

Drugsideeffect-test: A Lexicon-Driven Visualization Framework for Drug Side-Effect Signals in Text

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Software

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Summary

Drugsideeffect-test (v0.1.0) is a Python package (import as 'drugsideeffect') for exploring, categorizing, and visualizing drug side-effect mentions from textual data for research purposes; it is not intended for clinical diagnosis or decision-making. Repository: <https://github.com/debbdeb/drugsideeffect>. It can be installed via PyPI Test repository for testing: `pip install -i https://test.pypi.org/simple/ drugsideeffect-test`.

Key dependencies include: pandas ≥ 1.5 , numpy ≥ 1.23 , matplotlib ≥ 3.6 , seaborn ≥ 0.12 , plotly ≥ 5.11 , nltk ≥ 3.8 , textblob ≥ 0.17 , and spacy ≥ 3.5 . Pretrained models are included in the package (drugsideeffect/models/) [1][2].

For stable releases, the package will be available on PyPI: `pip install drugsideeffect-test`. The package provides tools for exploring, categorizing, and visualizing self-reported drug side-effect mentions from textual data for research purposes; it is not intended for clinical diagnosis or decision-making. The software integrates supervised machine learning classification with multi-layered lexicon-based extraction and visualization. It is specifically designed to bridge informal patient-generated content (e.g., tweets) with structured pharmacovigilance-oriented symptom categories.

The system combines: 1. A pretrained TF-IDF + Naive Bayes classifier pre-trained model for filtering side-effect-related text [3]. 2. A set of curated lexicons for common symptoms, uncommon vaccine-related adverse events, slang / figurative expressions, temporal patterns, and alert keywords. 3. A modular visualization layer for sentiment analysis, symptom distribution, temporal trends, engagement metrics, and onset/duration analysis.

The primary innovation of drugsideeffect-test lies in its lexicon architecture and its coupling with visual analytics. Rather than treating lexicons solely as keyword filters, the package operationalizes them as semantic layers that drive multi-dimensional visualizations.

The full pipeline (Figure 1) can be executed via a single function, `sideeffect_pipeline()`, which loads data, filters side-effect mentions, processes onset timing, and generates all visual outputs. The GitHub repository link is: <https://github.com/debbdeb/drugsideeffect>

Figure 1. Overview of the Drugsideeffect-test pipeline. The workflow begins with loading input CSV data, followed by Naive Bayes classification to filter texts mentioning side effects. Filtered texts are then processed using curated lexicons—including known symptoms, uncommon effects, slang, temporal patterns, and alert keywords—for multi-layered extraction. Finally, the extracted information feeds into the visualization module generating sentiment, symptom frequency, temporal trends, and engagement analyses.

Statement of Need

Pharmacovigilance traditionally relies on structured adverse event/side-effect reporting systems such as VAERS or FAERS [8][9]. However, patient-reported outcomes increasingly emerge in unstructured online and other environments including social media [13]. These sources contain valuable early signals but present substantial challenges: ■ Informal language and slang ■ Non-standard symptom descriptions ■ Temporal ambiguity ■ Sentiment bias and emotional framing ■ Misinformation amplification ■ Engagement-driven distortion (likes, retweets) ■ Metaphor, slang, hyperbole, simile, personification, irony, allusion, understatement, pun, oxymoron, colloquial/idiomatic expressions

Existing NLP tools often focus either on classification (trying to answer questions such as - is this a side-effect post?) or named entity recognition (extract medical terms) [6][7]. Few open-source tools integrate: ■ Informal-to-clinical lexical mapping ■ Temporal phrase detection ■ Sentiment context ■ Engagement metrics ■ Visualization of lexicon-derived features

Drugsideeffect-test aims to address this gap by combining machine learning filtering with a layered lexicon-driven visualization framework. The package can be particularly useful for: ■ Public health researchers ■ Computational social scientists ■ Pharmacovigilance analysts ■ Vaccine confidence researchers ■ NLP researchers studying health misinformation

Implementation

The system is structured into several components:

1. Side-Effect Classification (`processing.py`) The classification module loads pretrained artifacts included in the package (`drugsideeffect/models/`): ■ `sideeffect_nb.pkl`: Naive Bayes classifier ■ `tfidf_vectorizer.pkl`: TF-IDF feature extractor

The `classify_sideeffects` function takes a DataFrame containing a text column and predicts a binary label indicating likely side-effect mentions. ■ Requires a text column. ■ Vectorizes the text. ■ Predicts a binary label indicating likely side-effect mentions in text for exploratory research only; labels do not confirm medical events. ■ Filters the dataset to retain only side-effect text. This filtering reduces noise before lexicon-based extraction is applied.

3. Lexicon Architecture The lexicon layer is the core conceptual contribution of the package. It consists of five primary lexicon categories: A. Known Symptom Lexicon

A curated list of common side effects (particularly in the context of COVID-19), e.g., fever, headache, fatigue, muscle pain, insomnia, and anxiety disorders (representative, not exhaustive).

This lexicon supports: ■ Frequency visualization ■ Common symptom detection ■ Flag-based filtering

- B. Uncommon Vaccine Side Effects Lexicon

This lexicon includes severe or rare conditions, particularly in the context of COVID-19, (representative, not exhaustive): ■ myocarditis ■ thrombosis ■ stroke ■ psychosis ■ autoimmunity ■ long covid

The purpose is solely for detecting narrative prevalence in text data, not for clinical validation or assessment of patient risk.

Visualizations include: ■ Top uncommon side-effect frequency ■ Pie charts comparing common vs. uncommon symptom prevalence

- C. Slang-to-Symptom Lexicon

A mapping from informal expressions to symptom categories (representative, not exhaustive):

81 “feel like shit” → [“fatigue”, “malaise”] “brain fog” → [“cognitive”] “my head is pounding” →
82 [“headache”] “heart racing” → [“arrhythmia”]

83 This lexicon enables: ■ Informal phrase detection ■ Bridging colloquial and medical language
84 ■ Monthly trend analysis of slang usage ■ Sentiment-stratified slang frequency plots

85 This component is critical because social media [10][11][12] users rarely use formal clinical
86 terminology.

87 D. Temporal Pattern Lexicon

88 Regular expressions detect time references such as (representative, not exhaustive): ■ “2 days
89 after vaccination” ■ “few hours post-dose” ■ “day after the shot”

90 This supports: ■ Time-series visualization ■ Onset pattern extraction ■ Temporal clustering
91 analysis Temporal detection is essential for pharmacovigilance, as side effects are time-
92 dependent.

93 E. Alert Keyword Lexicon Terms indicating urgency or severity: ■ urgent ■ serious ■ critical

94 This lexicon captures emotional escalation or perceived severity.

95 Visualization Framework

96 The visualization layer integrates lexicon outputs into interpretable analytics.

97 Sentiment Distribution Using TextBlob polarity scoring [5]: ■ Positive ■ Neutral ■ Negative
98 This contextualizes symptom mentions within emotional framing.

99 English Word Proportion A linguistic quality control metric using NLTK’s word corpus [4]: ■
100 Measures proportion of recognized English tokens ■ Assesses data noise or bot-like behavior

101 Slang and Time-Series Visualizations The function `plot_visualize()` handles slang and temporal
102 pattern visualizations: ■ Explodes matched slang and time patterns ■ Computes tweet
103 volumes, average sentiment, and engagement ■ Produces bar plots (tweet volume) and line
104 plots (sentiment & engagement)

105 Engagement-Aware Visualization The function `plot_visualize()` integrates: ■ Tweet volume ■
106 Average sentiment polarity ■ Average RT_Like (engagement metric)

107 Using a triple-axis visualization: ■ Bar chart → tweet frequency ■ Line plot → sentiment ■
108 Line plot → engagement This reveals amplification dynamics, showing whether emotionally
109 charged posts receive disproportionate engagement.

110 Symptom Extraction Visualization `plot_symptom_extraction()`: ■ Extracts known and
111 uncommon symptoms ■ Flags posts mentioning each ■ Produces: ■ Top 10 bar charts ■ Pie
112 chart of common vs. uncommon vs. alert keywords

113 Onset and Duration Visualization `plot_onset_times()` visualizes: ■ Distribution of symptom
114 onset (in hours) ■ Duration of symptoms This component bridges textual temporal expressions
115 with quantitative modeling.

116 Pipeline Integration The `sideeffect_pipeline()` function orchestrates the entire workflow: ■
117 Load CSV ■ Print initial row count ■ Apply ML side-effect filter ■ Process onset timing ■
118 Generate all plots ■ Return filtered DataFrame This design ensures usability for non-expert
119 users.

120 Example Usage

121 `import drugsideeffect as dse df_filtered = dse.sideeffect_pipeline(“sample_data.csv”)`

122 Design Philosophy

123 The system follows four principles: 1. Layered Semantics: ML for text filtering, lexicons for
124 interpretability. 2. Visualization-Centered Analysis: Lexicons drives the visual analytic. 3.
125 Reproducibility: Pretrained models + deterministic lexicon rules. 4. Extensibility: Lexicons are
126 editable Python dictionaries/lists.

127 Limitations

128 ■ TextBlob sentiment is rule-based and may miss sarcasm. ■ Lexicons require manual curation.
129 ■ English-only focus. ■ Regex temporal extraction may miss complex phrasing. ■ Rare
130 condition mentions in social media posts should not be interpreted as medical diagnosis or
131 causal evidence. ■ The system is designed for signal exploration, not causal inference.

132 Extensibility

133 Future directions include: ■ Transformer-based sentiment models ■ Multilingual lexicons ■
134 Ontology integration ■ Network analysis of symptom co-occurrence ■ Dashboard deployment
135 (Streamlit or Dash)

136 Conclusion

137 Drugsideeffect-test provides a lexicon-driven framework for analyzing and visualizing drug
138 side-effect discourse in textual data. By combining supervised classification with structured
139 lexical layers and visual analytics, the package supports exploratory pharmacovigilance research
140 and digital epidemiology. The framework enables real-time exploration of textually-reported
141 side-effect narratives, quantifying and visualizing informal expressions (e.g., “drained”, “weary”),
142 temporal patterns (e.g., “days ago”), and sentiment dynamics. These capabilities complement
143 traditional pharmacovigilance methods in research contexts. The software is open source and
144 designed for transparency, reproducibility, and extension by the research community.

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