WeaNF: Weak Supervision with Normalizing Flows

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Abstract

A popular approach to decrease the need for costly manual annotation of large data sets is weak supervision, which introduces problems of noisy labels, coverage and bias. Methods for overcoming these problems have either relied on discriminative models, trained with cost functions specific to weak supervision, and more recently, generative models, trying to model the output of the automatic annotation process. In this work, we explore a novel direction of generative modeling for weak supervision: Instead of modeling the output of the annotation process (the labeling function matches), we generatively model the input-side data distributions (the feature space) covered by labeling functions. Specifically, we estimate a density for each weak labeling source, or labeling function, by using normalizing flows. An integral part of our method is the flow-based modeling of multiple simultaneously matching labeling functions, and therefore phenomena such as labeling function overlap and correlations are captured. We analyze the effectiveness and modeling capabilities on various commonly used weak supervision data sets, and show that weakly supervised normalizing flows compare favorably to standard weak supervision baselines.

1 Introduction

Currently an important portion of research in natural language processing is devoted to the goal of reducing or getting rid of large labeled datasets. Recent examples include language model fine-tuning (Devlin et al., 2019), transfer learning (Zoph et al., 2016) or few-shot learning (Brown et al., 2020). Another common approach is weakly supervised learning. The idea is to make use of human intuitions or already acquired human knowledge to create weak labels. Examples of such sources are keyword lists, regular expressions, heuristics or independently existing curated data sources, e.g. a movie database if the task is concerned with TV shows. While the resulting labels are noisy, they provide a quick and easy way to create large labeled datasets. In the following, we use the term labeling functions, introduced in Ratner et al. (2017), to describe functions which create weak labels based on the notions above.

Throughout the weak supervision literature generative modeling ideas are found (Takamatsu et al., 2012; Alfonseca et al., 2012; Ratner et al., 2017). Probably the most popular example of a system using generative modeling in weak supervision is the data programming paradigm of Snorkel (Ratner et al., 2017). It uses correlations within labeling functions to learn a graph capturing dependencies between labeling functions and true labels.

However, such an approach does not directly model biases of weak supervision reflected in the feature space. In order to directly model the relevant aspects in the feature space of a weakly supervised dataset, we investigate the use of density estimation using normalizing flows. More specifically, in this work, we model probability distributions over the input space induced by *labeling functions*, and combine those distributions for better weakly supervised prediction.

We propose and examine four novel models for weakly supervised learning based on normalizing flows (**WeaNF-***): Firstly, we introduce a **standard** model **WeaNF-S**, where each labeling function is represented by a multivariate normal distribution, and its **iterative** variant **WeaNF-I**. Furthermore **WeaNF-N** additionally learns the **negative** space, i.e. a density for the space where the labeling function does not match, and a **mixed** model, **WeaNF-M**, where correlations of sets of labeling functions are represented by the normalizing flow. As a consequence, the classification task is a two step procedure. The first step estimates the densities, and the second step aggregates them to model label prediction. Multiple alternatives are discussed and analyzed.

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We benchmark our approach on several commonly used weak supervision datasets. The results highlight that our proposed generative approach is competitive with standard weak supervision methods. Additionally the results show that smart aggregation schemes prove beneficial.

In summary, our contributions are i) the development of multiple models based on normalizing flows for weak supervision combined with density aggregation schemes, ii) a quantitative and qualitative analysis highlighting opportunities and problems and iii) an implementation of the method[1]. To the best of our knowledge we are the first to use normalizing flows to generatively model labeling functions.

2 Background and Related Work

We split this analysis into a weak supervision and a normalizing flow section as we build upon these two areas.

Weak supervision. A fundamental problem in machine learning is the need for massive amounts of manually labeled data. Among others, weak supervision provides a way to counter the problem. The idea is to use human knowledge to produce noisy, so called weak labels. Typically, keywords, heuristics or knowledge from external data sources is used. The latter is called distant supervision (Craven and Kumlien, 1999; Mintz et al., 2009). In Ratner et al. (2017), data programming is introduced, a paradigm to create and work with weak supervision sources programmatically. The goal is to learn the relation between weak labels and the true unknown labels (Ratner et al., 2017; Varma et al., 2019; Bach et al., 2017; Chatterjee et al., 2019). In Ren et al. (2020) the authors use iterative modeling for weak supervision. Software packages such as SPEAR (?), WRENCH (?) and Knodle (Sedova et al., 2021) allow a modular use and comparison of weak supervision methods. A recent trend is to use additional information to support the learning process. Chatterjee et al. (2019) allow labeling functions to assign a score to the weak label. In Ratner et al. (2018) the human provided class balance is used. Additionally Awasthi et al. (2020); Karamanolakis et al. (2021) use semi-supervised methods for weak supervision, where the idea is to use a small amount of labeled data to steer the learning process.

[1] `https://github.com/AndSt/wea_nf`

Normalizing flows. While the concept of normalizing flows is much older, Rezende and Mohamed (2016) introduced the concept to deep learning. In comparison to other generative neural networks, such as Generative Adversarial networks (Goodfellow et al., 2014) or Variational Autoencoders (Kingma and Welling, 2014), normalizing flows provide a tractable way to model high-dimensional distributions. So far, normalizing received rather little attention in the natural language processing community. Still, Tran et al. (2019) and Ziegler and Rush (2019) applied them successfully to language modeling. An excellent overview over recent normalizing flow research is given in Papamakarios et al. (2021). Normalizing flows are based on the change of variable formula, which uses a bijective function $g : Z \to X$ to transform a base distribution Z into a target distribution X:

$$p_X(x) = p_Z(z) \left| \det \left(\frac{\partial g(z)}{\partial z^T} \right) \right|^{-1}$$

where Z is typically a simple distribution, e.g. multivariate normal distribution, and X is a complicated data generating distribution. Typically, a neural network learns a function $f : X \to Z$ by minimizing the KL-divergence between the data generating distribution and the simple base distribution. As described in Papamakarios et al. (2021) this is achieved by minimizing negative log likelihood

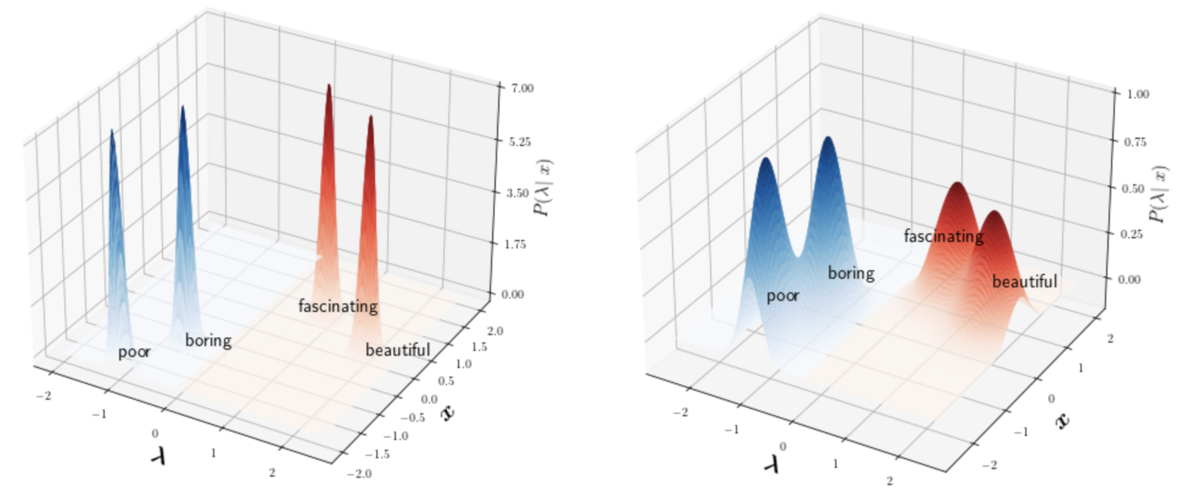
$$\log p_X(x) = \log p_Z(f(x)) + \log \left| \det \left(\frac{\partial f(x)}{\partial x^T} \right) \right|$$

The tricky part is to design efficient architectures which are invertible and provide an easy and efficient way to compute the determinant. The composition of bijective functions is again bijective which enables deep architectures $f = f_1 \circ \cdots \circ f_n$. Recent research focuses on the creation of more expressive transformation modules (Lu et al., 2021). In this work, we make use of an early, but well established model, called RealNVP (Dinh et al., 2017). In each layer, the input x is split in half and transformed according to

$$y_{1:d} = x_{1:d} \tag{1}$$

$$y_{d+1:D} = x_{d+1:D} \odot \exp\left(s(x_{1:d})\right) + t\left(x_{1:d}\right) \tag{2}$$

where $\odot$ is the pointwise multiplication and s and t neural networks. Using this formulation to realize



(a) Schematic view of the densities estimated by **WeaNF-S/I**. The concatenated input $[\boldsymbol{x}; \boldsymbol{\lambda}]$ is fed into the flow to learn the probability $P(x|\lambda)$. The graph shows the posterior $P(\lambda|x)$.

(b) **WeaNF-N** and **WeaNF-M** aim to smoothen the probability space, aiming to generalize more robustly to instances not directly matched by labeling functions.

Figure 1: Schematic overview of **WeaNF-***. The $X-$axis represents the labeling function embedding $\boldsymbol{\lambda}$, the $Y-$axis the text input $\boldsymbol{x}$. The $Z-$axis represents the learned density related to a labeling function. In this example we use the task sentiment analysis and keyword search as labeling functions. Blue denotes a negative sentiment and red a positive sentiment.

a layer f_i, it is easy and efficient to compute the inverse and the determinant.

Normalizing flows were used for semi-supervised classification (Izmailov et al., 2019; Atanov et al., 2020) but not for weakly supervised learning, which we introduce in the next chapter.

3 Model Description

In this section the models are introduced. The following example motivates the idea. Consider the sentence s, "The movie was fascinating, even though the graphics were poor, maybe due to a low budget.", the task sentiment analysis and labeling functions given by the keywords "fascinating" and "poor". Furthermore, "fascinating" is associated with the class POS, and "poor" with the class NEG. We aim to learn a neural network, which translates the complex object, text and a possible labeling function match, to a density, in the current example $P(s|\text{fascinating})$ and $P(s|\text{poor})$. We combine this information using basic probability calculus to make a classification prediction.

Multiple models are introduced. The standard model *WeaNF-S* naively learns to represent each labeling function as a multivariate normal distribution. In order to make use of unlabeled data, i.e. data where no labeling function matches, we iteratively apply the standard model *(WeaNF-I)*. Based on the observation that labeling functions overlap, we derive *WeaNF-N* modeling the negative space, i.e. the space where the labeling function does not match and the mixed model, *WeaNF-M*, using a common space for single labeling functions and the intersection of these. Furthermore, multiple aggregation schemes are used to combine the learned labeling function densities. See table 1 for an overview.

Before we dive into details, we introduce some notation. From the set of all possible inputs $\mathcal{X}$, e.g. texts, we denote an input sample by x and its corresponding vector representation by $\boldsymbol{x}$. The set of t labeling functions is $T = \{\lambda_1, \ldots, \lambda_t\}$ and the classes are $Y = \{y_1, \ldots, y_c\}$. Each labeling function $\lambda : \mathcal{X} \rightarrow \emptyset \cup \{y\}$ maps the input to a specific class $y \in Y$ or abstains from labeling. In some of our models, we also associate an embedding with each labeling function, which we denote by $\boldsymbol{\lambda} \in \mathbb{R}^h$. The set of labeling functions corresponding to label y is T_y.

WeaNF-S/I. The goal of the standard model is to learn a distribution $P(x|\lambda)$ for each labeling function λ. Similarly to Atanov et al. (2020) in semi-supervised learning, we use a randomly initialized embedding $\boldsymbol{\lambda} \in \mathbb{R}^h$ to create a representation for each labeling function in the input space. We concatenate input and labeling function vector and provide it as input to the normalizing flow, thus

	$P(y\|x) \propto$	WeaNF-S/I	WeaNF-N	WeaNF-M
Maximum	$\max_{\lambda \in T_y} P_\theta(x\|\lambda)$	$\surd$		$\surd$
Union	$\sum_{\lambda \in T_y} P(\lambda\|x)$		$\surd$	
NoisyOr	$1 - \prod_{\lambda \in T_y} (1 - P(\lambda\|x))$		$\surd$	
Simplex	$P\left(\left[\boldsymbol{x}; \frac{1}{\|T_y\|} \sum_{\lambda \in T_y} \boldsymbol{\lambda}\right]\right)$			$\surd$

Table 1: Overview over the used aggregation schemes. Note that $P(\lambda|x)$ is only accessible with WeaNF-N (see equation 4). Bold symbols denote vector representations.

learning $P([\boldsymbol{x}; \boldsymbol{\lambda}_i])$, where $[\cdot]$ describes the concatenation operation. A standard RealNVP (Dinh et al., 2017), as described in section 2 is used. See appendix B.1 for implementational details. In order to use the learned probabilities to perform label prediction, an aggregation scheme is needed. For the sake of simplicity, the model predicts the label corresponding to the labeling function with the highest likelihood, $y = \arg\max_{y \in Y} \max_{\lambda \in T_y} P(x|\lambda)$.

Additionally, to make use of the unlabeled data, i.e. the data points where no labeling function matches, an iterative version WeaNF-I is tested. For this, we use an EM-like (Dempster et al., 1977) iterative scheme where the predictions of the model trained in the previous iteration are used as labels for the unlabeled data. The corresponding pseudo-code is found in algorithm 1.

Algorithm 1 Iterative Model (WeaNF-I)

Require: $X_l \in \mathbb{R}^{n_l \times d}$, corresponding matches $\lambda_l \in \{0,1\}^{n_l \times t}$, unmatched $X_u \in \mathbb{R}^{n_u \times d}$
  $F = \text{train\_flow}(X_l, \lambda_l)$
  for $i = 1, \ldots, r$ **do**
    $(\lambda_u)_i = \arg\max_\lambda F((X_u)_i; \lambda)$
    $X = \text{concat}(X_l, X_u)$, $\lambda = \text{concat}(\lambda_l, \lambda_u)$
    $F = \text{train\_flow}(X, \lambda)$
  end for

Negative Model. In typical classification scenarios it is enough to learn $P(x|y)$ to compute a posterior $P(y|x)$ by applying Bayes' formula twice, resulting in

$$P(y|x) = \frac{P(x|y)P(y)}{P(x|y)P(y) + P(x|\neg y)P(\neg y)} \quad (3)$$

where the class prior $P(y)$ is typically approximated on the training data or passed as a parameter. This is not possible in the current setting as often two labeling functions match simultaneously. In order to learn $P(\lambda|x)$, we explore a novel variant that additionally learns $P(x|\neg\lambda)$. The learning process is similar to $P(x|\lambda)$, so a second embedding $\tilde{\boldsymbol{\lambda}}$ is introduced to represent $\neg\lambda$. We optimize $P([\boldsymbol{x}; \boldsymbol{\lambda}]$ and $P\left(\left[\boldsymbol{x}; \tilde{\boldsymbol{\lambda}}\right]\right)$ simultaneously. In each batch I, the positive sample pairs $(x_i, \lambda_i)_{i \in I}$ and negative pairs (x_i, λ_j), sampled such that $(x_i, \lambda_j) \notin \{(x_i, \lambda_i)\}_{i \in I}$, are used to train the network. The number of negative samples per positive sample is an additional hyperparameter. Now Bayes' formula can be used as in equation 3 to obtain

$$P(\lambda|x) = \frac{P(x|\lambda)P(\lambda)}{P(x|\lambda)P(y) + P(x|\neg\lambda)P(\neg\lambda)}. \quad (4)$$

The access to the posterior probability $P(\lambda|x)$ provides additional opportunities to model $P(y|x)$. After initial experimentation we settled on two options. A simple addition of probabilities neglecting intersection probability, equation 5, which we call Union, and the NoisyOr formula, equation 7, which has previously shown to be effective in weakly supervised learning (Keith et al., 2017):

$$P(y|x) \propto \sum_{\lambda \in T_y} P(\lambda|x) \quad (5)$$

$$P(y|x) = P(\{\vee_{\lambda \in T_y} \lambda\}|x) \quad (6)$$

$$= 1 - \prod_{\lambda \in T_y} (1 - P(\lambda|x)) \quad (7)$$

Mixed Model. It was already mentioned that it is common that two or multiple labeling functions hit simultaneously. While WeaNF-N provides access to a posterior distribution which allows to model these interactions, the goal of the mixed model WeaNF-M is to model these intersections explicitly already in the density of the normalizing flow. More specifically, we aim to learn $P(x|\{\lambda_i\}_{i \in I})$ for arbitrary index families I. Once again, the embeddings space is used to achieve this

Dataset	#Classes	#Train / #Test samples	#LF's	Coverage(%)	Class Balance
IMDb	2	39741 / 4993	20	0.60	1:1
Spouse	2	8530 / 1187	9	0.30	1:5
YouTube	2	1440 / 229	10	1.66	1:1
SMS	2	4208 / 494	73	0.51	1:6
Trec	6	4903 / 500	68	1.73	1:13:14:14:9:10

Table 2: Some basic statistics describing the datasets. Coverage is computed on the train set by #matches / #samples.

goal. For a given sample x and a family I of matching labeling functions, we uniformly sample from the simplex of all possible combinations and obtain $\boldsymbol{\lambda}_I = \sum_{i \in I} \alpha_i \boldsymbol{\lambda}_i, \alpha_i \geq 0, \sum_{i \in I} \alpha_i = 1$. Afterwards we concatenate the weighted sum of the labeling function embeddings $\boldsymbol{\lambda}_I$ with the input x and learn $P([\boldsymbol{x}; \boldsymbol{\lambda}_I])$. Now that the density is able to access the intersections of labeling functions, we derive a new direct aggregation scheme. By σ_y we denote the simplex generated by the set of boundary points $\{\boldsymbol{\lambda}\}_{\lambda \in T_y}$. It is important to think about this simplex, as it theoretically describes the input space where the model learns the density related to class y. We use the naive but efficient variant which just computes the center of the simplex:

$$P(y|x) \propto P\left(\left[\boldsymbol{x}; \frac{1}{|T_y|} \sum_{\lambda \in T_y} \boldsymbol{\lambda}\right]\right) \tag{8}$$

Implementation. In practice, sampling of data points has to be handled on multiple occasions. Empirically and during the inspection of related implementations, e.g. the Github repository accompanying Atanov et al. (2020), we found that it is beneficial if every labeling function is seen equally often during training. It supports preventing a biased density towards specific labeling functions. When training WeaNF-N, the negative space is much larger than the actual space, so an additional hyperparameter controlling the amount of negative samples is needed. WeaNF-M aims to model intersecting probabilities directly. Most intersections occur too rarely to model a reasonable density. Thus we decided to only take co-occures into account which occur more often than a certain threshold. See appendix A.3 to get a feeling for the correlations in the used datasets.

4 Experiments

In order to analyze the proposed models experiments on multiple standard weakly supervised classification problems are performed. In the following, we introduce datasets, baselines and training details.

4.1 Datasets

Within our experiments, we use five classification tasks. Table 2 gives an overview over some key statistics. Note that these might differ slightly compared to other papers due to the removal of duplicates. For a more detailed overview of our preprocessing steps, see appendix A.1.

The first dataset is **IMDb** (Internet Movie Database) and the accompanying sentiment analysis task (Maas et al., 2011). The goal is to classify whether a movie review describes a positive or a negative sentiment. We use 10 positive and 10 negative keywords as labeling functions. See Appendix A.2 for a detailed description.

The second dataset is the **Spouse** dataset (Corney et al., 2016). The task is to classify whether a text holds a spouse relation, e.g. "Mary is married to Tom". Here, 90% of the samples belong to the no-relation class, so we use macro-F_1 score to evaluate the performance. As the third dataset another binary classification problem is given by the **YouTube** Spam (Alberto et al., 2015) dataset. The model has to decide whether a YouTube comment is spam or not. For both, the Spouse and the YouTube dataset, the labeling functions are provided by the Snorkel framework (Ratner et al., 2017).

The **SMS** Spam detection dataset (Almeida et al., 2011), we abbreviate by SMS, also asks for spam but in the private messaging domain. The dataset is quite skewed, so once again macro-F_1 score is used. Lastly, a multi-class dataset, namely **TREC-6** (Li and Roth, 2002), is used. The task is to classify questions into six categories, namely Abbreviation, Entity, Description, Human and Location. The labeling functions provided by (Awasthi et al., 2020) are used for the SMS and the TREC dataset. We

	IMDb	Spouse(F_1)	YouTube	SMS (F_1)	Trec
MV	56.84	49.87	81.66	56.1	61.2
MV + MLP	73.20	29.96	**92.58**	92.41	53.27
DP + MLP	67.79	57.05	88.79	84.40	43.00
WeaNF-S	73.06	52.28	89.08	86.71	67.4
WeaNF-I	**74.08**	**57.96**	89.08	**93.54**	**67.8**
WeaNF-N (NoisyOr)	72.96	54.60	90.83	79.63	54.8
WeaNF-N (Union)	71.98	50.83	91.70	83.48	60.2
WeaNF-M (Max)	70.16	55.16	85.15	88.23	49.8
WeaNF-M (Simplex)	63.53	56.91	86.03	76.29	25.4

Table 3: Comparison of baselines to our model variants. The numbers reflect accuracies, or F_1-scores, where explicitly mentioned. Names in parenthesis describe the aggregation mechanism.

took the preprocessed versions of the data available within the Knodle weak supervision programming framework (Sedova et al., 2021).

4.2 Baselines

Three baselines are used. While there are many weak supervision systems, most use additional knowledge to improve performance. Examples are class balance (Chatterjee et al., 2019), semi-supervised learning with very little labels (Awasthi et al., 2020; Karamanolakis et al., 2021) or multi-task learning (Ratner et al., 2018). To ensure a fair comparison, only baselines are used that solely take input data and labeling function matches into account. First we use majority voting (MV) which takes the label where the most rules match. For instances where multiple classes have an equal vote or where no labeling function matches, a random vote is taken. Secondly, a multi-layer perceptron (MLP) is trained on top of the labels provided by majority vote. The third baseline uses the data programming (DP) paradigm. More explicitly, we use the model introduced by Ratner et al. (2018) implemented in the Snorkel (Ratner et al., 2017) programming framework. It performs a two-step approach to learning. Firstly, a generative model is trained to learn the most likely correlation between labeling functions and unknown true labels. Secondly, a discriminative model uses the labels of the generative model to train a final model. The same MLP as for second baseline is used for the final model.

4.3 Training Details

Text input embeddings are created with the SentenceTransformers library (Reimers and Gurevych, 2019) using the *bert-base-nli-mean-tokens* model. They serve as input to the baselines and the normalizing flows. Hyperparameter search is performed via grid search over learning rates of $\{1e-5, 1e-4\}$, weight decay of $\{1e-2, 1e-3\}$ and epochs in $\{30, 50, 100, 300, 450\}$, and label embedding dimension in $10, 15, 20$ times the number of classes. Additionally, the number of layers is in $\{6, 8\}$, and the negative sampling value for WeaNF is in $\{2, 3\}$. The full set up ran 30 hours on a single GPU on a DGX 1 server.

5 Analysis

The analysis is divided into three parts. Firstly, a general discussion of the results is given. Secondly, an analysis of the densities predicted by WeaNF-N is shown and lastly, a qualitative analysis is performed.

5.1 Overall Findings

Table 3 exposes the main evaluation. The horizontal line separates the baselines from our models. For WeaNF-N and WeaNF-M, no iterative schemes were trained. This enables a direct comparison to the standard model WeaNF-I.

Interestingly, the combination of Snorkel and MLP's is often not performing competitively. In the IMDb data set there is barely any correlation between labeling functions, complicating Snorkel's approach. The large number of labeling functions e.g. Trec, SMS, could also complicate correlation based approaches. Appendix A.3 shows correlation graphs.

As indicated by the bold numbers, the WeaNF-I is the best performing model. Only on the YouTube dataset, an iterative scheme could not improve the results. Related to this observation, in Ren

Labeling Function	Example	Dataset	$P(x\|\lambda)$	Label (λ)	Gold	Prediction
won .* claim	...won ... call ...	SMS	↑	Spam	Spam	Spam
.* I'll .*	sorry, **I'll** call later	SMS	↑	No Spam	No Spam	No Spam
.* i .*	**i** just saw ron burgundy captaining a party boat so yeah	SMS	↓	No Spam	No Spam	No Spam
(explain|what) .* mean .*	**What** does the abbreviation SOS **mean** ?	Trec	↑	DESCR	ABBR	DESCR
(explain|what) .* mean .*	What are Quaaludes ?	Trec	↑	DESCR	DESCR	DESCR
who.*	**Who** was the first man to ... Pacific Ocean ?	Trec	↓	HUMAN	HUMAN	HUMAN
check .* out .*	**Check out** this video on YouTube:	YouTube	↑	Spam	Spam	Spam
#words < 5	subscribe my	YouTube	↑	Spam	Spam	No Spam
.* song .*	This **Song** will never get old	YouTube	↓	No Spam	No Spam	No Spam
.* dreadful .*	...horrible performance .... annoying	IMDb	↑	NEG	NEG	NEG
.* hilarious .*	...liked the movie...funny catch-phrase...WORST...low grade...	IMDb	↑	POS	NEG	POS
.* disappointing .*	don't understand stereotype ... goofy ..	IMDb	↓	NEG	NEG	POS
.* (husband|wife) .*	...Jill.. she and her **husband**...	Spouse	↑	Spouses	Spouses	Spouses
.* married .*	... asked me to marry him and I said yes!	Spouse	↑	Spouses	No Spouses	Spouses
family word	Clearly excited, Coleen said: 'It's my eldest **son** Shane and Emma.	Spouse	↓	No Spouses	No Spouses	No Spouses

Table 4: Examples selected from the 10 most likely (↑) and 10 most unlikely (↓) combinations of sentences and labeling functions, using the density $P(x|\lambda)$ provided by WeaNF-I. Labeling function matches are bold. We observe that the flow often generalizes to unmatched examples. We slightly simplified some rules and shortened some texts in order to fit the page size.

	IMDb	**Spouse**	**YouTube**	**SMS**	**Trec**
Acc	72.38	74.04	78.17	88.71	72.63
P	5.93	5.1	38.95	23.3	13.65
R	37.53	39.31	55.01	44.34	61.07
F_1	10.25	9.02	45.61	30.55	22.31
Cov	4.31	5.74	19.31	3.01	4.39

Table 5: Evaluation of the labeling function prediction $P(\lambda|x)$. Precision, Recall and F_1 score are computed via the weighted average of the statistics of all labeling functions. Coverage is computed as #matches/#all possible matches.

Dataset	Labeling Fct.	Cov(%)	Prec	Recall
IMDb	*boring*	5.8	13.12	26.87
Spouse	family word	9. 0	16.53	35.96
YouTube	*song*	23.58	56.72	70.73
SMS	won *call*	0.81	66.67	1.0
Trec	how.*much	2.4	60.0	75.0

Table 6: Statistics for the labeling functions obtaining the highest F_1 score for the prediction $P(\lambda|x)$, using the WeaNF (NoisyOr) model.

Dataset	Labeling Fct.	Cov(%)	Prec	Recall
IMDb	*imaginative*	0.42	0.77	52.38
Spouse	spouse keyword	14.5	0	0
YouTube	person entity	2.62	6.45	33.33
SMS	I .* miss	0.6	0	0
Trec	what is .* name	2.2	2.26	100

Table 7: Same as table 6, but here the labeling functions obtaining the lowest F_1 score are shown. Only those are taken into account which occur more often than 10 times in the test set.

et al. (2020) the authors achieve promising results using iterative discriminative modeling for semi-supervised weak supervision.

WeaNF-N outperforms the standard model in three out of five datasets. We observe that these are the datasets with a large amount of labeling functions. Possibly, this biases the model towards a high value of $P(x|\neg\lambda)$ which confuses the prediction.

The simplex aggregation scheme only outperforms the maximum aggregation on two out of five datasets. We infer that the probability density over the labeling function input space is not smooth enough. Ideally, the simplex method should always have a high confidence in the prediction of a labeling function λ if its confident on the non-mixed embedding $\boldsymbol{\lambda}$ which is what Max is doing.

5.2 Density Analysis

We divide into a global analysis and a local, i.e. a per-labeling function, analysis. Table 5 provides some global statistics, table 6 and 7 subsequently show statistics related to the best and worst performing labeling function estimations. In the local analysis a labeling function is predicted if $P(\lambda|x) \geq 0.5$. The WeaNF-N model is used because it is the only model with direct access to $P(\lambda|x)$.

It is important to mention that in the local analysis, a perfect prediction of the matching labeling function is not wanted, as this would mean that there is no generalization. Thus, a low precision might be necessary for generalization, and a the recall would indicate how much of the original semantic or syntactic meaning of a labeling function is retained.

Interestingly, while the overall performance of WeaNF-N is competitive on the IMDb and the Spouse data sets, it is failing to predict the correct labeling function. One explanation might be that these are the data sets where the texts are substantially longer which might be complicated to model for normalizing flows. In table 7 typically the worst performing approximation of labeling function matches seems to be due to low coverage. An exception is the the Spouse labeling function.

5.3 Qualitative Analysis

In table 4 a number of examples are shown. We manually inspected samples with a very high or low density value. Note that density values related to $P(x|\lambda), \lambda \in T_y$ are functions f taking arbitrary values which only have to satisfy $\mathbb{E}_{x:\lambda(x)=y}[f(x)] = 1$.

We observed the phenomenon that either the same labeling functions take the highest density values $P(x|\lambda)$ or that a single sample often has a high likelihood for multiple labeling functions. In the table 4 one can find examples where the learned flows were able to generalize from the original labeling functions. For example, for the IMDb dataset, it detects the meaning "funny" even though the exact keyword is "hilarious".

6 Conclusion

This work explores the novel use of normalizing flows for weak supervision. The approach is divided into two logical steps. In the first step, normalizing flows are employed to learn a probability distribution over the input space related to a labeling function. Secondly, principles from basic probability calculus are used to aggregate the learned densities and make them usable for classification tasks. Motivated by aspects of weakly supervised learning, such as labeling function overlap or coverage, multiple models are derived each of which uses the information present in the latent space differently. We show competitive results on five weakly supervised classification tasks. Our analysis shows that the flow-based representations of labeling functions successfully generalize to samples otherwise not covered by labeling functions.

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positive	negative
beautiful	poor
pleasure	disappointing
recommendation	senseless
dazzling	second-rate
fascinating	silly
hilarious	boring
surprising	tiresome
interesting	uninteresting
imaginative	dreadful
original	outdated

Table 8: Keywords used to create rules for the IMDb dataset.

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A Additional Data Description

A.1 Preprocessing

A few steps were performed, to create a unified data format. The crucial difference to other papers is that we removed duplicated samples. There were two cases. Either there were very little duplicates or the duplication occurred because of the programmatic data generation, thus not resembling the real data generating process. Most notably, in the spouse data set 60% of all data points are duplicates. Furthermore, we only used rules which occurred more often than a certain threshold as it is impossible to learn densities on only a handful of examples. The threshold is In order to have unbiased baselines, we ran the baseline experiments on the full set of rules and the reduced set of rules and took the best performing number.

A.2 IMDb rules

The labeling functions for the IMDb dataset are defined by keywords. We manually chose the keywords. We defined them in such a way that their meaning has rather little semantic overlap. The keywords are shown in table 8.

A.3 Labeling Function Correlations

In order to use labeling functions for weakly supervised learning, it is important to know the correlation of labeling functions to i) derive methods to combine them and ii) help to understand phenomena of the model predictions.

Thus we decided to add correlation plots. More specifically, we use the Pearson Correlation coefficient.

B Additional Implementational Details

B.1 Architecture

As mentioned in section 3, the backbone of our flow is RealNVP architecture, which we introduced in section 2. With sticking to the notation in formula 2 the network layers to approximate the functions s and t are shown below

```
s = nn.Sequential(
    nn.Linear(dim, hidden_dim),
    nn.LeakyReLU(),
    nn.BatchNorm1d(hidden_dim),
    nn.Dropout(0.3),
    nn.Linear(hidden_dim, dim),
    nn.Tanh()
)
t = nn.Sequential(
    nn.Linear(dim, hidden_dim),
    nn.LeakyReLU(),
    nn.BatchNorm1d(hidden_dim),
    nn.Dropout(0.3),
    nn.Linear(hidden_dim, dim),
    nn.Tanh()
)
```

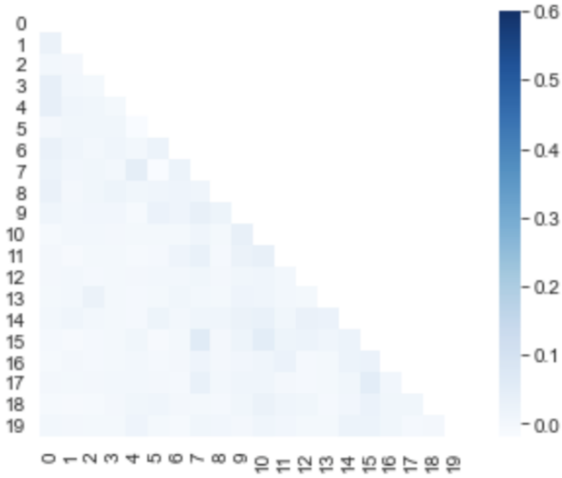
Hyperparameters are the depth, i.e. number of stacked layers, and the hidden dimension.

B.2 WeaNF-M Sampling

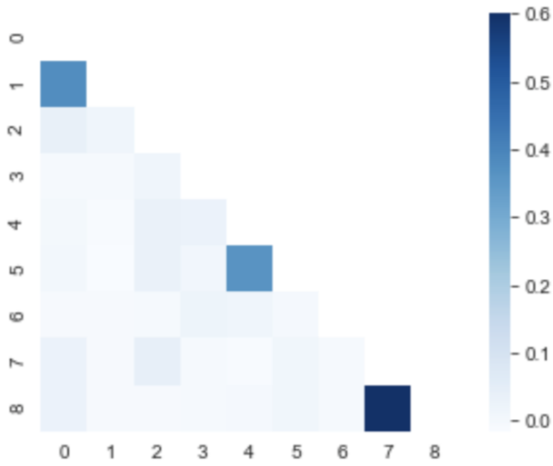
For the mixed model WeaNF-M the sampling process becomes rather complicated.

Next up, the code to produce the convex combination $\alpha_1, \ldots, \alpha_t$ is shown. The input tensor takes values in $\{0, 1\}$ and has shape $b \times t$ where b is the batch size and t the number of labeling functions.Note that some mass is put on every labeling functions. We realized that this bias imrpoves performance.

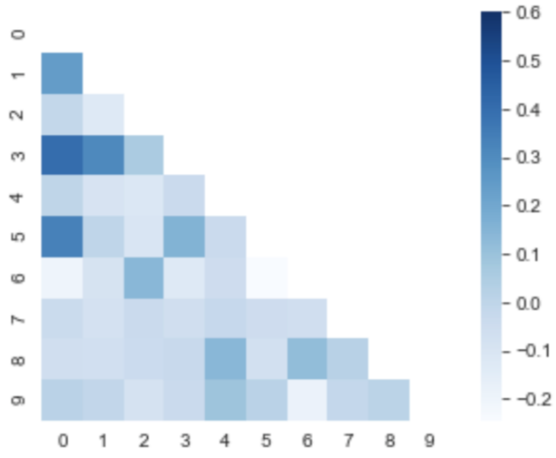
```
def weight_batch(self, batch_y: torch.Tensor):
    """Returns weighting array forming convex sum.
       Shape: (batch_dim, num_rules)
    """
    batch_y = batch_y.float()
    batch_y += 0.1 * torch.ones(batch_y.shape)
    batch_y = batch_y * torch.rand(batch_y.shape)
    row_sum = batch_y.sum(axis=1, keepdims=True)
    nbatch_y = batch_y / row_sum
    return nbatch_y
```



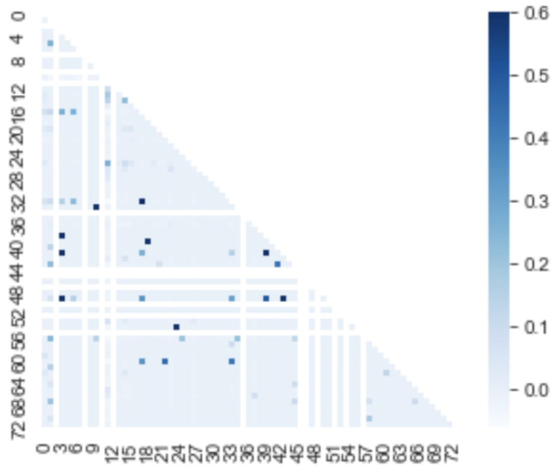
(a) IMDb



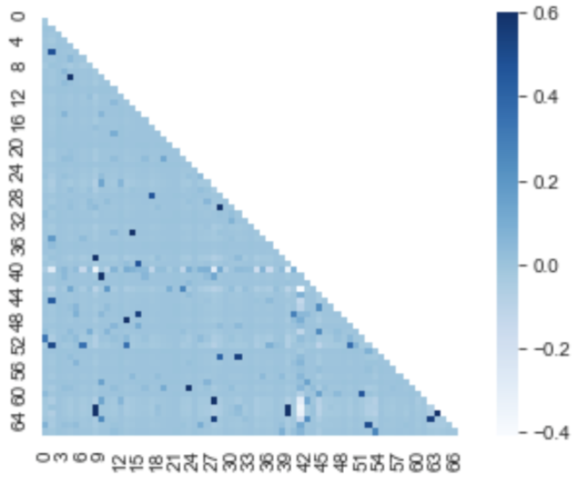
(b) Spouse



(c) YouTube



(d) SMS



(e) Trec