ARTICLE

XPASC: Measuring Generalization in Weak Supervision by Explainability and Association

Luisa März^{$\diamond,*,*$}, Ehsaneddin Asgari^{*}, Fabienne Braune^{*}, Franziska Zimmermann[°], and Benjamin Roth^{\diamond,\dagger}

[°] Research Group Data Mining and Machine Learning, Faculty of Computer Science, University of Vienna, Vienna, Austria

[†] Faculty of Philological and Cultural Studies, University of Vienna, Vienna, Austria

* AI Innovation & Pre-Development, Data:Lab, Volkswagen AG, Munich, Germany luisa.k.maerz@gmail.com

* UniVie Docotoral School Computer Science, Vienna, Austria

° CAPE Analytics, Mountain View, California, United States

(Received 06 May 2022; revised 22 November 2022; accepted xx xxx xxx)

Abstract

Weak supervision is leveraged in a wide range of domains and tasks due to its ability to create massive amounts of labeled data, requiring only little manual effort. Standard approaches use labeling functions to specify signals that are relevant for the labeling. It has been conjectured that weakly supervised models over-rely on those signals and as a result suffer from overfitting. To verify this assumption, we introduce a novel method, XPASC (eXPlainability-Association SCore), for measuring the generalization of a model trained with a weakly supervised dataset. Considering the occurrences of features, classes and labeling functions in a dataset, XPASC takes into account the relevance of each feature for the predictions (explainability) of the model as well as the connection of the feature with the class and the labeling function (association), respectively. The explainability is measured using occlusion in this work. The association in XPASC can be measured in two variants: XPASC-CHI SQUARE measures associations relative to their statistical significance, while XPASC-PPMI measures association strength more generally. We use XPASC to analyze KNOWMAN, an adversarial architecture intended to control the degree of generalization from the labeling functions and thus to mitigate the problem of overfitting. On one hand, we show that KNOWMAN is able to control the degree of generalization through a hyperparameter. On the other hand, results and qualitative analysis show that generalization and performance do not relate one-to-one, and that the highest degree of generalization does not necessarily imply the best performance.

Therefore methods that allow for controlling the amount of generalization can achieve the right degree of benign overfitting. Our contributions in this study are i) the XPASC score to measure generalization in weakly-supervised models, ii) evaluation of XPASC across datasets and models and iii) the release of the XPASC implementation.

1. Introduction

Many machine learning architectures still require large amounts of labeled training data, resulting in static data sets with limited usability for changing data distributions or task definitions. Manual annotation is both expensive and time-consuming and thus not always practically feasible or convenient. One way to circumvent this problem is to use weak supervision. Weak supervision methods utilize different knowledge sources such as knowledge bases, heuristics, or taxonomies to annotate large amounts of data automatically. The knowledge of the external sources is encoded in *labeling functions*, programmatically specified heuristics (e.g., keywords, patterns, database lookups) that trigger the automatic annotation of a specific output. A labeling function can also be thought of as a decision rule that is defined based on prior (expert) knowledge. If this rule is matched, the appropriate output is assigned to the instance. Due to the fact that labeling functions only consider a narrow context for triggering an annotation, it is likely that some weak labels are noisy and/or imprecise. Moreover, large sets of weakly annotated instances all follow similar patterns (captured by the same labeling function), and it has been conjectured that weakly supervised models rely too heavily on the labeling functions and therefore suffer from overfitting (März et al. 2021; Dehghani et al. 2017).

Approaches to tackle the problem of noisy weak labels can be categorized into two main groups: Those who try to filter out the noisy labels for training (Ren et al. 2020; Sukhbaatar et al. 2014; Dehghani et al. 2017) and those who try to estimate the accuracy of the labeling functions or the weak sources (Fu et al. 2020; Ratner et al. 2020). See Zhang et al. (2022a) for a detailed survey on weak supervision approaches and labeling function modeling. None of them addresses the problem of overfitting to (or, inversely, generalization from) labeling functions. As an alternative, we developed KNOWMAN (März et al. 2021), an adversarial architecture with the objective to shift the focus for the learned representation of a model away from the labeling functions towards a more general representation. This is achieved through a hyperparameter that controls the influence of the labeling functions on the feature representation. KNOWMAN has explicitly been designed to overcome the problem of overfitting to the noisy labeling function quality for the studied weakly supervised neural networks, it could not be *directly* evaluated whether the KNOWMAN actually increases generalization from the labeling functions.

In this study, we present **XPASC** (**eXPlainability-Association SCore**) to observe generalization from noisy signals in weakly supervised models more closely. The intuition behind the score is that models suffering from overfitting to labeling functions have a low ability to generalize, and will heavily rely on features associated with labeling functions for prediction. Generalization in the scope of this work means the capability of a model to abstract from the labeling function signals and to learn representations based on various signals and parts of the input. A higher generalization should ultimately lead to the representation being more robust against misleading labeling functions and being able to represent the input with as many aspects as possible. Accordingly, a greater generalization from the weak source indicates a smaller degree of overfitting. In this work we consider the strongly information-carrying surface forms, i.e. the individual tokens, of an instance as features. By using XPASC the generalization ability of a model, given a data set, can be measured. The score combines the relevance of each feature for the prediction of a weakly supervised model (explainability) with the connection of the feature with the class and the labeling function (association).

To measure prediction relevance of the single features we leverage a method from XAI (eXplainable AI), namely occlusion. In general, XAI methods aim to give insights into the output of machine learning models to make internal processes more transparent to users. Taking into account the explainability method is central to the analysis with XPASC, and also represents an unconventional use case of XAI.

To compute association in XPASC we propose two different methods: XPASC-CHI SQUARE which relies on statistical association strength, and XPASC-PPMI which measures the more general information-theoretic association strength.

Apart from introducing the formal details of XPASC, we study KNOWMAN and WEASEL as well as two traditional weak supervision approaches, MAJORITY VOTE and SNORKEL-DP (Data Programming), with respect to their generalization, as measured by XPASC. Our findings show that the KNOWMAN architecture is able to control the degree of generalization in direct relation to its hyperparameter λ . In fact, KNOWMAN can get the model to focus more on words that are associated with the class (generalize more), and even ignore features highly associated with single, misleading labeling functions.

We have observed that the generalization of a model and its performance are not one-to-one related, and that at a certain point there can be too much generalization from the weak signals. Our observations show that the two different association computations, PPMI and CHI SQUARE, behave analogously in the overall picture. However, we find that the values of the association based on PPMI are distributed across a larger space. This means that PPMI also takes into account the "long tail" of data sets and presents the reality in the data more straightforwardly. The values of the CHI SQUARE-based association, on the other hand, have a denser distribution. So CHI SQUARE also appears to be more resilient to outliers in the data.

Our main contributions in this paper are:

- the proposal and detailed introduction of XPASC to measure generalization from weak signals
- the evaluation of XPASC across models and data sets
- the confirmation of the hypothesis and functionality of KNOWMAN
- the release of the XPASC implementation^a.

The remainder of the paper is structured as follows: After investigating related work in the fields of weak supervision and overfitting metrics we describe the method the XPASC formally. Section §4 gives an overview over models and data sets used in this work. The analysis is divided in quantitative and linguistic results and followed by the conclusion.

2. Related Work

We consider the concepts of overfitting and generalization to be related in that overfitting can be a result of low generalization. In the weak supervision context, this means that a model that abstracts little from the labeling functions, i.e. has low generalization, is more likely to overfit to these misleading signals. In the following we present approaches that focus either on overfitting or on generalization. Some are tailored to weak supervision, while others deal with overfitting and generalization in natural language processing in general.

Overfitting of machine learning models has been repeatedly identified as a problem. In machine learning generally, overfitting means that a model has adapted too much to the training data and can therefore no longer perform well on newly seen data. Model performance on unseen data or held-out test sets is therefore typically used as an indicator for overfitting. If the result on unseen data is much worse than on training data it is likely that the model overfitted to the training data. Salman and Liu (2019) analyze the training dynamics and the application of models to unseen data to observe overfitting. Other works measure overfitting that a high number of parameters, where a low number of parameters indicates less overfitting than a high number of parameters. (Li et al. 2019) measure overfitting through the number of parameters of a model and its accuracy on the test set.

^ahttps://github.com/LuisaMaerz/XPASC

4 XPASC, März et.al

Roelofs et al. (2019) analyze overfitting caused by test set reuse on a large set of Kaggle competitions. The assumption is that if many models are centered towards one test set, overfitting of the models to that test set is likely. However, with their experiments they show that there is no significant overfitting due to test set reuse in Kaggle. Roelofs et al. (2019) provide a simple measurement for the adaptivity gap between the losses on train and test set. Here they use the fact that Kaggle provides two types of test sets with which this gap can be approximated very well. Unlike us, they cover overfitting to test set reuse rather than overfitting to labeling functions.

Due to the nature of weak supervision, models may overfit to systematic errors and biases introduced by the automatic labeling process. Yu et al. (2021) fine tune a pre-trained language model with weak supervision. This is challenging, because large language models have a higher risk to overfit due to their large amount of parameters anyways. Errors are more propagated due to overfitting, which degrades performance and prevents the models from learning properly. Yu et al. (2021) tackle this issue by contrastive self-training, what can be considered as denoising in the first place and reduces error propagation and overfitting to the noise. In their experiments, they use RoBERTa (Liu et al. 2019) and fine-tune a simple classification head. Like us, they use MAJORITY VOTE (exact match in their work) and SNORKEL-DP for weak labeling. However, they do not specifically address the impact of overfitting to labeling functions. As in our previous work with KNOWMAN (März et al. 2021), their model aims at learning better representations from weakly labeled data. Unlike us, they use a contrastive approach that pulls labels with similar weak supervision signals closer together and pushes others further away in the feature space, rather than an adversarial network as in KNOWMAN. In recent work Zhang et al. (2022b) propose the source-aware Influence Function to understand programmatic weak supervision. By observing changes in the loss of a model while utilizing the source-aware influence function, they gain insights in the influence of single data points, labeling functions or weak sources on model performance. Like us, they aim to identify important parts of the input to make the model output more explainable. Similar to KNOWMAN, they try to reduce the impact of misleading labeling functions on model training. Although they provide some insight into what influences the training through the source-aware influence function, they do not use this information to compare different models, which is different from our work.

Generalization refers to a model's ability to perform well on unseen data, i.e., a model generalizes well if it overfits only slightly. For example Ratner et al. (2019) consider generalization of weak supervision sources observable through the estimation error of their trustworthiness. They claim that the generalization error scales with the number of unlabeled data points and try to minimize the loss for predicting weak labels without loss of generality. By connecting generalization to the estimation error, generalization is not only observable, but also controllable. Like our metric, this can be viewed as a formal measurement of generalization. Unlike our metric, their measure is tightly coupled with their specific weak supervision approach and not generally applicable as a universal tool to compare generalization across models and data sets.

Many weak supervision approaches try to overcome a lack of generalization by denoising the weak sources (Ren et al. 2020; Hsieh et al. 2022). In contrast to these approaches, we address the issue of generalizing from weak supervision sources, instead of denoising them. Fu et al. (2020) provide a weak supervision framework to model and label data by leveraging different weak supervision sources. In addition, they provide a bound for generalization. To do so, they measure the performance gap between the end model parametrization using outputs of the label model and the optimal end model parametrization over the true distribution of labels. More efforts can be mentioned in studying generalization in general, e.g., measuring number of required "strong" labels (Robinson et al. 2020), studying generalization in algorithmic datasets (Power et al. 2022), generalization in generative models by measuring the uniqueness of generated sample (Mauri et al. 2022).

Although there is work on both overfitting and generalization, and both are considered to be important issues in weak supervision, to the best of our knowledge XPASC is the first universal



Figure 1. Modules of XPASC: product of *eXPlainability* and *Association*. The *eXPlainability* of a feature of an instance is calculated by the KL divergence of the class predictions for the entire instance and the instance without the respective feature. For each instance the explainability for all features is computed and the most important feature can be obtained. The *Association* for an instance given a feature is calculated as the difference of the association of the feature with the class and with the labeling function, which in practice is a matrix lookup. The matrices are computed in advance and are based on coocurrences of features, classes and labeling functions in the data corpus.

score measuring overfitting to and generalization from labeling functions in weakly supervised models. Moreover, since our approach is based on explainability methods, it makes transparent which features are mainly responsible for overfitting or generalization.

3. The Explainability-Association Score

The goal of XPASC is to measure generalization from weak signals for weakly supervised models. The intuition behind XPASC is that input parts or features that are most important for the class prediction of these models are highly associated with the heuristics used for annotating the training data. This is due to the fact that the model relies too much on the labeling functions and therefore tends to ignore other valuable signals for classification.

XPASC measures to what degree a model, trained with a weakly labeled data set, can generalize from the information associated with the features, classes and labeling functions present in the data. Several considerations such as how important features^b are for the classification and how much features, classes and labeling functions are correlated are taken into account. Therefore XPASC is composed of three parts: i) the explainability of each feature for a model, ii) its association with the class, and iii) its association with the labeling function. Note that both explainability and association contribute equally to XPASC. To calculate explainability, we use occlusion (Zeiler and Fergus 2014). The association strength is measured either with the PPMI or the CHI SQUARE-score. See Figure 1 for an illustration of XPASC.

3.1 Explainability

The term explainability expresses how important a single feature is for the classification of an instance, i.e., how the class prediction changes if the feature is omitted, masked or changed. To determine the importance of each feature of an instance for the classification task, we use the explainability method of occlusion. The idea for occlusion originally came from computer vision proposed by Zeiler and Fergus (2014), and since then it has been also used for Natural Language Processing, e.g., by Harbecke and Alt (2020), or Ancona et al. (2018).

^bIn this work, by features we mean the observable tokens of an input instance, in contrast to learned features from a network.

6 XPASC, März et.al

We perform occlusion in four steps as follows: we pass **i**) our input instance through our model and **ii**) the instance without the feature through the model. Explainability is then computed by **iii**) retrieving the prediction probabilities from both, and **iv**) calculating the Kullback-Leibler-Divergence (Kullback and Leibler 1951):

$$D_{KL}(P||Q) = \sum_{x \in X} P(x) \log\left(\frac{P(x)}{Q(x)}\right)$$
(1)

where P and Q are discrete probability distributions and X is a shared probability space. By computing how different two probability distributions are, the Kullback-Leibler-Divergence indicates how much the occlusion affects the prediction in our case. Accordingly, we define the explainability of an instance and a feature as:

$$S_{xp}(i,f) = D_{KL}\left(P(i)||Q(i \setminus f)\right)$$
⁽²⁾

where P(i) is the model prediction for the entire instance and $Q(i \setminus f)$ is the model prediction for the instance with feature f omitted. Note that both predictions are vectors of probability distributions over the set of possible classes. The smaller this difference of the two probability distributions, the less important the feature is for the classification result. In any case, the Kullback-Leibler-Divergence is between zero and one. The highest explainability is assigned to the features where the two prediction distributions differ the most, i.e., where the prediction changes greatly if the feature is omitted.

3.2 Association

Association measures the degree of correlation between observations. To find out how much a feature is correlated with its class and with its labeling function we calculate two association matrices with the following shapes:

$$|\mathbf{C}| = classes \times features$$

$|\mathbf{L}| = labeling_{-}functions \times features$

where C is the association matrix for classes and L is the matrix for labeling functions. The details for the matrix calculation are explained in section 3.2.1 and section 3.2.2. During the calculation of XPASC, the respective association value is looked up in the matrices for each feature given its class and its labeling function. To put both associations (feature and class/ feature and labeling function) in relation we subtract their scores and arrive with the overall association for a feature given its instance:

$$S_{asc}(i,f) = \sum_{j=1}^{N} \left(\mathbf{C}_{c^{i}f} - \mathbf{L}_{l_{j}^{i}f} \right)$$
(3)

where we iterate over all matching labeling functions l for instance i. Variable f denotes the feature, $\mathbf{C}_{c^i f}$ is the value of the association-matrix with respect to the class label of instance i, c_i , and $\mathbf{L}_{l_{j}^i f}$ the value for the j'th matching labeling function, l_{y}^i . By computing association that way the result can either be positive, negative or zero. Depending on the exact result, the score can then be interpreted directly. The larger (positive) S_{asc} , the more feature f is associated with the class, the smaller (negative) S_{asc} , the more feature f is associated with the class and the labeling function. The closer the score is to zero, the more similar the association of the feature with the class and the labeling function.

Association can be modeled in different ways. We calculate it in two manners: using i) a chi squared test or ii) the positive pointwise mutual information.

3.2.1 CHI SQUARE-based association

For this option we calculate the association matrices based on univariate feature selection. This works by selecting the best features based on univariate statistical tests, in our case a chi squared (χ^2) test.

CHI SQUARE
$$(z, f) = \frac{\left(o_{zf} - \tilde{o}_{zf}\right)^2}{\tilde{o}_{zf}}$$
 (4)

where f is the feature, z represents a label (either class label or labeling function), o_{zf} is the absolute frequency of the combination of class/ labeling function and a feature (observed value) and \tilde{o}_{zf} is the expected value of the absolute frequency of the combination of class / labeling function and a feature.

The χ^2 test measures the dependence between the features and the class/labeling function. Features with a high CHI SQUARE score are likely to be independent of the class/labeling function and therefore more irrelevant for the classification. The smaller the CHI SQUARE result, the more a feature is related to the class/labeling function and, consequently, the more important it is. Note that the CHI SQUARE association expresses which of the features are most associated with the class and include positive as well as negative correlation. Thus also negative examples can be found among the most associated ones, e.g. "brother" can have a very high association with the "married to" relation, although it is a negative indicator for that relation.

Formulas 5 and 6 define how to calculate one matrix entry for a feature and its corresponding class/ labeling function.

$$\mathbf{C}_{cf}^{\text{CHI SQUARE}} = \text{CHI SQUARE}(c, f)$$
(5)

$$\mathbf{L}_{lf}^{\text{CHI SQUARE}} = \text{CHI SQUARE}(l, f)$$
(6)

where c is the class, l the labeling function and f the feature.

3.2.2 PPMI-based association

As a second option we calculate the positive pointwise mutual information (Equation 8), where only the positive results of the pointwise mutual information (Equation 7) are taken into account. Assuming independence of two variables (in our case: a feature and a class/labeling function) PMI quantifies the discrepancy between the probability of their coincidence given their individual distributions and their joint distribution.

$$PMI(f,z) = log\left(\frac{P(f,z)}{P(f)P(z)}\right)$$
(7)

$$PPMI(f, z) = \begin{cases} PMI, \text{ if } PMI > 0\\ 0 \quad else \end{cases}$$
(8)

where f is a feature, z a label (either class label or labeling function), P(f, z) the joint probability of a feature and a label, P(f) the probability of the feature and P(z) the probability of a label. Formulas 9 and 10 define how to calculate one matrix entry for a feature and its corresponding class/ labeling function.

$$\mathbf{C}_{cf}^{\mathrm{PPMI}} = \mathrm{PPMI}(f, c) \tag{9}$$

$$\mathbf{L}_{lf}^{\text{PPMI}} = \text{PPMI}(f, l) \tag{10}$$

where c is the class, l the labeling function and f the feature.

3.3 The Combined Score: XPASC

XPASC (eXPlainability Association SCore) combines both explainability and association for one data set and a model. It measures how important each feature of an instance is and if it is more correlated with the class or with the labeling function. By multiplying the two measures and summing up over all instances and features we obtain:

$$S_{\text{XPASC}}(d,m) = 1 + \left(\frac{1}{N \times M} \sum_{i=1}^{N} \sum_{f=1}^{M} S_{xp}(i,f) \times S_{asc}(i,f)\right)$$
(11)

where d is the data set, m is the pre-trained model, N is the number of instances and M is the number of features. To make sure that XPASC is comparable across models and data sets we normalize by the data set size (number of instances times the number of features). Multiplying both components gives small negative values, so we add one to the result to make the final XPASC value above zero. The multiplication allows to put the importance of a feature in relation to its association with the class and the labeling function.

The sharpness of the explainability measure could be increased by a temperature hyperparameter γ for putting the focus only on the most relevant features ($\gamma \rightarrow \infty$) or equally on all features ($\gamma \rightarrow 0$), changing the XPASC formula as follows: $(S_{xp}(i, f)^{\gamma}) \times (S_{asc}(i, f))$. In this work, we considered the unchanged importance as given by the explainability algorithm ($\gamma = 1$).

Thus, a high XPASC indicates that many of the most important features (those that are effectively used for prediction) are correlated with the class instead of the labeling function. We can conclude that a high XPASC indicates more independence from the labeling functions and accordingly a greater generalization from the weak source. This also indicates a smaller degree of overfitting to the weak signals. Note that the results of CHI SQUARE-based XPASC and PPMIbased XPASC are scaled differently. This is due to their different characteristics, as well as the specific result values of the two calculations.

4. Weak Supervision Methods and Datasets

For our experiments we study four different weak supervision approaches, KNOWMAN, MAJORITY VOTE, SNORKEL-DP (Data Programming) (Ratner et al. 2020) and WEASEL (Cachay et al. 2021). Of those, only KNOWMAN provides an explicit mechanism for controlling the degree of generalization from the labeling functions. The latter three methods have been developed without any mechanism to control generalization.

Experiments are conducted for four classifications tasks: sentiment analysis, spam detection, detection of the spouse relationship and question classification. Four data sets that are common in weak supervision are used, which are SPAM, SPOUSE, IMDb and TREC, see Section 4.2.



Figure 2. KNOWMAN architecture. One iteration for a pass of one batch of inputs. The correct class and labeling function for the example instance are highlighted. The parameters of C and \mathcal{F} are updated together, the labeling function discriminator \mathcal{D} is updated with a separate optimizer. Solid lines indicate forward, dashed lines the backward passes. ∇ indicates the (reversed) gradient. Before entering \mathcal{F} the gradient is flipped. The influence of \mathcal{D} can be controlled by hyperparameter λ . Strength of λ equals generalization strength.

4.1 Models

We use a pre-trained DistilBERT language model to encode the input texts. Similar to BERT (Devlin et al. 2019), DistilBERT is a masked transformer language model, which is a smaller, lighter, and faster version leveraging knowledge distillation while retaining 97% of BERT's language understanding capabilities (Sanh et al. 2019).

To arrive with the DistilBERT input encodings we first tokenize the texts using the DistilBERT tokenizer. After that, the tokenized input is converted to the DistilBERT transformer encoding, consisting of the input ids as well as the attention mask. We use that representation across KNOWMAN, SNORKEL-DP and MAJORITY VOTE models.

For WEASEL we encode the input using RoBERTa (Liu et al. 2019), a optimized version of the BERT language model, because DistilBERT is not supported by WEASEL.

4.1.1 KNOWMAN

In previous work we proposed KNOWMAN (März et al. 2021). The ultimate goal of KNOWMAN is to learn a feature representation that is invariant to the labeling functions which annotated the weakly supervised data. We showed that this representation is more general and more robust to incorrect classes that have been assigned by the labeling functions.

The architecture is designed as an adversarial model and contains three modules: i) a shared feature extractor \mathcal{F} , ii) a classifier \mathcal{C} and iii) a labeling function discriminator \mathcal{D} . See Figure 2 for an illustration of the architecture. The classifier \mathcal{C} is trained to predict the labels of a downstream task. The gradient of the loss function is used to optimize the classifier itself as well as the shared feature extractor. At the same time, the discriminator \mathcal{D} is learned to distinguish between the different labeling functions and should predict which of the labeling functions was responsible for labeling an instance. The gradient of the discriminators loss function is used to optimize \mathcal{D} . In addition, the *reversed* gradient of \mathcal{D} is used to optimize the feature extractor \mathcal{F} . This adversarial update leads to a weakening of the labeling function discrimination information and therefore to a better generalization. KNOWMAN uses a hyperparameter λ to control the level of weakening the signals. Consequently, XPASC allows us to study how changes in λ affect the degree of generalization of trained KNOWMAN models.

KNOWMAN is implemented as follows: the discriminator \mathcal{D} is trained with a separate optimizer than \mathcal{C} and \mathcal{F} . When \mathcal{D} is trained, the parameters of \mathcal{C} and \mathcal{F} are frozen and vice versa. The losses for both, the classifier and the discriminator, are computed using negative log-likelihood (NLL). The classification NLL can be formalized as:

Table 1. KNOWMAN results on the test sets.

	SPAM		SPOUSE		IMDb
	Acc	Р	R	F1	Acc
MAJORITY VOTE TF-IDF	0.87	0.12	0.83	0.20	0.65
BLIND KNOWMAN TF-IDF	0.91	0.12	0.76	0.21	0.75
SNORKEL-DP TF-IDF	0.81	0.18	0.63	0.28	0.50
KNOWMAN TF-IDF	0.94	0.16	0.72	0.35	0.77
Fine-tuned DistilBERT	0.92	0.14	0.78	0.24	0.70
MAJORITY VOTE DistilBERT	0.87	0.09	0.90	0.17	0.67
BLIND KNOWMAN DistilBERT	0.86	0.18	0.80	0.29	0.74
SNORKEL-DP DistilBERT	0.88	0.13	0.70	0.23	0.49
KNOWMAN DistilBERT	0.90	0.27	0.67	0.39	0.76

$$\mathcal{L}_C(\hat{c}_i, c_i) = -\log P(\hat{c}_i = c_i) \tag{12}$$

where c_i is the (weakly supervised) annotated class and \hat{c}_i is the prediction of the classifier module C, for a training sample *i*. Analogously, the NLL for the labeling function discriminator is defined as:

$$\mathcal{L}_{\mathcal{D}}(\hat{l}_i, l_i) = -\log P(\hat{l}_i = l_i)$$
(13)

where l_i is the actual labeling function used for annotating sample *i* and \hat{l}_i is the predicted labeling function by the discriminator \mathcal{D} .

The results of the experiments with KNOWMAN are shown in Table 1. As mentioned above, we encode the inputs with DistilBERT. In März et al. (2021) we did that for the experiments with KNOWMAN as well and additionally encoded the input with TF-IDF. Table 1 reports the results for experiments with both, DistilBERT and TF-IDF encodings. The baselines are a MAJORITY VOTE model as well a SNORKEL-DP model. The functionality of both models is explained in section 4.1.2. For DistilBERT encoded input we also trained a fine-tuned DistilBERT model and utilized it for prediction.

We refer to the KNOWMAN model with a λ value of zero as BLIND KNOWMAN. Setting λ to zero means disabling the generalization mechanism, because the feature extractor \mathcal{F} is blind for the loss of the discriminator \mathcal{D} . KNOWMAN TF-IDF and KNOWMAN DistilBERT refer to a KNOWMAN model with optimal λ (tuned on the dev set through Bayesian hyperparameter optimization) for the respective dataset. KNOWMAN is able to outperform the baselines for all data sets. The only exception is fine-tuned DistilBERT, which performs better for SPAM.

4.1.2 Models without generalization mechanism

We also study three methods with no generalization control. This demonstrates that XPASC allows highlighting generalization across different approaches. The first method is majority voting. The second approach follows the data programming paradigm (DP) proposed by Ratner et al. (2016). The third approach (Cachay et al. 2021), WeaSEL, aims to learn in an end-to-end fashion from the labeling function output directly.

MAJORITY VOTE. For the majority vote classifier a matrix that holds the mapping between each labeling function and the corresponding class (the labeling function it is associated with) is needed. For each instance of the train set it is checked which labeling functions apply. Based

Data set	original size	size after filtering	percentage of original size	labeling functions
SPAM	1586	1382	87.1	10
TREC	4965	4723	95.1%	68
SPOUSE	22254	5734	25.8%	9
IMDb	40000	39998	99.9%	6786

Table 2. Statistics on data set sizes. *Size after filtering* is the size of the data sets after instances without labeling function matches were filtered out.

on this information it is looked up which class each matching labeling function would assign to the instance and if there is a majority for one class among them. If so, the class is assigned. If not, the class is either chosen at random from among the matching classes, or another special class is assigned to this instance. After labeling the training data in this way, we use the uncased DistilBERT model provided by Hugging Face (Wolf et al. 2019) as the prediction model.

SNORKEL-DP. We also compare to training models on labels denoised by SNORKEL-DP (Data Programming) (Ratner et al. 2020). To do this, we use Knodle's SNORKEL-DP wrapper (Sedova et al. 2021), where first a generative SNORKEL-DP model is learned, generating weak labels for the instances, and then a classification model (used for prediction) is trained with those labels. SNORKEL-DP works with a set of given labeling functions and learns a label model that focuses on the conflicts and agreements between the labeling functions to estimate their accuracy. For each labeling function an accuracy value is estimated to weigh their votes on each instance. Taking into account the weighted labeling functions, the label model can assign a probabilistic class to each instance and arrives with a weakly supervised data set. As with MAJORITY VOTE, the prediction model trained on the weak labels is uncased DistilBERT. The cross-entropy loss is optimzed on the probabilistic SNORKEL-DP labels.

WEASEL. In addition, we train models with WEASEL, an end-to-end model for weak supervision that does not take the noisy weak class labels, but the labeling function output as input for model training (Cachay et al. 2021). The approach produces accuracy scores for each labeling source (in our case labeling function) and trains both a neural encoder and a downstream model at the same time on the same loss by using each other's predicted labels as input. We use the WEASEL implementation of Zhang et al. (2021), train with the default hyperparameters and use RoBERTa as an encoder.

4.2 Data sets

For our experiments we use four standard data sets for weak supervision. In addition to the three binary data sets covered by KNOWMAN (SPAM, SPOUSE, IMDb) we also study one multi class data set (TREC). While SPAM, TREC and IMDb are classification tasks, SPOUSE addresses relation extraction.

4.2.1 SPAM

SNORKEL-DP provides a small subset of the YouTube comments data set (Alberto et al. 2015) where the task is to classify whether a text is relevant to a certain YouTube video or contains spam. Ten different labeling functions are used to assign the classes, mostly based on keywords and regular expressions. In contrast to other datasets, no development set is provided for SPAM, which is not relevant for XPASC but for downstream task training.

4.2.2 TREC

Another text classification data set is TREC which was proposed by (Li and Roth 2002) and addresses question classification. The data set contains automatically retrieved as well as manually constructed questions from six different classes. Multiple classes can be assigned for each instance, but the authors chose to design TREC as a single-class dataset. Therefore, the data set was manually annotated with one class per instance. However, the result of the initial overlapping of classes for each instance is that TREC is difficult to learn. We use the version of the data set provided by Zhang et al. (2021) within the WRENCH framework, containing 68 keyword-based labeling functions which have been generated by Awasthi et al. (2020).

4.2.3 SPOUSE

This data set addresses a binary relation extraction problem and aims to identify the *spouse* relation in text snippets. It has also been created by SNORKEL-DP and is based on the Signal Media One-Million News Articles Data set (Corney et al. 2016). The nine labeling functions use information from a knowledge base, keywords and patterns. One peculiarity of this data set is that it is very skewed, with over 90% of the instances not holding a spouse relation.

4.2.4 IMDb

The largest data set we use is IMDb, which contains movie reviews and is based on the data set from Maas et al. (2011). We use the IMDb version compiled by Sedova et al. (2021). All of the labeling functions used for this data set are occurrences of positive and negative keywords from Hu and Liu (2004). The addressed task for IMDb is binary sentiment analysis, classifying the reviews as either positive or negative. Unlike for the other two data sets, there are 6800 labeling functions for IMDb, which constitutes a particular challenge to the SNORKEL-DP denoising framework.

5. Experiments with XPASC

We present here the setup and findings of our analysis of different models, using XPASC. We evaluated XPASC both quantitatively across all models and with a qualitative feature analysis for KNOWMAN.

5.1 Evaluation settings

Since we want to calculate the correlations in XPASC on a representative amount of data for one data set, we use the train sets for the XPASC computations. Moreover, in a practical weak supervision setting (where XPASC might be used, e.g. for model selection), the existence of labeled development and test sets cannot be assumed, and the XPASC calculation needs to rely on weakly labeled training data only.

When using weak supervision to assign classes with labeling functions it can happen that instances do not have a labeling function match. Especially, for SPAM and SPOUSE many instances lack a labeling function match. Therefore, we filter out those instances with no labeling function matches for all our experiments and arrive with smaller data sets. For IMDb and TREC the number of instances does only change slightly, since there are very few instances without labeling function matches. Fortunately, the already very small SPAM data set does not get much smaller after filtering. For SPOUSE, we observe the greatest difference and only 25% of the original data set remain after filtering. See Table 2 for the data set sizes of the train sets.

In contrast to the results reported in März et al. (2021), we average results across 15 different seeds for SPAM and SPOUSE and across 5 different seeds for TREC to achieve more stable



Figure 3. Evaluation of XPASC across baselines and KNOWMAN models for SPAM. BLIND KNOWMAN is a KNOWMAN model with λ set to 0. KNOWMAN for SPAM means a model trained with λ set to 2.



Figure 5. Evaluation of XPASC across baselines and KNOWMAN models for SPOUSE. BLIND KNOWMAN means a KNOWMAN model with λ set to 0. KNOWMAN for SPOUSE means a model trained with λ set to 0.5.



Figure 4. Evaluation of XPASC across baselines and KNOWMAN models for TREC. BLIND KNOWMAN is a KNOWMAN model with λ set to 0. KNOWMAN for TREC means a model trained with λ set to 0.001.



Figure 6. Evaluation of XPASC across baselines and KNOWMAN models for IMDb. BLIND KNOWMAN means a KNOWMAN model with λ set to 0. KNOWMAN for IMDb means a model trained with λ set to 0.5.

results. Due to the size of IMDb one XPASC run takes three days. To consume less resources, we performed one XPASC run with one seed for this data set only.

In our study of KNOWMAN with XPASC, we experiment with different values of λ . As the hyperparameter λ is intended to control the degree of generalization, this sheds light onto the the functionality of KNOWMAN. Specifically, it is useful for examining the hypothesis whether the model is able to generalize from the labeling functions when tuning λ . Our expectation is that the higher the value chosen for λ , the higher the XPASC result. With the experiments in this paper, we want to confirm that expectation and validate KNOWMAN with XPASC and vice versa. For MAJORITY VOTE, SNORKEL-DP and WEASEL we do not have a presumption of the XPASC result, but assume that the score could be higher than for KNOWMAN because these models have fewer parameters.

5.2 Quantitative evaluation

Our quantitative evaluation includes XPASC results across all models mentioned in section 4.1, as well as the results for different λ values for KNOWMAN. In addition, we evaluated KNOWMAN with XPASC for both association measures, CHI SQUARE and PPMI.

5.2.1 XPASC results across all models

We calculated XPASC with CHI SQUARE-based association for MAJORITY VOTE, SNORKEL-DP, WEASEL and KNOWMAN on all data sets.

The evaluation of SPAM (see Figure 3) shows the highest generalization for WEASEL and the SNORKEL-DP model achieves the second highest XPASC. Generalization scores for MAJORITY VOTE and the KNOWMAN model with the optimal λ value of 2 are similar and slightly worse than for SNORKEL-DP. The generalization of the BLIND KNOWMAN model with the disabled generalization mechanism is in contrast the lowest. The observations are different for the class prediction performance of the models. Here WEASEL and KNOWMAN give the highest, whereas MAJORITY VOTE gives the worst classification accuracy.

For TREC we observe the highest generalization for SNORKEL-DP and WEASEL (see Figure 4). Both achieve low classification numbers, although their performance differs significantly. SNORKEL-DP achieves the lowest results and WEASEL achieves results similar to BLIND KNOWMAN and MAJORITY VOTE. MAJORITY VOTE shows a similar classification performance as KNOWMAN but much higher generalization. The KNOWMAN models achieve the best classification performance, but have the lowest XPASC. Unlike for the other data sets, using KNOWMAN decreases the XPASC value slightly.

The evaluation of SPOUSE (see Figure 5) shows a picture similar to SPAM. Again, SNORKEL-DP achieves the highest XPASC. The scores of both KNOWMAN models are close to the generalization score of the WEASEL model. The difference between BLIND KNOWMAN and KNOWMAN is smaller than in the other data sets. In terms of performance, the models are ranked differently. Both KNOWMAN models perform better than SNORKEL-DP or MAJORITY VOTE. Indeed, the performance of SNORKEL-DP is the lowest, while this model has a high generalization value. The WEASEL model gives unreasonably low results for both, XPASC and F1 score, and like Stephan et al. (2022) we assume that this is due to the fact that they did not integrate large pre-trained language models like RoBERTa in their original work.

For IMDb the results are in agreement with the insights of the other data sets (see Figure 6). Again, SNORKEL-DP gives the highest XPASC and WEASEL the second highest XPASC result. Since BLIND KNOWMAN and KNOWMAN are only different by a λ value of 0.5, their generalization scores are close to each other. Again, MAJORITY VOTE reaches a slightly higher XPASC than the KNOWMAN models. The classification accuracy gives the same ranking as for SPOUSE, except for the WEASEL model, which performs best on the IMDb data set. Both KNOWMAN models perform better than SNORKEL-DP and MAJORITY VOTE, while having smaller XPASC results.

Overall we observe that models without explicit generalization modeling achieve higher XPASC values than KNOWMAN. This can be explained by the fact that these models employ a smaller number of layers, thus are less complex and enable greater generalization more easily. The more complex a model becomes and the more parameters it consists of, the more likely it is to overfit and thus generalization is more difficult to achieve. Another observation that can easily be drawn from the plots is that performance and generalization are not related one-to-one. Indeed, it seems like greater generalization leads to less (over-)fitting, what can also harm performance. The works of Bartlett et al. (2019) and Zhang et al. (2020) show that models that overfit to noisy data still can achieve good performance and that the noise doesn't harm the performance



Figure 7. Chi-square-based XPASC and accuracy for SPAM across different λ values.



Figure 9. Chi-squared-based XPASC and accuracy for TREC across different λ values.



Figure 8. PPMI-based XPASC and accuracy for SPAM across different λ values.



Figure 10. PPMI-based XPASC and accuracy for TREC across different λ values.

as much as expected. Still, Sanyal et al. (2021) claim that overfitting might not harm the performance of a model, but its robustness and that too much overfitting makes a model vulnerable (e.g. to adversarial attacks).

5.2.2 XPASC results across KNOWMAN models

To figure out if the degree of generalization can be controlled via the hyperparameter λ in the KNOWMAN models, we calculate XPASC for different λ values. We calculate both, XPASC CHI SQUARE and XPASC PPMI for SPAM, TREC and SPOUSE. For IMDb we calculate XPASC CHI SQUARE only, to save resources.

Figures 7 and 8 show the results for SPAM. It can be clearly seen that XPASC increases with increasing λ . The performance has its peak when using a λ value of 2.0. Both XPASC curves of the two association options are very similar in their shape, though, we find slightly smaller values for XPASC CHI SQUARE. To compare the two options for calculating association we draw scatter plots that depict the performance and generalization per run and seed (see Figures 14 and 15).





Figure 11. Chi-squared-based XPASC and F1 for SPOUSE across different λ values.

Figure 12. PPMI-based XPASC and accuracy for SPOUSE across different λ values.



Figure 13. Chi-squared-based XPASC and accuracy for IMDb across different λ values.

For the CHI SQUARE option the accuracy and XPASC scores are clustered clearly recognizable for each λ value. For PPMI we observe slightly different results. Especially for lower λ s the distributions are more mixed up. Still, both plots reflect the clustering of XPASC-values according to the chosen λ -values, and the performance trends, nicely.

The results for TREC (see Figures 9, 10) show that KNOWMAN is sensitive to small values of the hyperparameter λ in the multi-class setting. Using smaller λ values (in comparison to binary models) does improve the performance of the TREC model, whereas using greater λ values is less effective. The model with the best classification performance is trained with $\lambda = 0.001$. With regard to XPASC, one can clearly see from the curve that smaller λ values increase the generalization to a lesser extent than larger λ values. Moreover, the trends are less clear and effects are more brittle in this setting.

For SPOUSE, we observe a clear positive correlation of XPASC in relation to larger λ as well (see Figures 11, 12). Unlike for the SPAM and IMDb the curve is not strictly monotonically increasing, however. The scatter plots with the distributions of all results across the 15 runs show that for those λ values that cause the dips in the curve, there are some outliers that cause the lowerings (see Figures 16 and 17). In general SPOUSE appears more challenging and unstable,



Figure 14. XPASC-CHI SQUARE and accuracy results of runs across 15 seeds for SPAM. Different colors indicate different λ values. Numbers in brackets must be multiplied by the subscript value, 10^{-4} .



Figure 16. XPASC-CHI SQUARE and accuracy results of runs across 15 seeds for SPOUSE. Different colors indicate different λ values. Numbers in brackets must be multiplied by the subscript value, 10^{-3} .



Figure 15. XPASC-PPMI and accuracy results of runs across 15 seeds for SPAM. Different colors indicate different λ values. Numbers in brackets must be multiplied by the subscript value, 10^{-3} .



Figure 17. XPASC-PPMI and accuracy results of runs across 15 seeds for SPOUSE. Different colors indicate different λ values. Numbers in brackets must be multiplied by the subscript value, 10^{-4} .

having more outliers for both axes, XPASC and F1 score. In terms of performance, the optimum is reached with a λ value of 0.5 and decreases drastically with λ values being higher than 1.

The XPASC curve for IMDb increases monotonically in relation to λ (see Figure 13). There are no lowerings or peaks in the XPASC curve for this data set. As for SPOUSE, the best performance is reached with $\lambda = 0.5$ and decreases with λ being higher than 1.

Overall, we can conclude that it is possible to control the degree of generalization for the KNOWMAN models by using the respective hyperparameter λ . In addition, the results confirm our assumption that XPASC can reflect the generalization of models. As for the evaluation across all models, it shows that performance and generalization are not the same. The highest performance is not achieved with the greatest degree of generalization.

5.2.3 Magnitude of XPASC

The results show that the values for XPASC are very small. This is a consequence of composition of the formula: On the one hand, the CHI SQUARE and PPMI values are low (often zero or close to zero) already and the final association value (Formula 3) becomes even smaller due to the subtraction. On the other hand, the explainability values come from a probability distribution and therefore range between zero and one. By multiplying these small values, the results become even smaller. To bring the XPASC to a range with higher magnitude values, we experimented with the following normalization steps to calculate a scaled version of XPASC:

• scaling the range of the PPMI values between zero and one by using the normalized pointwise mutual information:

$$NPMI(f,z) = \frac{PMI(f,z)}{h(f,z)}$$
(14)

where the pointwise mutual information in Equation 7 is normalized by h(f, z), with h(f, z) being the joint self-information -log(P(f, z)).

• scaling the explainability score to range between zero and one by normalizing the explainability of feature *f* given instance *i* by the maximum explainability value per instance:

$$S_{xp}(i,f) = \frac{D_{KL}\left(P(i)||Q(i \setminus f)\right)}{max\left(\{\forall f' \in i \mid D_{KL}\left(P(i)||Q(i \setminus f')\right)\}\right)}$$
(15)

where P(i) is the model prediction for the entire instance and $Q(i \setminus f)$ or $Q(i \setminus f')$ is the model prediction for the instance with feature f or f' omitted.

• scaling the distribution of both, explainability and association, to range between zero and one each by using MinMax scaling:

$$X_{std} = \frac{(X - X.min)}{(X.max - X.min)}$$
(16)

$$X_{scaled} = X_{std} \times (max - min) + min)$$
(17)

where X is the array of all values (explainability or association) and min/max indicate the minimum/maximum value of the array.

This results in larger XPASC values, but normalizing and scaling the values can discard useful information. To investigate if there is an information loss due to the normalizing of the score, we compute another scatter plot that depicts the performance and generalization per run and seed for SPAM after applying the above mentioned steps to XPASC (see Figure 18). As one can clearly see, the individual characteristics are no longer as distinctly recognizable in the normalized version of XPASC (right plot) as they had been before (left plot). While the values for the individual KNOWMAN models used to be clearly separated from each other, the normalization has mixed them up. We conclude that important information is lost due to the normalization of the values. For this reason we accept the small values of the original formula in order to be able to optimally represent all information.



Figure 18. Original and **normalized** XPASC-CHI SQUARE and accuracy results of runs across 15 seeds for SPAM. Different colors indicate different λ values. Numbers in brackets must be multiplied by the subscript value, 10^{-4} .

5.3 Qualitative Feature Analysis

To confirm the functionality of XPASC qualitatively we took a close look at the data and their linguistic features to find instances that illustrate XPASC and its components.

First, we examined the association matrices to verify that they reflect the actual association of features, classes and labeling functions. See Tables 3 and 4 for the top five association values (for both CHI SQUARE and PPMI) of labeling functions and features for SPAM and SPOUSE. Because of the larger number of labeling functions we did not conduct this analysis for TREC and IMDb.

With regard to the CHI SQUARE-based association, the association between the labeling functions and the features can be understood easily. Many of the features most associated with their labeling function would also be considered very relevant by a human. In some cases, the features are even part of the pattern of the labeling function. For the PPMI-based association the top features contain parts of the patterns only rarely. Note, that PPMI is very sensitive to features that occur only once. These features obtain very high PPMI-based association scores because they are observed exclusively with a single class or labeling function. However, since these features all have a low frequency (occur only once), this is not a problem for the calculation of XPASC. Still, one can find words that are part of common expressions together with the keyword of the labeling function, e.g. "ALBUM" is associated with "my". For SPOUSE one can find a lot of names among the PPMI-based association. To figure out if persons are married it is plausible that persons names are considered a lot.

The association of features with the classes is not as intuitive as for the labeling functions. For CHI SQUARE-based association the top ten features are identical for the classes for SPAM and almost identical for SPOUSE. Note that the CHI SQUARE-association only expresses which features were particularly relevant for determining the class. However, the correlation of these features with the class can be both positive (the feature is strongly associated because it gives a clue to the correct class) and negative (the feature is strongly associated because it gives a clue to distinguish it from other classes). The association with each class for the TREC data set is more intuitive in some cases. Words like "odor" or "malawi" are associated with the class "human being", "cpr" or "p.m." with "abbreviation", what is plausible. On the other hand words like "make up" are associated with "location". Since only one gold class could be chosen by the annotators

labeling function	class	CHI SQUARE	PPMI
keyword "my"	SPAM	my, channel, Hey, MY, probably	Cyphers, ALBUM, TOMORROW, READING, tvcmcadavid.weebly
keyword "subscribe"	SPAM	me, subscribe, to, subscribers, subscribe	Del, Rey, Drake, Macklemore, Pink
link	SPAM	V, STYLE, fight, 'http://youtu.be/9bZkp7q19f0'	scrubs, ./r, MontageParodies, AND, OTHER
keyword "Please"	SPAM	plz, please, Please, PLEASE, school	-, †, , PLZZ, supporters
keyword "song"	HAM	song, This, songs, fun, Best	spare, upcoming, uk, rapper.please, worries
regex "Check out"	SPAM	out, this, on, Check, video	act, retain, delightful, system, rhythm
short comment	HAM	out, this, on, _, and	BR, sparkling-heart emoji, won- derful, LOST?, heart emoji
has person	HAM	Katy, Perry, Official, Charlie, Eminem	belle, chanson, lost?, clean, Eminem
polarity > 0.9	HAM	best, photo, Oppa, Yeah, Best	MOVES, MAKES, MEH, SMILE, EVER
subjectivity >= 0.5	HAM	only, views, YouTube:, love, out	Driveshaft, YEAH, Crazy, Flow, Ill

Table 3. Top 5 labeling function related features SPAM.

 Table 4. Top 5 labeling function related features for SPOUSE.

labeling function	class	CHI SQUARE	РРМІ
keyword "husband/wife"	SPOUSE	married, son, wife, husband, boyfriend	Peck, Veronique, glitters, Sweeting's, Body
keyword "husband/wife" left window	SPOUSE	written, wife, husband, con- spiring, tunnel	Guys, Running, Role, wres- tle, Off
same last name	SPOUSE	son, wife, husband, after- noon, daughter	Dudley, Hales, facilitating, Thomson, M&F
keyword "married"	SPOUSE	married, relationship, 2007., who, trainer	wakes, Gordon-Levitt, row- ing, Regardless, minorities
familiar relationship	NO SPOUSE	son, wife, husband, sister, daughter	Fire, window, forcing, ribs, Claims
familiar relationship left win- dow	NO SPOUSE	on, husband, half-brother, daughter, mother	hopelessness, hairdresser, sponsoring, Tailyour, Commandant
regex other relationship	NO SPOUSE	husband, boyfriend, planted, Gamble, David	Rita, Ora, Grimshaw, Zeinat, ordinary
known spouses from database	SPOUSE	Martin, denim, afternoon, Gwyneth, Paltrow	lacing, Amicable, exes, shifts, Basinger
last name known spouses	SPOUSE	Mara, mirror, tank, Paltrow, beauties	reported, Radar, spousal, gro- cery, head-on

Table 5. Top 10 class related features.

data set	class	Chi Square	PPMI	
SDAM	SPAM	subscribe, please, check, out, my, channel, song, Please, on, Check	beat, losing, ideas, lies, his- tory, Driveshaft, YEAH, hot, Beats!!, STTUUPID	
STAM	НАМ	subscribe, please, check, out, my, will, channel, song, Please, on	Drake, Macklemore, Pink, countless, inspire, FYI, free- dom, speech, Lil, uploaded	
TREC	description	cleaveland, cavaliers, monar- chy, added, quisling, reposse- sion, butcher, handful, spine, currency	per, chicken, dog, capital, university, black, island, san, south, west	
	entity	sailed, talk-show, lends, surroundings, thalia, shake- spearean, shylock, airforce, compiled, won-lost	leader, animals, words, father, christmas, held, nicknae, law, only, john	
	human being	builds, resistance, odor, auh2o, mccain, rifleman, lai, malawi, zebulon, pike	god, square, mile, gas, strip court, basketball, nationality rock,month	
	abbreviation	olympic, original, commit- tee, aids, manufacturer, cpr, abbreviation, p.m., trinitro- toluene, equipment	monarchy, added, quisling, puerto, rico, repossession, butcher, handful, spine, 's	
	location	aborigines, adventours, tours, photosynthesis, makeup, erykah, badu, m, ayer, bend	said, so, letter, kennedy, bridge, human, nixon, no, river, his	
	numeric value	56-game, streak, graffiti, quilting, iran-contra, deere, tractors, cherubs, puerto, rico	square, strip, court, jackson, basketball, numbers, univer- sity, john, show	
SPOUSE	SPOUSE	married, son, wife, husband, boyfriend,, young, family, sister, daughter	ringing, Sweeting's, Body, Cutting, Crap, Australians, marches, splashes, Kingi	
	NO SPOUSE	married, son, wife, husband, boyfriend,, young, family, younger, sister	ordinary, rank-and-file, handpicked, Abu, Bakr, al-Baghdadi, L.L., J.'s, trendy	
IMDB	negative	Instead, back, character, too, much, does, entire, cast, So, bizarre	Zwarts, Fredrikstad, Hilarios!10, wawa, CONSIDERING, Hobb's, Smooch, Investigative, belly-dancers, retirony	
	positive	writing, It's, most, drag, you, us, won, Oscar, those, endless	Culpability, Package, slip- ups, AARP, Symona, Boniface, Lorch, Lynton, Tyrrell, Heinie	

model	instance	class		
BlindKnowMAN	The daughter of Kate's father and second wife Inger, Kate and Lottie have grown up with a close bond, often accompanying each other to parties and fashion events.	spouse		
KnowMAN	The daughter of Kate's father and second wife Inger, Kate and Lottie have grown up with a close bond, often accompanying each other to parties and fashion events.	spouse		
BlindKnowMAN	thought this was a quiet good movie. It was fun positive to watch it. What I liked best where the 'Outtakes' at the end of the movie. They were GREAT.	positive		
KnowMAN	thought this was a quiet good movie. It was fun positive to watch it. What I liked best where the 'Outtakes' at the end of the movie. They were GREAT .	positive		
labeling function association class association most important feature				

Figure 19. Examples from SPOUSE and IMDb where the feature with the highest explainability is shifted from a misleading labeling function towards the correct class. Association is based on CHI SQUARE and KNOWMAN uses $\lambda = 4$.

during the labeling of the data set, it is likely that some words would also be suitable for another class that had been in the set of suitable classes associated with the instance. For IMDb the features are different for both classes and very intuitive for a human. Features like "bizarre" or "Oscar" clearly point to a certain sentiment.

For PPMI-based association the top ten features are different for all data sets. Again this ranking is not easily interpretable for a human, but reflects the association and co-occurrence in the weakly supervised data sets. Because of the sensitivity to rare words, we found many features with the same association score, and the top n features in Table 5 are therefore only an excerpt.

Next, we looked for instances that confirm the functionality of XPASC and KNOWMAN. Therefore, we compared BLIND KNOWMAN and KNOWMAN with $\lambda = 4$. The ultimate and most challenging requirement for the models would be the following: Shift the focus from features that are associated with a deceptive labeling function towards features that are associated with the correct class. Two kinds of information need to be found for that goal: i) a feature that is very important for the classification (has a very high explainability score) and is associated most with a misleading labeling function, pointing to the wrong class, in BLIND KNOWMAN and ii) the KNOWMAN model is able to shift the highest explainability to a feature that is not associated with the misleading labeling function anymore, but with the correct class. Thus in the KNOWMAN model the most important feature should be associated with the correct class most. For example in Figure 19 the first instance should be classified as holding a *spouse* relation. The most important feature for BLIND KNOWMAN is father, what actually would lead to the classification of no spouse. The KNOWMAN model achieves the shift to the feature wife, that is a better indicator for the spouse relation. The second example in Figure 19 is drawn from IMDb. The review is *positive* and the feature 'I' is associated with the negative class. KNOWMAN manages to shift the focus to the feature 'GREAT', what is a better indicator for a positive sentiment.

We also measured this shift of the most important feature quantitatively. For SPAM, we found a shift is achieved for 12 instances and for SPOUSE 267 instances (both on average across seeds).

model	instance	class	
BlindKnowMAN	Front row: Kim Kardashian was seen with daughter North on her lap as she sat next to Vogue editor Anna Wintour at Kanye West's Yeezy Season Two show for New York Fashion Week on Wednesday. Pretty but pouty: North stole the show as she sat on her mother's lap.	no spouse	
KnowMAN	Front row: Kim Kardashian was seen with daughter North on her lap as she <u>sat next</u> to Vogue editor Anna Wintour at husband Kanye West's Yeezy Season Two show for New York Fashion Week on Wednesday. Pretty but <u>pouty</u> : North stole the show as she sat on her mother's lap.	no spouse	
BlindKnowMAN	subscribed :) btw(you) have a good style keep it up brother :))	НАМ	
KnowMAN	subscribed :) btw(you)have a good style keep it up brother :))	НАМ	
class association most important feature			

Figure 20. Examples from SPAM and SPOUSE. Highest explainability is shifted from features that are associated with the labeling function to other features. Association is based on CHI SQUARE and KNOWMAN uses $\lambda = 4$.

For IMDb the model manages to shift the misleading feature to the correct one for 7 instances. This comparison always refers to BLIND KNOWMAN and KNOWMAN with $\lambda = 4$.

A better generalization can also be achieved if the focus is shifted from the misleading feature to another feature that is not associated with the correct class, but at least is no longer associated with the labeling function. See Figure 20 for examples that illustrate this. The first example, again from SPOUSE, expresses a *no spouse* relation, but the most important feature for BLIND KNOWMAN is **husband**. Shifting the focus to another word - **pouty** - KNOWMAN is able to assign the correct label. The second example is comes from SPAM, where BLIND KNOWMAN considers the most important feature as **subscribed** for an instance that actual belongs to the *HAM* class. Since this is misleading, KNOWMAN focuses on the emoticon in the instance and assigns the correct label.

In addition, we noticed in the linguistic feature-based analysis that the weak labels for SPOUSE are very noisy and imprecise. We found many instances where a human annotator would have assigned another class than the labeling functions assigned.

Overall, the quantitative results can confirm our findings of the qualitative analysis. The KNOWMAN architecture is able to increase generalization and XPASC is a good indicator for the generalization ability of models.

6. Conclusion

We presented XPASC, a novel score to measure generalization for weakly supervised models. Our extensive analysis shows that XPASC is able to reflect the generalization of models given a dataset and the labeling functions used to perform weak supervision. In addition, we studied the adversarial approach KNOWMAN, designed to enable the control of generalization in weakly supervised models. We confirmed the hypothesis that the architecture is able to control the shift from labeling functions to other signals by a hyperparameter. We also showed that performance and generalization do not relate one-to-one and it has to be decided based on the task, dataset and model, which degree of generalization is desired. XPASC can be used with any pre-trained weakly supervised model, a dataset and its set of applied labeling functions. Assuming that many neural models, designed to work with noisy weakly supervised data, are complex and thus suffer from overfitting, XPASC can serve as an indicator for their ability to fit unseen data. In general the core components of XPASC, explainability and association, are interchangeable, what makes the score flexible in practice.

Competing interests declaration

Competing interests: The authors declare none.

Acknowledgements

This research was funded by the WWTF through the project "Knowledge-infused Deep Learning for Natural Language Processing" (WWTF Vienna Research Group VRG19-008).

References

- Alberto, T. C., Lochter, J. V., and Almeida, T. A. 2015. Tubespam: Comment spam filtering on youtube. In Li, T., Kurgan, L. A., Palade, V., Goebel, R., Holzinger, A., Verspoor, K., and Wani, M. A., editors, 14th IEEE International Conference on Machine Learning and Applications, ICMLA 2015, Miami, FL, USA, December 9-11, 2015, pp. 138–143. IEEE.
- Ancona, M., Ceolini, E., Öztireli, C., and Gross, M. 2018. Towards better understanding of gradient-based attribution methods for deep neural networks. In 6th International Conference on Learning Representations, ICLR 2018, Vancouver, BC, Canada, April 30 - May 3, 2018, Conference Track Proceedings. OpenReview.net.
- Awasthi, A., Ghosh, S., Goyal, R., and Sarawagi, S. 2020. Learning from rules generalizing labeled exemplars. In 8th International Conference on Learning Representations, ICLR 2020, Addis Ababa, Ethiopia, April 26-30, 2020. OpenReview.net.
- Bartlett, P. L., Long, P. M., Lugosi, G., and Tsigler, A. 2019. Benign overfitting in linear regression. CoRR, abs/1906.11300.
- Cachay, S. R., Boecking, B., and Dubrawski, A. 2021. End-to-end weak supervision. In Ranzato, M., Beygelzimer, A., Dauphin, Y. N., Liang, P., and Vaughan, J. W., editors, Advances in Neural Information Processing Systems 34: Annual Conference on Neural Information Processing Systems 2021, NeurIPS 2021, December 6-14, 2021, virtual, pp. 1845–1857.
- Corney, D. P. A., Albakour, D., Martinez-Alvarez, M., and Moussa, S. 2016. What do a million news articles look like? In Martinez-Alvarez, M., Kruschwitz, U., Kazai, G., Hopfgartner, F., Corney, D. P. A., Campos, R., and Albakour, D., editors, Proceedings of the First International Workshop on Recent Trends in News Information Retrieval co-located with 38th European Conference on Information Retrieval (ECIR 2016), Padua, Italy, March 20, 2016, volume 1568 of CEUR Workshop Proceedings, pp. 42–47. CEUR-WS.org.
- Dehghani, M., Severyn, A., Rothe, S., and Kamps, J. 2017. Avoiding your teacher's mistakes: Training neural networks with controlled weak supervision. *CoRR*, abs/1711.00313.
- Devlin, J., Chang, M., Lee, K., and Toutanova, K. 2019. BERT: pre-training of deep bidirectional transformers for language understanding. In Burstein, J., Doran, C., and Solorio, T., editors, Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT 2019, Minneapolis, MN, USA, June 2-7, 2019, Volume 1 (Long and Short Papers), pp. 4171–4186. Association for Computational Linguistics.
- Fu, D. Y., Chen, M. F., Sala, F., Hooper, S. M., Fatahalian, K., and Ré, C. 2020. Fast and three-rious: Speeding up weak supervision with triplet methods. In *Proceedings of the 37th International Conference on Machine Learning, ICML 2020,* 13-18 July 2020, Virtual Event, volume 119 of Proceedings of Machine Learning Research, pp. 3280–3291. PMLR.
- Harbecke, D. and Alt, C. 2020. Considering likelihood in NLP classification explanations with occlusion and language modeling. In Rijhwani, S., Liu, J., Wang, Y., and Dror, R., editors, Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics: Student Research Workshop, ACL 2020, Online, July 5-10, 2020, pp. 111–117. Association for Computational Linguistics.
- Hsieh, C., Zhang, J., and Ratner, A. 2022. Nemo: Guiding and contextualizing weak supervision for interactive data programming. *CoRR*, abs/2203.01382.
- Hu, M. and Liu, B. 2004. Mining and summarizing customer reviews. In Kim, W., Kohavi, R., Gehrke, J., and DuMouchel,

W., editors, Proceedings of the Tenth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, Seattle, Washington, USA, August 22-25, 2004, pp. 168–177. ACM.

- Kullback, S. and Leibler, R. A. 1951. On information and sufficiency. The annals of mathematical statistics, 22(1):79-86.
- Li, H., Li, J., Guan, X., Liang, B., Lai, Y., and Luo, X. 2019. Research on overfitting of deep learning. In 15th International Conference on Computational Intelligence and Security, CIS 2019, Macao, SAR, China, December 13-16, 2019, pp. 78–81. IEEE.
- Li, X. and Roth, D. 2002. Learning question classifiers. In 19th International Conference on Computational Linguistics, COLING 2002, Howard International House and Academia Sinica, Taipei, Taiwan, August 24 - September 1, 2002.
- Liu, Y., Ott, M., Goyal, N., Du, J., Joshi, M., Chen, D., Levy, O., Lewis, M., Zettlemoyer, L., and Stoyanov, V. 2019. Roberta: A robustly optimized BERT pretraining approach. *CoRR*, abs/1907.11692.
- Maas, A. L., Daly, R. E., Pham, P. T., Huang, D., Ng, A. Y., and Potts, C. 2011. Learning word vectors for sentiment analysis. In Lin, D., Matsumoto, Y., and Mihalcea, R., editors, *The 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies, Proceedings of the Conference, 19-24 June, 2011, Portland, Oregon, USA*, pp. 142–150. The Association for Computer Linguistics.
- März, L., Asgari, E., Braune, F., Zimmermann, F., and Roth, B. 2021. Knowman: Weakly supervised multinomial adversarial networks. In Moens, M., Huang, X., Specia, L., and Yih, S. W., editors, Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing, EMNLP 2021, Virtual Event / Punta Cana, Dominican Republic, 7-11 November, 2021, pp. 9549–9557. Association for Computational Linguistics.
- Mauri, M., Gili, K., and Perdomo-Ortiz, A. 2022. Evaluating generalization in classical and quantum generative machine learning models: Part i. *Bulletin of the American Physical Society*.
- Power, A., Burda, Y., Edwards, H., Babuschkin, I., and Misra, V. 2022. Grokking: Generalization beyond overfitting on small algorithmic datasets. *CoRR*, abs/2201.02177.
- Ratner, A., Bach, S. H., Ehrenberg, H. R., Fries, J. A., Wu, S., and Ré, C. 2020. Snorkel: rapid training data creation with weak supervision. *VLDB J.*, 29(2-3):709–730.
- Ratner, A., Hancock, B., Dunnmon, J., Sala, F., Pandey, S., and Ré, C. 2019. Training complex models with multi-task weak supervision. In *The Thirty-Third AAAI Conference on Artificial Intelligence, AAAI 2019, The Thirty-First Innovative Applications of Artificial Intelligence Conference, IAAI 2019, The Ninth AAAI Symposium on Educational Advances in Artificial Intelligence, EAAI 2019, Honolulu, Hawaii, USA, January 27 - February 1, 2019*, pp. 4763–4771. AAAI Press.
- Ratner, A. J., Sa, C. D., Wu, S., Selsam, D., and Ré, C. 2016. Data programming: Creating large training sets, quickly. In Lee, D. D., Sugiyama, M., von Luxburg, U., Guyon, I., and Garnett, R., editors, Advances in Neural Information Processing Systems 29: Annual Conference on Neural Information Processing Systems 2016, December 5-10, 2016, Barcelona, Spain, pp. 3567–3575.
- Ren, W., Li, Y., Su, H., Kartchner, D., Mitchell, C. S., and Zhang, C. 2020. Denoising multi-source weak supervision for neural text classification. In Cohn, T., He, Y., and Liu, Y., editors, *Findings of the Association for Computational Linguistics: EMNLP 2020, Online Event, 16-20 November 2020*, volume EMNLP 2020 of *Findings of ACL*, pp. 3739– 3754. Association for Computational Linguistics.
- Robinson, J., Jegelka, S., and Sra, S. 2020. Strength from weakness: Fast learning using weak supervision. In Proceedings of the 37th International Conference on Machine Learning, ICML 2020, 13-18 July 2020, Virtual Event, volume 119 of Proceedings of Machine Learning Research, pp. 8127–8136. PMLR.
- Roelofs, R., Shankar, V., Recht, B., Fridovich-Keil, S., Hardt, M., Miller, J., and Schmidt, L. 2019. A meta-analysis of overfitting in machine learning. In Wallach, H. M., Larochelle, H., Beygelzimer, A., d'Alché-Buc, F., Fox, E. B., and Garnett, R., editors, Advances in Neural Information Processing Systems 32: Annual Conference on Neural Information Processing Systems 2019, NeurIPS 2019, December 8-14, 2019, Vancouver, BC, Canada, pp. 9175–9185.
- Salman, S. and Liu, X. 2019. Overfitting mechanism and avoidance in deep neural networks. CoRR, abs/1901.06566.
- Sanh, V., Debut, L., Chaumond, J., and Wolf, T. 2019. Distilbert, a distilled version of BERT: smaller, faster, cheaper and lighter. CoRR, abs/1910.01108.
- Sanyal, A., Dokania, P. K., Kanade, V., and Torr, P. H. S. 2021. How benign is benign overfitting ? In 9th International Conference on Learning Representations, ICLR 2021, Virtual Event, Austria, May 3-7, 2021. OpenReview.net.
- Sedova, A., Stephan, A., Speranskaya, M., and Roth, B. 2021. Knodle: Modular weakly supervised learning with pytorch. In Rogers, A., Calixto, I., Vulic, I., Saphra, N., Kassner, N., Camburu, O., Bansal, T., and Shwartz, V., editors, *Proceedings of the 6th Workshop on Representation Learning for NLP, RepL4NLP@ACL-IJCNLP 2021, Online, August* 6, 2021, pp. 100–111. Association for Computational Linguistics.
- Stephan, A., Kougia, V., and Roth, B. 2022. SeplI: Separating latent class labels from weak supervision noise. CoRR, abs/2210.13898.
- Sukhbaatar, S., Bruna, J., Paluri, M., Bourdev, L. D., and Fergus, R. 2014. Training convolutional networks with noisy labels. arXiv: Computer Vision and Pattern Recognition.
- Wolf, T., Debut, L., Sanh, V., Chaumond, J., Delangue, C., Moi, A., Cistac, P., Rault, T., Louf, R., Funtowicz, M., and Brew, J. 2019. Huggingface's transformers: State-of-the-art natural language processing. *CoRR*, abs/1910.03771.
- Yu, Y., Zuo, S., Jiang, H., Ren, W., Zhao, T., and Zhang, C. 2021. Fine-tuning pre-trained language model with

weak supervision: A contrastive-regularized self-training approach. In **Toutanova, K., Rumshisky, A., Zettlemoyer, L., Hakkani-Tür, D., Beltagy, I., Bethard, S., Cotterell, R., Chakraborty, T., and Zhou, Y.**, editors, *Proceedings of the* 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT 2021, Online, June 6-11, 2021, pp. 1063–1077. Association for Computational Linguistics.

- Zeiler, M. D. and Fergus, R. 2014. Visualizing and understanding convolutional networks. In Fleet, D. J., Pajdla, T., Schiele, B., and Tuytelaars, T., editors, Computer Vision - ECCV 2014 - 13th European Conference, Zurich, Switzerland, September 6-12, 2014, Proceedings, Part I, volume 8689 of Lecture Notes in Computer Science, pp. 818–833. Springer.
- Zhang, J., Hsieh, C., Yu, Y., Zhang, C., and Ratner, A. 2022a. A survey on programmatic weak supervision. *CoRR*, abs/2202.05433.
- Zhang, J., Wang, H., Hsieh, C., and Ratner, A. 2022b. Understanding programmatic weak supervision via source-aware influence function. CoRR, abs/2205.12879.
- Zhang, J., Yu, Y., NameError, Wang, Y., Yang, Y., Yang, M., and Ratner, A. 2021. WRENCH: A comprehensive benchmark for weak supervision. In Vanschoren, J. and Yeung, S., editors, Proceedings of the Neural Information Processing Systems Track on Datasets and Benchmarks 1, NeurIPS Datasets and Benchmarks 2021, December 2021, virtual.
- Zhang, M., Fujinuma, Y., Paul, M. J., and Boyd-Graber, J. L. 2020. Why overfitting isn't always bad: Retrofitting crosslingual word embeddings to dictionaries. In Jurafsky, D., Chai, J., Schluter, N., and Tetreault, J. R., editors, Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, ACL 2020, Online, July 5-10, 2020, pp. 2214–2220. Association for Computational Linguistics.