WALNUT: A Benchmark on Weakly Supervised Learning for Natural Language Understanding

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Abstract

Building machine learning models for natural language understanding (NLU) tasks relies heavily on labeled data. Weak supervision has been shown to provide valuable supervision when large amount of labeled data is unavailable or expensive to obtain. Existing works studying weak supervision for NLU either mostly focus on a specific task or simulate weak supervision signals from ground-truth labels. To date a benchmark for NLU with real world weak supervision signals for a collection of NLU tasks is still not available. In this paper, we propose such a benchmark, named WALNUT\(^1\), to advocate and facilitate research on weak supervision for NLU. WALNUT consists of NLU tasks with different types, including both document-level prediction tasks and token-level prediction tasks and for each task contains weak labels generated by multiple real-world weak sources. We conduct baseline evaluations on the benchmark to systematically test the value of weak supervision for NLU tasks, with various weak supervision methods and model architectures. We demonstrate the benefits of weak supervision for low-resource NLU tasks and expect WALNUT to stimulate further research on methodologies to best leverage weak supervision. The benchmark and code for baselines will be publicly available at aka.ms/walnut_benchmark.

1 Introduction

To tackle natural language understanding (NLU) tasks via supervised learning, high-quality labeled examples are crucial. Recent advances on large pre-trained language models [24, 5, 27] lead impressive gains on NLU benchmarks, including GLUE [46] and SuperGLUE [45], at the assumption that large amount of labeled examples are available. The increasingly large model sizes call for additional labeled data to reach the best performance on the tasks. For many real-world applications, however, it is expensive and time-consuming to manually obtain large-scale high-quality labels, while it is relatively easier to obtain auxiliary supervision signals, or weak supervision, as a viable source to boost model performance without expensive data annotation process.

Learning from weak supervision for NLU tasks is attracting increasing attention. Various types of weak supervision have been considered, such as knowledge bases [21, 49], keywords [13, 30], regular expression patterns [1], and other metadata such as user interactions in social media [39]. Also, there is increasing research interest in integrating heterogeneous weak supervision sources via the abstraction of labeling functions, and effectively alleviating the inherent noise from such

\(^1\)WALNUT: WeAkly supervised Learning for Natural language Understanding Testbed

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weak sources for training robust classifiers [28, 2, 14]. However, a unified and systematic study on weak supervision for NLU tasks is rather limited. On the one hand, many existing works only study specific NLU tasks with weak supervision, thus evaluations of proposed techniques leveraging weak supervision on a small set of tasks do not necessarily generalized onto other NLU tasks. For example, weak supervision models designed for relation extraction [26] may not be directly applied to document classification tasks. On the other hand, some works rely on simulated weak supervision, such as weak labels corrupted from ground-truth labels [11], while real-world weak supervision signals can be far more complex than simulated ones. Existing weak supervision approaches are evaluated on different data with different metrics and weak sources, and, to the best of our knowledge, a benchmark consisting of a collection of NLU tasks with real-world weak supervision signals does not exist as of yet.

To better advocate and facilitate research on leveraging weak supervision for NLU, in this paper we propose WALNUT, a benchmark of NLU tasks with real-world weak supervision signals. Following the tradition of existing benchmarks (e.g., GLUE), we propose to cover different types of NLU tasks and domains, including document-level classification tasks (e.g., sentiment analysis on online reviews, fake news detection on news articles), and token-level classification tasks (e.g., named entity recognition in news and biomedical documents). In contrast to existing benchmarks, and to facilitate the future research development and reproducibility of weak supervision approaches, we include tasks where real-world weak supervision signals (weak rules or the corresponding weak labels) are publicly available, we integrate multiple datasets and the corresponding weak signals in a unified format, and we publish our pre-processed data splits, weak labels, and code.

In addition to the proposed benchmark, to shed light on how weak supervision can help NLU in a collective manner, we evaluate a set of representative baseline methods of leveraging weak supervision to improve the tasks. We show that weak supervision is valuable for low-resource NLU tasks, and larger transformer models such as RoBERTa [18] give better results across tasks. However, more complex weak supervision paradigms (e.g., MetaWN [36]) do not guarantee a better performance than simple ones, which suggests the need to develop more robust and transparent weak supervision models. Moreover, we identify challenges of leveraging weak supervision for NLU tasks, particularly with the prevailing pre-trained language models and shed light on possible future work based on WALNUT.

The main contributions of this paper are: (1) We propose a new benchmark on weak supervision learning for NLU, which covers eight established annotated datasets and various text genres, dataset sizes, and degrees of task difficulty; (2) We conduct an exploratory analysis from different perspectives to demonstrate and analyze the results for several major existing weak supervision approaches across applications; and (3) We discuss the benefits and provide insights for potential weak supervision studies for representative NLU tasks.

2 Related Work

2.1 Learning with Weak Supervision for NLU

Document-level classification. Document-level text classification (also referred as sequence classification) is to classify a piece of text to a corresponding label in specific domains such as sentiment analysis [51], topic classification [51], and fake news detection [40]. Recent years have witnessed the rapid development of deep neural networks (DNNs) for this problem, from Bi-directional Long Short-Term Memory Networks (BiLSTM) [9], to large pre-trained language models such as RoBERTa [18]. However, these deep learning models usually rely on large scale labeled data to achieve good performances, and obtaining large amounts of labeled data is often prohibitively expensive.

Existing works on weak supervision learning attempt to rectify the weak labels by incorporating a loss correction mechanism for text classification [41, 22]. Other works consider the scenario where a small set of clean labels are available [11, 29, 42, 38]. Recent works also consider the scenario where weak signals are available from multiple sources [28, 20, 30] to exploit the redundancy as well as the consistency in the labeling information. Despite the recent progress on weak supervision for text classification, there is no agreed upon benchmark that can guide future directions and development of NLU tasks with weak supervision. Without loss of generality, we focus on document-level text classification tasks where limited clean labels can be obtained and weak labels can be derived automatically in different ways such as pattern matching [30], meta-data extraction [38], etc.
Token-level classification  

Token-level classification (also referred as sequence tagging) tasks such as Named Entity Recognition (NER) classify each individual token of the input sequence to a class from a pre-defined class set. (We describe the token-level classification setup in Section 3.1.2) Original token-level classification approaches rely on manually-annotated data and train sequence tagging models, such as CRFs and BiLSTMs [15, 4, 50]. Recently, approaches leveraging deep contextualised representations [24, 5] have been shown to achieve state-of-the-art performance on NER tasks. Such approaches employ supervised learning and require large-scale annotated datasets.

An alternative to supervised learning is to automatically generate labeled sequences for token-level classification. One of the most common approaches is distant supervision [21], which uses knowledge bases to heuristically annotate training data. Besides distant supervision, several approaches have recently addressed NER using weak supervision [7, 28, 35, 32, 17]. Such work introduced various types of labeling functions, for example based on keywords and lexicons. [7] presented a weak supervision approach to NER in the biomedical domain, which relies on a mechanism for generating candidate spans for weak annotation but do not provide their labeling functions. Safranchik et al. [32] presented an extension of Hidden Markov Models (HMMs) called Linked HMMs for leveraging more complex type of weak rules, called linking rules. Lison et al. [17] presented an extensive set of weak rules for named entity recognition in the CoNLL dataset. Our benchmark integrates weak rules from both [32] and [17] into a unified format with pre-computed labels.

2.2 NLU Benchmarks

Accompanying the emerging of large pre-trained language models, NLU benchmarks has been a focus for NLP research, including GLUE [47] and SuperGLUE [44]. On such benchmarks, the major focus is put on obtaining best possible performance [10] under the full training setting, which assumes that a large quantity of manually labeled examples are available for all tasks. Though research in weak supervision in NLU has gained significant interest, most of these work either focus on a small set of tasks or simulate weak supervision signals from ground-truth labels, hindering its generalization ability to real-world NLU tasks. The lack of a unified test bed covering different NLU task types and data domains motivates us to construct such a benchmark to better understand and leverage weak supervision for NLU in this paper.

In contrast to existing work based on crowd-sourcing [31, 12, 8] to obtain noisy labels, we focus specifically on the weakly-supervised learning setting, where we collect tasks with weak labels obtained from human-written labeling rules. To the best of our knowledge, WALNUT is the first weak supervision benchmark for NLU.

3 WALNUT

Dataset Selection Criterion  

We aim to create a testbed which covers a broad range of NLU tasks for which real-world weak supervision signals are available. To this end, WALNUT includes eight English text understanding tasks with a broad range of domains. As the focus of WALNUT is to facilitate research on weak supervision, each dataset is accompanied with weak labels generated by real-world weak rules (labeling functions) of different accuracy and coverage. To spur future research on the integration of semi-supervised and weakly-supervised approaches, each dataset contains both a small number of clean labeled instances and a large number of weakly-labeled instances. Each weakly-labeled instance comes with multiple weak labels (assigned by multiple rules) and a single weak label computed by taking the majority vote of the weak rules.

3.1 Task Categories

Here, we describe the eight tasks in WALNUT (Table 1), grouped into four document-level classification tasks (Section 3.1.1) and four token-level classification tasks (Section 3.1.2). All datasets come with various types of weak supervision, such as seed words (class-indicative keywords), lexicons, knowledge bases, and user interactions.

3.1.1 Document-level Classification

The goal of document-level classification tasks is to classify a sequence of tokens $x_1, \ldots, x_N$ to a class $c \in C$, where $C$ is a pre-defined set of classes. We consider binary and multi-class
Table 1: The statistics of the datasets in WALNUT. “Clean” refers to instances with clean labels, whereas “Weak” refers to instances with weak labels obtained using weak rules (labeling functions).

classification problems from different application domains such as sentiment classification [51], fake news detection [40], and topic classification [51]. We evaluate weak supervision methods using the following widely-used document-level text classification datasets:

- **AGNews**: and multi-class topic classification (world vs. sports vs. business vs. sci/tech) on news articles from the AGNews dataset [51].
- **Yelp**: binary sentiment classification (negative vs. positive) of Yelp restaurant reviews [51].
- **IMDB**: binary sentiment classification (negative vs. positive) of IMDB movie reviews [19].
- **GossipCop**: binary fake news detection (fake vs. not fake) on news articles from the GossipCop fact-checking websites. The GossipCop dataset is part of the fake news detection benchmark FakeNewsNet [37]. (We only include the results of Gossipcop to represent fake news classification task as the results for Politifact are similar.)

For Yelp, IMDB, and AGNews, the weak rules are derived from the text using keyword-based heuristics, third-party tools as detailed in [30]. For GossipCop, the weak labeling rules are derived from social context information accompanying the news articles, including related users’ social engagements on the news items (e.g., user comments in Twitter). For example, a weak labeling rule for fake news can be “If a news piece has a standard deviation of user sentiment scores greater than a threshold, then the news is weakly labeled as fake news. ” [40].

### 3.1.2 Token-level Classification

The goal of token-level classification tasks is to classify a sequence of tokens $x_1, \ldots, x_N$ to a sequence of tags $y_1, \ldots, y_N \in C'$, where $C'$ is a pre-defined set of tag classes (e.g., person or organization). As one of the most common token-level classification tasks, Named Entity Recognition (NER) deals with recognizing categories of named entities (e.g., person, organization, location) and is a core component in several NLP pipelines, including information extraction and question answering. According to the BIO tagging scheme, “B,” “I,” and “O,” represent the beginning, inside, and outside, of a named entity span, respectively. (Not extracting any values corresponds to a sequence of “O”-only tags.)

Consider, for example, named entity recognition in the CoNLL dataset:

| Tokens | Barack Obama lives in Washington |
|--------|----------------------------------|
| Tags   | B-PERSON I-PERSON O O B-LOCATION |

We include in WALNUT the following four NER datasets from different domains, for which weak rules are available:

- **CoNLL**: the CoNLL 2003 dataset [33] contains news articles from Reuters (split into sentences). In total, there are 35,089 entities from 4 types: organization (ORG), person (PER), location (LOC), and miscellaneous (MISC). Tag classes $C'$: ['O', 'B-PER', 'I-PER', 'B-ORG', 'I-ORG', 'B-LOC', 'I-LOC', 'B-MISC', 'I-MISC']
- **NCBI**: the NCBI Disease corpus [6] contains PubMed abstracts with 6,866 disease mentions. Tag types: ['O', 'B', 'I']

\[\text{https://www.gossipcop.com/}\]
To ease experimentation with our benchmark, we integrate datasets using the Huggingface Datasets library \cite{Wolf2019HuggingFacesTS}.

To simulate the low-resource scenario for weak supervision approaches, we split the training dataset into a small subset with clean labels ($D_C$) and a large subset with weak labels ($D_W$). (In the original datasets, all the training examples come with clean labels, which are ignored as common practice by most weak supervision methods.) For robust evaluation, we create five different clean/weak train splits as we noticed that the base model performance varies substantially with the choice of clean train instances. The validation and test sets are always the same across splits.

Because of different dataset characteristics (e.g., differences in number of classes, difficulty) we choose a different size for $D_C$ per dataset. (After having selected the instances for the $D_C$, we consider the remaining instances as part of the $D_W$ split.) We defined the size of $D_C$ such that we demonstrate the benefits of weak supervision and at the same time leave substantial room for improvement in future research. To this end, we compare the performances of the same base classification model (e.g., BiLSTM), trained using only $D_C$ (“Clean” approach) v.s. using both $D_C$ and $D_W$ (“Clean+Weak” approach). Based on the results in Figure 1, for each dataset, we choose a small size of $D_C$ (left region of the x-axis), such that the “Clean+Weak” approach has a substantially higher F1 score than the “Clean” approach and at the same time the “Clean” approach has no trivial F1 score.

The statistics of the pre-processed datasets used in WALNUT are shown in Table 1. To ease access and reproducibility, we plan to publish all datasets with pre-computed weak labels and clean/weak splits in the Huggingface Datasets Hub.\footnote{https://huggingface.co/docs/datasets/} Loading the pre-computed dataset splits and weak labels will thus require a few lines of code in Python.\footnote{https://huggingface.co/datasets/}

For the CoNLL dataset, we use weak rules provided by \cite{Kuo2012} to annotate the original CoNLL dataset. For the NCBI, BC5CDR, and LaptopReview dataset, we use weak rules provided by \cite{Lawrence2016}.

\subsection{3.1.3 Dataset Pre-Processing}

To encourage reproducibility, for each instance in the dataset we provide pre-computed weak labels (generated by multiple rules) and a single aggregate labels computed as the majority vote of the individual weak rules.

The importance of weak supervision is more evident for settings with smaller numbers of instances, where the gap in performance between the “Clean” approach and “Clean+Weak” approach is larger.
4 Baseline Evaluation in WALNUT

In this section, we describe the baselines and evaluation procedure (Section 4.1), and discuss evaluation results in WALNUT (Section 4.2). Our results highlight the value of weak supervision, important differences across different baselines, and the potential utility of WALNUT for future research on weak supervision.

4.1 Baselines and Evaluation Procedure

We evaluate several baseline approaches in WALNUT by considering different base models (text encoders) and different weak supervision methods (used to train the base model).

**Base Models** For the base model, we experiment with various text encoders, including smaller LSTMs and pre-trained transformer-based encoders [43]. In particular, we consider the following base models:

- **BiLSTM**: a bidirectional LSTM (BiLSTM) based on 50-dimension Glove embeddings [23] (20M parameters), followed by a classification head.
- **BERT**: pre-trained BERT [5] (110M parameters) followed by a classification head.
- **DistilBERT**: pre-trained DistilBERT [34] (66M parameters), a distilled version of BERT, followed by a classification head.
- **RoBERTa**: pre-trained RoBERTa [18] (125M parameters), a robustly optimized extension of BERT, followed by a classification head.

For the transformer-based base models, we use default implementations in the huggingface library [48]. For the BiLSTM, we use Pytorch and integrate the model class with the default hugging-face trainers to ensure a fair comparison with the rest of the transformer-based models. The base model is trained using the cross-entropy objective as the classification loss function by updating all trainable parameters. For more details on the base model configuration see appendix A.2. Each base model is trained using various methods, as described next.

**Supervision Methods** We evaluate the following supervision methods:

- **Full Clean**: Base model trained on all the clean instances before subsampling. This approach is not comparable to the rest of the approaches that consider fewer (or no) clean labeled data.
- **Clean (C)**: Base model is trained on only the available clean instances ($D_C$).
- **Weak-Majority (W)**: Base model trained on weakly-labeled instances ($D_W$), where labels are created by aggregating the predictions from multiple weak rules via majority voting. The weak labels are treated as regular clean labels.
- **Weak-Snorkel (Snorkel)** [28]: Base model trained on weakly-labeled instances ($D_W$), where labels are created by aggregating the predictions from multiple weak rules using Snorkel [28]. Snorkel estimates rule weights using an unsupervised agreement-based objective.
- **Clean+Weak-Majority (C+W)**: Base model trained on both clean and weakly-labeled data. In this setting, we simply merge both the clean and weak sets (essentially treating the weak labels to be as reliable as the clean ones) and use them together for training different encoders.
- **Clean+Weak-Snorkel (C+Snorkel)**: Base model trained on both clean and weakly-labeled data. We combine clean labels and the weak labels generated by Snorkel for classification.
- **GLC** [11]: A label correction approach based on estimating the label correction probabilities from the available clean and noisy instances.
- **MetaWN** [36, 29]: A meta-learning based approach to learn to assign importance weights to examples for the weak labels which mostly benefits task model training.
- **MLC** [52]: A meta-learning based label correction approach, which models weak label correction as a meta-process and learns both the task model and meta-model in a bi-level optimization fashion.
Table 2: Main results on W ALNUT with F1 score (in %) on all tasks. The rightmost column reports the average F1 score across all tasks. (See Table 6 in Appendix for detailed standard deviations.)

### BiLSTM (20M parameters)

| Method | AGNews | IMDB | Yelp | GossipCop | CoNLL | NCBI | BC5CDR | LaptopReview | AVG |
|--------|--------|------|------|-----------|-------|------|--------|--------------|-----|
| Full Clean | 89.4 | 83.1 | 86.4 | 64.5 | 31.9 | 69.9 | 74.7 | 62.6 | 70.3 |
| C | 79.5 | 56.2 | 59.5 | 50.8 | 00.8 | 58.2 | 64.0 | 42.3 | 51.4 |
| W | 78.0 | 75.2 | 70.8 | 62.0 | 11.1 | 52.3 | 71.9 | 49.4 | 58.8 |
| Snorkel | 79.9 | 75.4 | 76.0 | 61.4 | 06.7 | 52.5 | 71.8 | 49.4 | 59.1 |
| C+W | 82.9 | 75.6 | 70.2 | 64.1 | 17.2 | 56.8 | 73.6 | 51.2 | 61.3 |
| C+Snorkel | 82.9 | 75.4 | 66.5 | 62.6 | 07.7 | 59.2 | 73.5 | 53.8 | 60.2 |
| GLC | 56.5 | 72.2 | 63.7 | 60.5 | 05.1 | 58.2 | 73.6 | 51.3 | 52.6 |
| MetaWN | 55.3 | 72.3 | 65.7 | 52.5 | 00.0 | 52.5 | 70.6 | 51.5 | 52.6 |
| MLC | 55.3 | 72.3 | 65.7 | 52.5 | 00.0 | 52.5 | 70.6 | 51.5 | 52.6 |

### DistilBERT-base (66M parameters)

| Method | AGNews | IMDB | Yelp | GossipCop | CoNLL | NCBI | BC5CDR | LaptopReview | AVG |
|--------|--------|------|------|-----------|-------|------|--------|--------------|-----|
| Full Clean | 92.1 | 88.8 | 93.7 | 75.1 | 88.6 | 75.7 | 76.8 | 75.8 | 83.3 |
| C | 80.8 | 71.2 | 73.1 | 55.3 | 51.4 | 57.7 | 61.6 | 53.0 | 63.0 |
| W | 72.2 | 75.0 | 70.2 | 70.8 | 66.9 | 62.0 | 72.5 | 53.8 | 67.9 |
| Snorkel | 70.2 | 70.7 | 65.9 | 68.4 | 64.3 | 62.9 | 72.5 | 54.0 | 66.1 |
| C+W | 83.3 | 74.8 | 71.5 | 67.2 | 66.9 | 66.2 | 75.0 | 57.3 | 70.8 |
| C+Snorkel | 84.3 | 81.7 | 81.8 | 69.1 | 64.6 | 67.8 | 75.0 | 57.5 | 72.7 |
| GLC | 67.8 | 74.1 | 68.1 | 67.3 | 72.4 | 72.8 | 77.3 | 66.8 | 70.8 |
| MetaWN | 70.0 | 74.4 | 69.3 | 70.0 | 65.7 | 64.2 | 75.5 | 58.2 | 68.4 |
| MLC | 70.4 | 74.3 | 69.4 | 69.6 | 69.2 | 66.2 | 76.2 | 58.0 | 69.2 |

### BERT-base (110M parameters)

| Method | AGNews | IMDB | Yelp | GossipCop | CoNLL | NCBI | BC5CDR | LaptopReview | AVG |
|--------|--------|------|------|-----------|-------|------|--------|--------------|-----|
| Full Clean | 92.5 | 90.0 | 74.7 | 74.7 | 89.4 | 78.4 | 79.1 | 76.2 | 81.9 |
| C | 82.9 | 63.8 | 60.3 | 57.1 | 67.3 | 66.6 | 70.9 | 54.6 | 65.4 |
| W | 72.3 | 75.5 | 69.0 | 69.0 | 67.5 | 59.5 | 73.9 | 55.9 | 67.9 |
| Snorkel | 73.7 | 72.9 | 65.6 | 68.2 | 65.1 | 60.9 | 74.0 | 56.2 | 67.1 |
| C+W | 80.1 | 81.8 | 71.3 | 68.4 | 64.8 | 67.9 | 77.5 | 59.2 | 71.8 |
| C+Snorkel | 76.2 | 82.6 | 75.3 | 67.1 | 65.9 | 69.9 | 77.4 | 59.6 | 71.8 |
| GLC | 68.8 | 75.7 | 68.8 | 68.1 | 74.7 | 74.7 | 79.3 | 65.8 | 72.0 |
| MetaWN | 72.8 | 75.2 | 68.1 | 69.8 | 66.9 | 64.7 | 77.0 | 59.2 | 69.5 |
| MLC | 73.0 | 74.7 | 70.0 | 71.3 | 70.4 | 68.4 | 77.7 | 59.7 | 70.7 |

### RoBERTa-base (125M parameters)

| Method | AGNews | IMDB | Yelp | GossipCop | CoNLL | NCBI | BC5CDR | LaptopReview | AVG |
|--------|--------|------|------|-----------|-------|------|--------|--------------|-----|
| Full Clean | 92.8 | 92.4 | 95.9 | 77.2 | 91.2 | 83.1 | 83.6 | 80.2 | 87.1 |
| C | 84.1 | 74.5 | 70.2 | 57.4 | 72.9 | 72.9 | 77.7 | 61.3 | 71.4 |
| W | 66.4 | 76.1 | 70.4 | 71.4 | 64.9 | 69.9 | 79.9 | 58.9 | 69.7 |
| Snorkel | 71.9 | 70.1 | 66.3 | 69.2 | 61.2 | 70.0 | 80.3 | 59.7 | 68.6 |
| C+W | 70.6 | 76.5 | 70.4 | 72.2 | 64.1 | 74.0 | 82.0 | 61.2 | 71.4 |
| C+Snorkel | 74.6 | 68.2 | 66.4 | 71.4 | 62.2 | 73.4 | 82.1 | 61.6 | 70.0 |
| GLC | 67.6 | 74.9 | 69.0 | 68.0 | 74.6 | 79.1 | 82.9 | 71.5 | 73.4 |
| MetaWN | 69.6 | 75.4 | 69.0 | 71.8 | 63.8 | 69.9 | 80.7 | 62.5 | 70.4 |
| MLC | 70.4 | 74.5 | 69.9 | 72.9 | 68.3 | 74.3 | 81.5 | 63.6 | 71.9 |

### Rules (no base model)

| Method | AGNews | IMDB | Yelp | GossipCop | CoNLL | NCBI | BC5CDR | LaptopReview | AVG |
|--------|--------|------|------|-----------|-------|------|--------|--------------|-----|
| Rules | 61.8 | 73.9 | 65.9 | 73.5 | 61.3 | 64.7 | 83.1 | 60.0 | 68.0 |

#### Experimental Procedure
For a robust evaluation, we repeat each experiment five times on the five splits of $D_C$ and $D_W$ (clean and weak examples for each task; see Section 3.1.3) using a separate seed per split, and report the average scores and the standard deviation across the five runs. In WALNUT, we report the average micro-average F1 score on the test set.\(^5\)

#### 4.2 Experimental Results and Analysis
Table 2 shows the main evaluation results on WALNUT. Rows correspond to supervision methods for the base model, columns correspond to tasks, and each block corresponds to a different base model. Unless explicitly mentioned, in the rest of this section we will compare approaches based on their average performance across tasks (rightmost column in Table 2).

As expected, training with Full Clean achieves the highest F1 score, corresponding to the high-resource setting where all clean labeled data are available. Such method is not directly comparable to the rest of the methods but serves as an estimate of the ceiling performance for WALNUT, and could

\(^5\)For token-level tasks, we use the conlleval implementation provided by huggingface: [https://huggingface.co/metrics/seqeval](https://huggingface.co/metrics/seqeval)
Table 3: Average F1 score across the eight tasks in WALNUT. The right-most column reports the average F1 score across tasks and model architectures. The bottom row computes the average F1 score across tasks and supervision methods. The parentheses report the average standard deviations across tasks, model architectures, and supervision methods. Larger transformer-based models lead to higher F1 score. The Clean (C) approach has the lowest F1 score and highest standard deviation across tasks and model architectures (red color), while all other methods exploiting weak supervision exhibit similarly lower variance.

|                | BiLSTM | DistilBERT | BERT  | RoBERTa | AVG (AVG std) |
|----------------|--------|------------|-------|---------|---------------|
| Full Clean     | 70.31 (1.73) | 83.33 (0.91) | 81.88 (0.71) | 87.05 (0.71) | 80.64 (1.02) |
| C              | 51.41 (2.35) | 63.01 (4.43) | 65.44 (2.74) | 71.38 (3.59) | 62.81 (3.28) |
| W              | 58.84 (2.05) | 67.93 (1.50) | 67.90 (1.65) | 69.74 (1.50) | 66.10 (1.68) |
| Snorkel        | 59.14 (1.53) | 66.11 (1.36) | 67.08 (1.91) | 68.59 (1.99) | 65.23 (1.70) |
| C+W            | 61.34 (1.85) | 70.80 (1.14) | 71.83 (1.06) | 71.38 (1.75) | 68.83 (1.45) |
| C+Snorkel      | 60.20 (1.41) | 72.73 (1.35) | 71.75 (1.18) | 69.99 (2.21) | 68.67 (1.54) |
| GLC            | 55.41 (1.74) | 70.82 (1.54) | 71.97 (1.57) | 73.45 (1.35) | 67.91 (1.55) |
| MetaWN         | 53.38 (0.94) | 68.41 (1.25) | 69.46 (1.16) | 70.35 (1.26) | 65.40 (1.15) |
| MLC            | 52.55 (1.23) | 69.15 (1.39) | 70.65 (1.37) | 71.93 (1.55) | 66.07 (1.38) |
| AVG (AVG std)  | 58.06 (1.65) | 70.25 (1.65) | 70.88 (1.48) | 72.65 (1.77) |

Table 4: Overall performance gain and gap of all weak supervision methods (Weak Sup, by averaging performance of W, Snorkel, C+W, C+Snorkel, GLC, MetaWN and MLC) against no weak supervision (C) and full clean training.

|                | BiLSTM | DistilBERT | BERT  | RoBERTa | AVG |
|----------------|--------|------------|-------|---------|-----|
| Performance gain: Weak Sup − C | 5.16 | 7.37 | 5.69 | 0.04 | 4.57 |
| Performance gap: Full Clean − Weak Sup | 13.74 | 12.94 | 10.74 | 15.63 | 13.26 |

Weak supervision is valuable for low-resource NLU. “W” and “Snorkel” achieve better F1 scores than “C” for most base models (except RoBERTa-base, which we will mention later): even using only weakly-labeled data in \( D_W \) is more effective than using just \( D_C \), thus demonstrating that simple weak supervision approaches can be useful in the low-resource setting.

Approaches such as “C+W” and “C+Snorkel” lead to further improvements, highlighting that even simple approaches for integrating clean and weak labeled data (here by concatenating \( D_C \) and \( D_W \)) are more effective than considering each separately. Interestingly, “C+W” and “C+Snorkel” sometimes perform better than more complicated approaches, such as GLC, MetaWN and MLC.

Our results indicate that the performance of weak supervision techniques varies substantially across tasks. Therefore, it is important to evaluate such techniques in a diverse set of tasks to achieve a fair comparison and more complete picture of their performance. The performance of various techniques also varies across different runs (See Table 6 in Appendix for variances of all experiments).

A comparison of different base model architectures. We further aggregate statistics across tasks, methods, and base models in Table 3. The bottom row reports the average performance across methods for each base model and leads to a consistent ranking in F1 score among base models: BiLSTM \leq \text{DistilBERT} \leq \text{BERT} \leq \text{RoBERTa}. Observing higher scores for larger transformer models such as RoBERTa agrees with previous observations [3].

Another question that we attempt to address in WALNUT is on whether weak supervision equally benefits each base model architecture. We aggregate performances of all weak supervision methods (W, Snorkel, C+W, C+Snorkel, GLC, MetaWN and MLC) by computing the average F1 score, and compare it with training with clean data (C) only. Table 4 shows consistent benefits of weak supervi-
sion, with RoBERTa as an exception (only demonstrating a gain of 0.04 in average). Additionally, by comparing the averaged performance of all weak supervision methods (Weak Sup) against full clean data training (Full Clean), larger models are more effective in bridging the gap (as the gap from ceiling performance decreases from BiLSTM to DistilBERT and then to BERT), again with RoBERTa as an exception (a gap of 15.63 F1 points). Note that this does not contradict with the overall best absolute performance with RoBERTa (72.65 in Table 3) among all methods except for Full Clean. Our hypothesis is that it’s either that Full Clean with RoBERTa is more effective in leveraging all labeled data (thus a higher ceiling performance) due to its larger model capacity or that RoBERTa is less effective in leveraging weak supervision compared to BERT when full labeled data is not available. We leave this as future work.

Analysis of weak rules. For now, we have focused on the evaluation of base models trained using weak labels generated by multiple weak rules (labeling functions). It is interesting also to decouple the base model performance from the rule aggregation technique (e.g., majority voting, Snorkel) that was used to generate the training labels, which is an essential modeling component for weak supervision. The bottom row in Table 2 (“Rules”) reports the test performance of rules computed by taking the majority voting of weak labels on the test instances. (For test instances that are not covered by any rules, a random class is predicted.) Such majority label is available in our pre-processed datasets. Interestingly, “Rules” sometimes outperforms base models trained using weak labels (“W”, “Snorkel”). Note however that “Rules” assumes access for all weak labels on the test set, which might not always be available. On the other hand, the base model learns text features beyond the heuristic-based rules and does not require access to rules during test time and thus can be applied for any test instance.

For a more in-depth analysis of the rule quality, WALNUT also supports the analysis of individual rules and multi-source aggregation techniques. Due to space limitations we report the performance of each individual weak rule in the appendix (Tables 7-13). Figure 2 shows a precision-recall scatter plot for each rule in the BC5CDR dataset. Rules vary in characteristics, where most rules have a relatively low recall while there are a few rules that have substantially higher recall than the rest. Across datasets, we observe that rules have higher precision than recall, as most rules are sparse, i.e., apply to a small number of instances in the dataset (e.g., instances containing a specific keyword). For details about weak rules, see the appendix.

5 Conclusions and Future Work

Motivated by the lack of a unified evaluation platform for weakly supervised learning for low-resource NLU, in this paper we propose a new benchmark WALNUT covering a broad range of data domains to advocate research on leveraging weak supervision. We evaluate a series of different weak supervision methods with different model architecture on both document-level and token-level classification tasks, and demonstrate the utility of weak supervision signals in real-world NLU tasks. We also perform fine-grained analysis on how various weak rules affect the NLU task performances of different algorithms across different tasks. We expect WALNUT to enable systematic evaluations of weak supervision methods and stimulate further research in directions such as more efficient and effective learning paradigms coping with weak supervision.

There are several interesting directions for future work. First, WALNUT can be extended to support more NLU tasks and more languages. Second, studying which model architecture works best for the proposed benchmark is worth pursing. Third, WALNUT can be extended and integrated into front-end interfaces that enables users to provide more weak supervision signals.
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A Additional Details

A.1 Additional Dataset Details

Table 5 shows detailed statistics for token-level classification datasets. More dataset statistics are provided in Table 1.

| Table 5: Extra token-level statistics for the token-level classification datasets. |
|---------------------------------|------------|------------|-----------|------------|
|                                | CoNLL      | NCBI       | BC5CDR    | LaptopReview |
| # train tokens                 | 203,621    | 135,572    | 115,621   | 41,525      |
| # dev tokens                   | 51,362     | 23,789     | 114,681   | 9,970       |
| # test tokens                  | 46,435     | 24,219     | 121,227   | 11,884      |

A.2 Implementation Details

We implement all baseline experiments with PyTorch and each experiment runs on a single NVIDIA GPU. The same learning rates of 0.005 is used for BiLSTM models, and 0.00001 for transformer-based models. Below are hyper-parameter specifications for all baseline methods (hyperparameters not mentioned below are given default values):

- Full Clean, C, C+W, Snorkel, C+Snorkel: Batch size is 32 for document-level classification datasets and 16 for the token-level classification datasets. The code for Snorkel is adapted from: https://github.com/snorkel-team/snorkel. Each training experiment is conducted for the 10 epochs with the checkpoint with the best validation performance saved for evaluation on the test set.
- GLC: Code is adapted from https://github.com/mmazeika/glc. Batch size is 16 for the 4 document-level classification datasets and 8 for the 4 token-level classification datasets. Each experiment trains for 75 epochs with the checkpoint with the best validation performance saved for evaluation on test set.
- MetaWN: Code is adapted from https://github.com/xjtushujun/meta-weight-net. Batch size is 8 for the 4 document-level classification datasets and 4 for the 4 token-level classification datasets. The meta-network is a three-layer feed-forward network with hidden dimension of 128. Each experiment trains for 75 epochs with the checkpoint with the best validation performance saved for evaluation on test set.
- MLC: Code is adapted from https://github.com/microsoft/MLC. Batch size is 8 for the 4 document-level classification datasets and 4 for the 4 token-level classification datasets. The meta-network is a three-layer feed-forward network with hidden dimension of 128; the label embedding dimension used in the meta-network is 64. Each experiment trains for 75 epochs with the checkpoint with the best validation performance saved for evaluation on test set.

B Additional Results

Table 6 shows standard deviation results for all datasets, methods, and base models. The rightmost column responds the average standard deviation (AVG std) across tasks, which we also reported in Table 3.

Figure 3 shows the performance of different transformer models trained with varying numbers of clean labeled data. RoBERTa has substantially higher F1 score than BERT and DistilBERT and shows strongest improvements in the low-resource setting (left region of the x-axis).

Analysis of individual weak rules. Tables 7-13 show performance results for each weak rule for the datasets in WALNUT. We evaluate two different strategies for majority voting in case of an instance that is not covered by any rules: (1) “Strict” counts the instance as misclassified and (2) “Loose” assigns a random label to the instance. Most rules have very low F1 score while there are a few rules with a relatively high F1 score.
Table 6: Standard deviation results on W ALNUT.

Table 7: Performance of each rule on AGNews.

Figure 4 shows the precision-recall scatter plots for each weak rule individually. (We skip the scatter plot for GossipCop as it has just 3 rules.) Several rules have relatively high precision but most rules have very low recall.
Figure 3: F1 score for token-level classification with varying training sizes for different transformer-based models: DistilBERT, BERT, and RoBERTa.

Table 8: Performance of each rule on IMDB.

| Rule | unlabeled | IMDB | validation | test |
|------|-----------|------|------------|------|
|      | Prec | Rec | F1 | Prec | Rec | F1 | Prec | Rec | F1 | Prec | Rec | F1 |
| rule 0 | 0.182 | 0.001 | 0.001 | 0.000 | 0.000 | 0.000 | 0.333 | 0.000 | 0.001 | 0.000 | 0.000 | 0.000 |
| rule 1 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| rule 2 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| rule 3 | 0.497 | 0.405 | 0.446 | 0.502 | 0.478 | 0.489 | 0.505 | 0.404 | 0.448 | 0.513 | 0.423 | 0.463 |
| rule 4 | 0.538 | 0.044 | 0.073 | 0.548 | 0.045 | 0.075 | 0.408 | 0.039 | 0.067 | 0.481 | 0.046 | 0.077 |
| rule 5 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| rule 6 | 0.457 | 0.109 | 0.176 | 0.463 | 0.120 | 0.190 | 0.448 | 0.095 | 0.156 | 0.459 | 0.115 | 0.183 |
| rule 7 | 0.655 | 0.006 | 0.012 | 0.644 | 0.004 | 0.009 | 0.630 | 0.008 | 0.015 | 0.667 | 0.008 | 0.015 |
| Majority (strict) | 0.495 | 0.26 | 0.457 | 0.274 | 0.749 | 0.745 | 0.745 | 0.274 | 0.749 | 0.745 | 0.745 | 0.745 |
| Majority (loose) | 0.708 | 0.707 | 0.706 | 0.749 | 0.745 | 0.745 | 0.710 | 0.708 | 0.708 | 0.740 | 0.739 | 0.739 |

Table 9: Performance of each rule on Yelp.

| Rule | unlabeled | Yelp | validation | test |
|------|-----------|------|------------|------|
|      | Prec | Rec | F1 | Prec | Rec | F1 | Prec | Rec | F1 | Prec | Rec | F1 |
| rule 0 | 0.642 | 0.047 | 0.085 | 0.638 | 0.053 | 0.094 | 0.643 | 0.052 | 0.093 | 0.614 | 0.042 | 0.076 |
| rule 1 | 0.214 | 0.029 | 0.051 | 0.221 | 0.036 | 0.063 | 0.213 | 0.028 | 0.050 | 0.239 | 0.031 | 0.054 |
| rule 2 | 0.501 | 0.328 | 0.371 | 0.504 | 0.393 | 0.419 | 0.514 | 0.338 | 0.381 | 0.492 | 0.324 | 0.367 |
| rule 3 | 0.498 | 0.064 | 0.114 | 0.485 | 0.081 | 0.139 | 0.501 | 0.069 | 0.121 | 0.491 | 0.066 | 0.117 |
| rule 4 | 0.502 | 0.101 | 0.163 | 0.503 | 0.122 | 0.191 | 0.489 | 0.090 | 0.147 | 0.519 | 0.105 | 0.168 |
| rule 5 | 0.426 | 0.035 | 0.065 | 0.433 | 0.046 | 0.083 | 0.417 | 0.036 | 0.066 | 0.398 | 0.036 | 0.066 |
| rule 6 | 0.486 | 0.044 | 0.081 | 0.484 | 0.053 | 0.095 | 0.509 | 0.044 | 0.081 | 0.479 | 0.039 | 0.071 |
| rule 7 | 0.553 | 0.049 | 0.085 | 0.556 | 0.060 | 0.103 | 0.515 | 0.049 | 0.086 | 0.553 | 0.053 | 0.092 |
| Majority (strict) | 0.508 | 0.389 | 0.411 | 0.762 | 0.700 | 0.692 | 0.515 | 0.392 | 0.415 | 0.498 | 0.381 | 0.404 |
| Majority (loose) | 0.710 | 0.677 | 0.663 | 0.762 | 0.700 | 0.692 | 0.719 | 0.683 | 0.671 | 0.706 | 0.672 | 0.659 |
### Table 10: Performance of each rule on GossipCop.

| Rule  | train Prec | train Rec | train F1 | validation Prec | validation Rec | validation F1 | test Prec | test Rec | test F1 |
|-------|------------|-----------|----------|-----------------|----------------|---------------|----------|--------|--------|
| rule 0 | 0.632      | 0.629     | 0.627    | 0.614           | 0.610          | 0.607         | 0.629    | 0.627  | 0.625  |
| rule 1 | 0.648      | 0.622     | 0.604    | 0.643           | 0.620          | 0.604         | 0.658    | 0.630  | 0.613  |
| rule 2 | 0.740      | 0.731     | 0.728    | 0.754           | 0.746          | 0.744         | 0.732    | 0.726  | 0.724  |
| majority | 0.758      | 0.732     | 0.725    | 0.757           | 0.728          | 0.721         | 0.760    | 0.740  | 0.735  |

### Table 11: Performance of each rule on NCBI.

| Rule  | train Prec | train Rec | train F1 | validation Prec | validation Rec | validation F1 | test Prec | test Rec | test F1 |
|-------|------------|-----------|----------|-----------------|----------------|---------------|----------|--------|--------|
| rule 0 | 0.490      | 0.025     | 0.047    | 0.460           | 0.066          | 0.116         | 0.537    | 0.031  | 0.058  |
| rule 1 | 0.514      | 0.017     | 0.034    | 0.140           | 0.010          | 0.019         | 0.349    | 0.016  | 0.030  |
| rule 2 | 0.317      | 0.035     | 0.064    | 0.241           | 0.018          | 0.033         | 0.295    | 0.024  | 0.045  |
| rule 3 | 0.875      | 0.219     | 0.350    | 0.911           | 0.118          | 0.208         | 0.807    | 0.172  | 0.283  |
| rule 4 | 0.823      | 0.412     | 0.549    | 0.707           | 0.445          | 0.546         | 0.793    | 0.412  | 0.542  |
| rule 5 | 0.678      | 0.037     | 0.071    | 0.794           | 0.035          | 0.066         | 0.667    | 0.030  | 0.057  |
| rule 6 | 0.227      | 0.002     | 0.004    | 0.333           | 0.001          | 0.003         | 0.000    | 0.000  | 0.000  |
| rule 7 | 0.250      | 0.001     | 0.001    | 0.000           | 0.000          | 0.000         | 0.000    | 0.000  | 0.000  |
| rule 8 | 0.000      | 0.000     | 0.000    | 0.000           | 0.000          | 0.000         | 0.000    | 0.000  | 0.000  |
| rule 9 | 0.000      | 0.000     | 0.000    | 0.000           | 0.000          | 0.000         | 0.000    | 0.000  | 0.000  |
| rule 10| 0.000      | 0.000     | 0.000    | 0.000           | 0.000          | 0.000         | 0.000    | 0.000  | 0.000  |
| rule 11| 0.325      | 0.016     | 0.031    | 0.036           | 0.001          | 0.002         | 0.375    | 0.013  | 0.024  |
| majority | 0.749      | 0.637     | 0.688    | 0.659           | 0.566          | 0.609         | 0.716    | 0.590  | 0.647  |
Table 12: Performance of each rule on BC5CDR.

| Rule | train Prec | train Rec | train F1 | validation Prec | validation Rec | validation F1 | test Prec | test Rec | test F1 |
|------|------------|-----------|----------|----------------|---------------|---------------|-----------|---------|--------|
| rule 0 | 0.579 | 0.005 | 0.009 | 0.704 | 0.006 | 0.012 | 0.667 | 0.004 | 0.009 |
| rule 1 | 0.813 | 0.062 | 0.116 | 0.870 | 0.071 | 0.131 | 0.862 | 0.089 | 0.161 |
| rule 2 | 0.923 | 0.022 | 0.042 | 0.923 | 0.033 | 0.063 | 0.908 | 0.023 | 0.045 |
| rule 3 | 0.701 | 0.007 | 0.014 | 0.664 | 0.009 | 0.017 | 0.615 | 0.010 | 0.020 |
| rule 4 | 0.531 | 0.006 | 0.011 | 0.634 | 0.008 | 0.016 | 0.474 | 0.005 | 0.009 |
| rule 5 | 0.874 | 0.225 | 0.358 | 0.901 | 0.225 | 0.360 | 0.875 | 0.215 | 0.345 |
| rule 6 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| rule 7 | 0.556 | 0.001 | 0.002 | 0.400 | 0.001 | 0.001 | 0.545 | 0.001 | 0.002 |
| rule 8 | 0.933 | 0.411 | 0.571 | 0.924 | 0.324 | 0.480 | 0.925 | 0.294 | 0.446 |
| rule 9 | 0.890 | 0.051 | 0.097 | 0.863 | 0.028 | 0.055 | 0.871 | 0.032 | 0.061 |
| rule 10 | 0.874 | 0.291 | 0.436 | 0.858 | 0.264 | 0.404 | 0.843 | 0.267 | 0.406 |
| rule 11 | 0.842 | 0.014 | 0.028 | 0.836 | 0.010 | 0.020 | 0.814 | 0.011 | 0.021 |
| rule 12 | 0.485 | 0.002 | 0.003 | 0.556 | 0.004 | 0.007 | 0.386 | 0.002 | 0.004 |
| rule 13 | 0.780 | 0.124 | 0.214 | 0.788 | 0.125 | 0.215 | 0.778 | 0.126 | 0.216 |
| rule 14 | 0.800 | 0.025 | 0.048 | 0.819 | 0.026 | 0.050 | 0.797 | 0.028 | 0.055 |
| rule 15 | 0.604 | 0.049 | 0.091 | 0.608 | 0.051 | 0.094 | 0.647 | 0.059 | 0.108 |
| rule 16 | 0.824 | 0.001 | 0.003 | 0.812 | 0.001 | 0.003 | 0.652 | 0.002 | 0.003 |
| rule 17 | 0.683 | 0.016 | 0.031 | 0.822 | 0.025 | 0.049 | 0.734 | 0.019 | 0.038 |
| rule 18 | 0.808 | 0.029 | 0.056 | 0.841 | 0.031 | 0.060 | 0.833 | 0.027 | 0.053 |
| rule 19 | 0.167 | 0.000 | 0.000 | 0.471 | 0.001 | 0.002 | 0.250 | 0.000 | 0.000 |
| rule 20 | 0.905 | 0.301 | 0.452 | 0.922 | 0.315 | 0.470 | 0.901 | 0.295 | 0.444 |
| rule 21 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| rule 22 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| rule 23 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| rule 24 | 0.263 | 0.001 | 0.002 | 0.333 | 0.002 | 0.003 | 0.410 | 0.002 | 0.003 |
| rule 25 | 0.842 | 0.003 | 0.007 | 1.000 | 0.002 | 0.005 | 1.000 | 0.001 | 0.001 |
| Majority | 0.863 | 0.837 | 0.849 | 0.868 | 0.821 | 0.844 | 0.851 | 0.812 | 0.831 |

Table 13: Performance of each rule on LaptopReview.

| Rule | train Prec | train Rec | train F1 | validation Prec | validation Rec | validation F1 | test Prec | test Rec | test F1 |
|------|------------|-----------|----------|----------------|---------------|---------------|-----------|---------|--------|
| rule 0 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| rule 1 | 0.679 | 0.595 | 0.634 | 0.656 | 0.584 | 0.618 | 0.722 | 0.512 | 0.599 |
| rule 2 | 0.667 | 0.003 | 0.006 | 1.000 | 0.004 | 0.008 | 0.500 | 0.003 | 0.006 |
| rule 3 | 0.500 | 0.006 | 0.012 | 0.400 | 0.009 | 0.017 | 0.750 | 0.009 | 0.018 |
| rule 4 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| rule 5 | 0.423 | 0.006 | 0.011 | 0.467 | 0.015 | 0.029 | 0.000 | 0.000 | 0.000 |
| rule 6 | 1.000 | 0.001 | 0.002 | 0.500 | 0.002 | 0.004 | 0.000 | 0.000 | 0.000 |
| rule 7 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| rule 8 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| rule 9 | 0.333 | 0.001 | 0.001 | 1.000 | 0.002 | 0.004 | 0.000 | 0.000 | 0.000 |
| rule 10 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| rule 11 | 0.735 | 0.013 | 0.026 | 0.800 | 0.009 | 0.017 | 0.250 | 0.006 | 0.012 |
| Majority | 0.671 | 0.609 | 0.638 | 0.644 | 0.599 | 0.621 | 0.706 | 0.521 | 0.600 |
Figure 4: Rule precision-recall scatterplots.