

In summary, the training set is fundamental to the learning process, as it enables the model to build a solid understanding of how inputs relate to outputs. The quality, size, and diversity of the training set greatly influence the model's ability to generalize and perform effectively on unseen data [54].

3.4.2 Validation Set

The validation set is a distinct subset of the dataset that plays a critical role during the training process of a machine learning model. Unlike the training set, which is used to adjust the model's internal parameters, the validation set is utilized to fine-tune the model's hyperparameters—these include settings such as the learning rate, number of layers, batch size, regularization strength, and other configuration options that are not learned directly from the data [55].

One of the primary purposes of the validation set is to assess how well the model generalizes to unseen data during the training phase. It provides a performance checkpoint that allows developers to detect issues such as overfitting, where the model performs exceptionally well on the training data but struggles to generalize to new or different inputs [54].

Importantly, the validation set is not used to update the model's weights. Instead, it serves purely for evaluation. After each training epoch or iteration, the model's performance is tested on the validation set to monitor progress and guide decisions about adjustments. For instance, if performance on the validation set begins to degrade while training performance improves, it may indicate that the model is overfitting, prompting appropriate measures—such as early stopping or increased regularization—to be implemented [53].

In summary, the validation set acts as a crucial tool for model optimization, helping to ensure that the model not only learns effectively but also performs reliably on new data [52].

3.4.3 Test Set

The test set is a distinct portion of the dataset that is used exclusively after the training and validation processes are fully completed. Its primary purpose is to provide an objective and unbiased evaluation of the final model's performance. This assessment reflects how well the model is expected to perform when it encounters new, unseen data in real-world applications [**?**].

Unlike the training and validation sets, the test set is never used during the learning or optimization phases. The model does not have access to this data while it is being trained or while its hyperparameters are being tuned. This strict separation ensures that the results obtained from the test set offer a realistic measure of the model's generalization ability [54]. Evaluating the model on the test set allows researchers and developers to gauge the model's true predictive power and robustness. It essentially simulates real-world scenarios, where the model must make predictions on data it has never encountered before. The performance metrics obtained from the test set—such as accuracy, precision, recall, F1-score, and others—serve as a final benchmark to determine whether the model is ready for deployment or if further refinement is needed [53]. In summary, the test set acts as the ultimate judge of the model's effectiveness. It plays a crucial role in validating that the model is not merely memorizing the training data but is genuinely capable of applying what it has learned to new and diverse situations [52].

3.5 Tools and Libraries Used

3.5.1 Tools

- **Google Colab:** Google Colaboratory (Google Colab) serves as the primary computational environment for this research. It provides free access to GPU acceleration, 12.72 GB of RAM, and over 350 GB of temporary storage, enabling efficient processing of large datasets. Its seamless integration with Python and popular machine learning libraries makes it a practical and powerful platform for research and development [56].

- **Python:** Python is a high-level, interpreted programming language known for its simplicity and readability. It supports multiple programming paradigms and boasts a vast ecosystem of libraries and frameworks, making it one of the most widely used languages in data science, machine learning, web development, and automation [57].

- **Excel:** Excel is a robust spreadsheet application developed by Microsoft, widely used for data entry, analysis, visualization, and basic computations. It allows users to organize data in tabular form, perform complex calculations using formulas and functions, create charts, and automate tasks through built-in tools and macros. Excel is commonly applied in engineering, business, and academic research for managing and analyzing structured data [58].

3.5.2 Libraries used

To manage data uploading and processing within the Google Colab environment, two primary Python libraries were employed:

- **Google API**: The Google Application Programming Interface (API) is a suite of tools and protocols that facilitate programmatic interaction with various Google services, including Google Maps, YouTube, Google Search, and Google Translate. These APIs provide secure and efficient access to Google's data and functionalities, enabling developers to seamlessly integrate Google's features into their applications and websites [59].
- **Google Colab**: The `google.colab` module offers tools specifically designed for Google Colaboratory, a cloud-based platform for executing Python code in a Jupyter-like environment. In this project, the `google.colab.files` submodule was utilized to upload local CSV files into the Colab environment for subsequent analysis [60].
- **Pandas**: Pandas is a widely-used open-source Python library that provides high-performance, user-friendly data structures and data analysis tools. It was employed in this work to load CSV files into a DataFrame using the `pd.read_csv()` function, and to perform value frequency counting on specific columns using `value_counts()`, which is crucial for understanding the distribution of topics [61].
- **scikit-learn (sklearn)**: This popular Python machine learning library offers efficient tools for classification, regression, clustering, dimensionality reduction, model selection, and preprocessing [62].
- **TfidfVectorizer (from sklearn.feature_extraction.text)**: A feature extraction method that converts text into numeric feature vectors using the term frequency–inverse document frequency (TF-IDF) approach. This technique captures the importance of words across different documents [63].
- **LogisticRegression (from sklearn.linear_model)**: A linear classification model used to predict binary outcomes. It is commonly applied in text classification tasks, such as sentiment analysis and toxic comment detection [64].
- **classification_report (from sklearn.metrics)**: This function generates a report that includes precision, recall, F1-score, and accuracy metrics to evaluate classification models [65].

3.6 ALG-Sentiment Analysis

The construction of our dataset, **ALG-Sentiment Analysis**, involved several key phases, including data collection, careful filtering, and manual annotation by native speakers. The following are the detailed steps of the process of its creation:

3.6.1 Data Collection

The primary objective of this study is to analyze misogyny in online spaces, with a specific focus on YouTube comments written in Algerian dialects and multilingual forms. To construct a representative and high-quality dataset, we designed a data collection strategy that targets a variety of content types where gender-based hostility or stereotypes are likely to emerge.

Our data collection plan was based on selecting **50 videos per channel** and retrieving at least **250 comments per video**. This approach was intended to ensure both

quantity and diversity in user engagement. However, due to certain limitations such as the unavailability of comments on some videos or API quota restrictions, we were not able to meet the full target for every video, but we succeeded in gathering a substantial number of relevant comments.

We focused on channels that are among the **most viewed and followed in Algeria**, ensuring strong viewer interaction. From each domain (e.g., culinary, music, lifestyle, comedy, etc.), we selected only **two channels per category**, respecting the time and resource constraints of this project. This selective approach allowed us to concentrate on channels with significant influence and activity.

The selected YouTube channels include:

This mix of channels reflects both gendered content spaces (e.g., beauty, cooking) and broader societal discussions (e.g., news, satire, music), enabling a multifaceted study of misogyny in Algerian digital discourse. Comments were collected using the YouTube Data API via a Python script, and metadata for each video and comment was retained for annotation and further linguistic analysis.

3.6.2 Manual Data Annotation

To ensure high quality and consistency, multiple trained annotators participated in the labeling process, and inter-annotator agreement metrics were calculated to validate the reliability of the annotations. This meticulous manual annotation process is essential for providing a trustworthy ground truth dataset that supports the development and evaluation of machine learning models aimed at detecting sentiment in online comments.

- **Language and dialect:** Identifying the primary language and dialect of each comment, with particular attention to Algerian Arabic and other dialectal variations.
- **Sentiment analysis:** Specifically labeling comments based on their emotional tone, such as positive, negative, or neutral sentiments.

The final dataset consists of over 17,000 manually annotated YouTube comments collected from a variety of Algerian channels. Each comment was labeled according to its sentiment content using a binary classification: positive or negative.

Although negative sentiment constitutes a minority of the dataset, its social and psychological impact justifies the importance of focused detection and analysis.

In addition to sentiment labels, the dataset exhibits significant linguistic diversity, reflecting the multilingual nature of Algerian online discourse. The language or dialect of each comment was manually identified as part of the annotation process. The distribution is as follows:

- **Modern Standard Arabic (MSA)**: 300 comments (1.69%)
- **Algerian Arabic (Darja)**: 15,201 comments (86.1%)
- **Arabizi (Arabic written in Latin script)**: 1,240 comments (7%)
- **French**: 730 comments (4.13%)
- **English**: 183 comments (1.03%)

This linguistic diversity poses unique challenges for sentiment detection, as each language or dialect requires different preprocessing, tokenization, and cultural interpretation strategies.

Examples of Annotated Comments:

Table 3.2: Sample of annotated comments with Sentiment Analysis labels

Comment	Language/Dialect	Sentiment Analysis
"مقروطات قطعتيهم كبار بزاف واصلا مدوبلتيش المقادير هاذا عيد تاكلي نت وراجلك وولادك وتدي للعايلة منضنش يكفي."	Algerian	Neutral
"وصفة رووووووعة نقدر نبدل الفلو كرامل بي فلو شكولة ؟ من فضلك ام وليد ربي يخليك."	Algerian	Positive
"ماشي شابة معجبتنيش"	Algerian	Negative
"اللهم صلي وسلم على نبينا محمد."	Modern Standard Arabic (MSA) MSA	Neutral
Bonsoir bravo bravo machaallah rabi yahafdik inchallah saha ftourkoum.	Arabizi	Positive
Tres belle cuisine designe vraiment top j prit une idées tu mérites tout le bonheur hicham.	French	Positive
A woman talking about equality? That's not her place.	English	Neutral
"شكرا غاليتي "	MSA MSA	Neutral
"Amira Ria is a shining example of a strong Algerian woman, inspiring many with her courage and resilience."	English	Positive

3.6.3 Data Preparation

Prior to integration, a thorough data preparation and preprocessing phase was undertaken to ensure the dataset's quality and relevance. This step is crucial for creating a well-curated corpus suitable for misogyny detection in the Algerian dialect.

Initially, our corpus included approximately 120,000 comments collected from YouTube. Despite time constraints and the complexity of the task, we successfully labeled over 17,000 comments through careful manual annotation. The annotated corpus displayed considerable linguistic diversity, incorporating Algerian Arabic (in both Arabic script and Arabizi), Modern Standard Arabic (MSA), French, and English, often characterized by frequent code-switching. However, since our research specifically targets the Algerian dialect, we implemented a series of filters to retain only the most pertinent data. We removed duplicate entries, comments consisting solely of emojis, and those not written in Algerian Arabic (in either script). Consequently, we refined our dataset to include 15,135 manually annotated comments in Algerian Arabic, with:

- **872** comments were labeled as *negative*, representing approximately **5.76%** of the

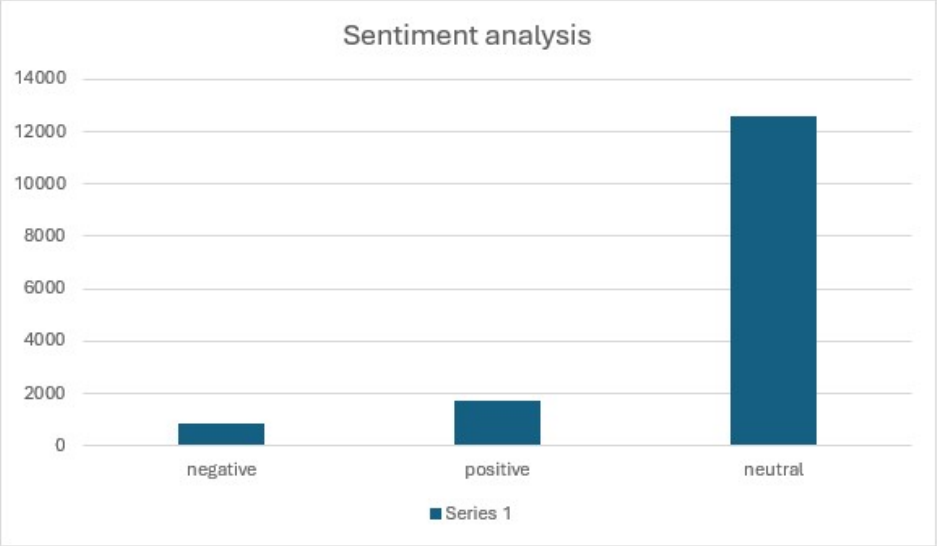

Figure 3.1: Class Distribution Before Balancing (ALG-Sentiment Analysis)

dataset.

- **1,690** comments were labeled as *positive*, accounting for about **11.17%**.
- **12,573** comments were labeled as *neutral*, accounting for about **83.07%**.

3.6.4 Data Balancing

Following data preprocessing and the integration of the two corpora, we turned our attention to addressing the significant class imbalance in the ALG-Sentiment Analysis dataset. As detailed in Section 3.6.3, the current distribution is notably skewed: 872 instances (5.76%) are annotated as negative, 1,690 instances (11.16%) are classified as positive, and 12,573 instances (83.06%) are categorized as neutral.

Addressing this class imbalance is crucial for constructing robust machine learning models. A skewed class distribution can result in biased predictions and poor generalization, as algorithms tend to favor the majority class and may overlook the minority class during training. By balancing the dataset, we ensure that the model encounters a comparable number of examples from each class, thereby minimizing the risk of bias toward the majority class and enhancing the model's capability to accurately detect sentiment in the content.

To tackle the pronounced class imbalance in our dataset, we employed a random undersampling strategy. This method involved reducing the number of samples in the majority class (neutral comments) to align with the size of the minority class (negative comments). By equalizing the representation of both classes, we aimed to create a more balanced training set. This strategy is widely acknowledged for its effectiveness in mitigating model bias and enhancing the reliability of classification results, especially in scenarios where one class significantly outnumbers the other.

To achieve a balanced class distribution, we retained all 872 neutral comments and randomly selected an equal number of negative comments (872) and positive comments (872) from our annotated corpus. This random undersampling approach was chosen to ensure equal representation of both classes in the training set, thereby reducing the risk of

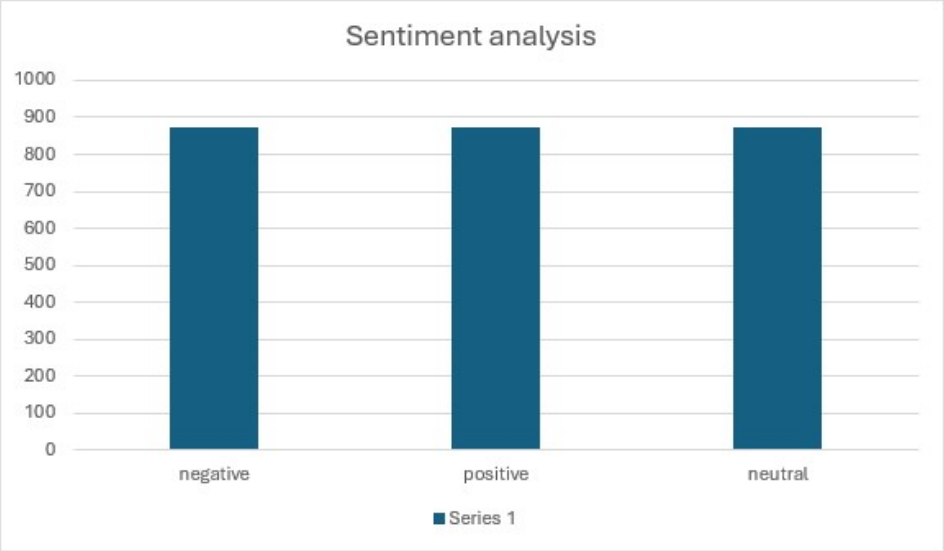

Figure 3.2: Class Distribution After Balancing (ALG-Sentiment Analysis Dataset)

model bias and improving classification reliability. The final balanced dataset comprises 2,616 comments, resulting in a 33/33/34 class distribution.

Table 3.3: Class Distribution Before and After Balancing

Dataset	negative	positive	neutral	Total
ALG-Sentiment Analysis (Before Balancing)	**872**	**1,690**	**12,573**	**15,136**
ALG-Sentiment Analysis (After Balancing)	**872**	**872**	**872**	**2,616**

As demonstrated in Table 3.3, the ALG-Sentiment Analysis dataset exhibited a significant imbalance prior to balancing, which is common in hate speech detection tasks and can result in biased model predictions if not addressed. After balancing, the dataset was reduced to 2,616 comments, with each class equally represented, as shown in Figure 3.2. This balanced structure facilitates the training of more robust and generalizable machine learning models for misogyny detection in Algerian dialect content. By ensuring that positive, negative, and neutral examples are equally represented, the risk of model bias is minimized, and the reliability of classification outcomes is enhanced. The inclusion of clear visualizations—such as bar and pie charts—further improves the interpretability and communication of these results.

3.6.5 Data validation

To ensure the quality and reliability of the ALG-Sentiment Analysis dataset, we implemented a manual validation process, also known as manual review. This step is crucial in the dataset construction pipeline, as human experts meticulously examine samples to verify annotation accuracy, linguistic authenticity, and overall data integrity. Manual validation is particularly important for complex tasks such as sentiment analysis in the Algerian dialect, where subtle cultural and linguistic nuances may not be adequately captured by automated methods.

Since the integrated portion of the dataset (sourced from external origins) had already been validated, our validation process concentrated solely on the manually annotated

segment. The validation process focused on the following key aspects:

- **Annotation Accuracy:** Reviewers confirmed that comments labeled as negative, positive, or neutral accurately reflected their intended categories. The previously validated integrated portion was not subjected to further review.
- **Inter-Annotator Agreement:** All reviewers independently annotated overlapping subsets of the data to assess consistency and reliability. Agreement metrics, such as Cohen's Kappa, were employed to quantify this consistency.
- **Quality Control Sampling:** Rather than reviewing the entire dataset, a representative sample was selected for detailed inspection. This process was overseen by a fifth reviewer, ensuring that the sample was both representative and thoroughly evaluated.

This approach guarantees that only the manually annotated content undergoes new validation while leveraging the reliability of the previously validated data. The process contributes to the development of a high-quality, trustworthy dataset for sentiment analysis in the Algerian dialect.

3.7 ALG-Sentiment Analysis Characteristics

Data Types: short text .

- **Comments** The final dataset consists of short text.
- **Columns (Features):** The final dataset contains the following key columns:
  - `comment` – The text (comment).
  - `Sentiment Analysis` – a label indicating whether the comment is sentiment analysis (negative), (positive), or (neutral).
  - `language` – allvalues are: Algerian Arabic.
  - `Source:` YouTube.

Data Structure:
- The dataset is structured in a tabular format (CSV file), with rows corresponding to individual comments and columns representing various attributes.

Balance/Imbalance: The dataset is Balanced.

Dataset Language: Algerian Arabic

3.8 Experimentation and Testing

3.8.1 Pre-treatment

Lowercasing: All text was converted to lowercase to eliminate case-sensitive inconsistencies and ensure uniformity throughout the dataset.

- **Removal of Punctuation, HTML Tags, and Hyperlinks:** Punctuation marks, HTML tags, and hyperlinks were removed to eliminate non-informative tokens and reduce textual noise.
- **Stop Word Removal:** Common stop words (e.g., articles, prepositions, conjunctions) were eliminated, as they contribute little meaning in classification tasks. This process included the removal of both Arabic and English stop words using predefined lists.
- **Emoji Handling:** Emojis were either removed or mapped to textual descriptions when relevant, considering their frequent use in social media and their potential role in expressing sentiment or intent.
- **Dialect Filtering:** Only comments written in Algerian Arabic were retained. Comments in Modern

3.8.2 Splitting

After completing the preprocessing phase, the dataset was split into three subsets to facilitate model training, validation, and evaluation. The splitting process ensures that the models are trained on a representative portion of the data while preserving a separate and unseen set for fair evaluation.

Specifically, the dataset was divided as follows:

- **Training Set (80%):** This subset was used to train the machine learning and deep learning models. It represents the majority of the data and allows the model to learn patterns and features associated with negative and positive and neutral, content.
- **Validation Set (10%):** This subset was employed during training to monitor performance and fine-tune hyperparameters. It aids in detecting overfitting and ensures that the model generalizes well to unseen data.
- **Test Set (10%):** This final subset was reserved for evaluating the performance of the trained models. It was not involved in any part of the training process, providing an unbiased assessment of the model's accuracy and robustness.

To ensure stratification, the split maintained the original class distribution of negative, positive, and neutral labels across all subsets. This approach helped prevent data imbalance in any partition, ensuring reliable and meaningful evaluation results.

3.8.3 The Proposed Models

To tackle the challenge of Sentiment Analysis detection in Algerian Arabic comments, two deep learning architectures were implemented and trained: a Long Short-Term Memory (LSTM) model and a Bidirectional Long Short-Term Memory (BiLSTM) model. These models were developed using TensorFlow and specifically designed for binary classification—distinguishing between misogynistic and non-misogynistic comments.

LSTM networks are particularly effective for sequential data as they retain long-term dependencies, which is crucial in dialectal content where context is significant. The BiLSTM model enhances this capability by processing the sequence in both forward and

backward directions, enabling it to better capture subtle or implicit expressions of Sentiment Analysis that are prevalent in informal social media discourse.

Both models utilized pre-trained GloVe embeddings for semantic representation. The input text underwent several preprocessing steps, including normalization, tokenization, stop word removal, and padding. The LSTM architecture comprised an LSTM layer followed by dense layers and a sigmoid activation function for binary output. In contrast, the BiLSTM model included a bidirectional LSTM layer, dense layers, and dropout for regularization.

Training was conducted using the Adam optimizer with binary crossentropy as the loss function. Model performance was monitored through training and validation accuracy and loss curves to identify potential overfitting or underfitting. The final evaluation was based on standard classification metrics: accuracy, precision, recall, and F1-score.

3.8.4 Evaluation Metrics

The performance of the proposed models was evaluated using the following standard metrics:

- **Accuracy** $= \dfrac{TP + TN}{TP + TN + FP + FN}$
- **Precision** $= \dfrac{TP}{TP + FP}$
- **Recall** $= \dfrac{TP}{TP + FN}$
- **F1-score** $= 2 \times \dfrac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$

Where:

TP: True Positives TN: True Negatives FP: False Positives FN: False Negatives The final calculations and interpretations of these metrics will be validated and completed by the thesis supervisor, who will also populate the subsequent result tables.

3.8.5 Result and Evaluation

The following table 3.4 summarizes the performance of the two deep learning models implemented: LSTM and Bi-LSTM. Each model was evaluated on its ability to classify .

Table 3.4: Performance of All Models

Model	Precision	Recall	F1-Score	Accuracy
LSTM	82.13%	79.03%	77.89%	83.14%
BiLSTM	84.07%	84.21 %	85.01%	84.63%

The performance evaluation reveals that the BiLSTM model consistently outperforms the LSTM model across all key metrics in the context of text classification. The BiLSTM achieved an accuracy of approximately 84.63%, which represents an improvement

of around 1.49 percentage points compared to the LSTM's 83.14%. Regarding precision, BiLSTM attained a value of 84.07%, exceeding the LSTM's 82.13% by 1.94 percentage points. The recall score further highlights this advantage, with the BiLSTM reaching 84.21%, outperforming the LSTM's 79.03% by 5.18 percentage points. Notably, the F1 score of BiLSTM was 85.01%, a substantial margin of 7.12 percentage points higher than the LSTM's 77.89%.

These results suggest that the bidirectional nature of BiLSTM enhances its ability to extract richer contextual representations from sequential data, thereby improving classification performance. However, it is important to recognize that these outcomes are dependent on several experimental factors, including the nature of the dataset, the scale of training data, model hyperparameters, and the evaluation framework. It is also worth noting that these figures were obtained from training each model for 10 epochs out of a possible 32, indicating potential for further optimization.

3.9 Conclusion

This chapter outlined the methodological framework followed in the creation of the dataset utilized throughout this study. It elaborated on the procedures of data acquisition, annotation, and labeling, emphasizing the integration of both manual and automated techniques to ensure high-quality and contextually appropriate data. The resulting dataset, referred to as ALG-Sentiment Analysis, served as the core resource for experimental evaluation and yielded promising and satisfactory outcomes in the task of sentiment analysis detection.

General Conclusion

This research aimed to explore and address a specific problem within the domain of natural language processing, focusing in particular on sentiment analysis. Through a well-structured methodological approach encompassing dataset construction, preprocessing, model selection, and performance evaluation, we were able to obtain significant and meaningful results. The implementation of advanced deep learning architectures—such as LSTM and BiLSTM—demonstrated the effectiveness of leveraging sequential models in understanding and classifying textual sentiment. Notably, the BiLSTM model exhibited superior performance across multiple evaluation metrics, underscoring its ability to capture bidirectional contextual information from the data.

The construction of the **ALG-Sentiment Analysis** dataset also played a central role in the success of this study, providing a reliable and domain-relevant foundation for training and testing. The careful process of data collection, annotation, and validation contributed to the quality and relevance of the results obtained.

In conclusion, this study contributes both methodologically and empirically to the ongoing research in sentiment analysis for the Arabic language. It highlights the importance of high-quality datasets and robust modeling techniques. Future work may explore more complex transformer-based architectures (e.g., BERT, AraBERT), incorporate larger and more diverse datasets, or extend the framework to multilingual or multimodal sentiment analysis tasks.

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