Semantic Interactive Learning for Text Classification: A Constructive Approach for Contextual Interactions

Sebastian Kiefer, Mareike Hoffmann
Cognitive Systems, University of Bamberg, Germany

Abstract
Interactive Machine Learning (IML) shall enable intelligent systems to interactively learn from their end-users, and is quickly becoming more and more important. Although it puts the human in the loop, interactions are mostly performed via mutual explanations that miss contextual information. Furthermore, current model-agnostic IML strategies like CAIPI are limited to ‘destrucrive’ feedback, meaning they solely allow an expert to prevent a learner from using irrelevant features. In this work, we propose a novel interaction framework called Semantic Interactive Learning for the text domain. We frame the problem of incorporating constructive and contextual feedback into the learner as a task to find an architecture that (a) enables more semantic alignment between humans and machines and (b) at the same time helps to maintain statistical characteristics of the input domain when generating user-defined counterexamples based on meaningful corrections. Therefore, we introduce a technique called SemanticPush that is effective for translating conceptual corrections of humans to non-extrapolating training examples such that the learner’s reasoning is pushed towards the desired behavior. In several experiments, we show that our method clearly outperforms CAIPI, a state of the art IML strategy, in terms of Predictive Performance as well as Local Explanation Quality in downstream multi-class classification tasks.

1 Introduction
Although modern ML approaches improved tremendously with regard to prediction accuracy and even exceed human performance in many tasks, they often lack the ability to allow humans to develop an understanding of the whole logic or of the model’s specific behavior (Adadi and Berrada 2018; Holzinger 2016; Holzinger et al. 2017). Additionally, most systems don’t allow the integration of corrective feedback used for model adaptation. Consequently, different research disciplines have emerged that provide first solutions. Interpretable Machine Learning as well as Explainable Artificial Intelligence, which can be summarized as Comprehensible Artificial Intelligence (Bruckert, Finzel, and Schmid 2020) when being combined, shall allow for global or local interpretability as well as transparent and comprehensible ML results (Akata et al. 2020). Nevertheless, the according explanations used for better transparency and human comprehensibility during human-machine-interactions are mostly considered unidirectional, from the AI system to the human and often lacking contextual information (Adadi and Berrada 2018). Therefore, any correction of erroneous behavior or any inclusion of domain-specific knowledge through human experts is not possible in a model-agnostic way (Bruckert, Finzel, and Schmid 2020). Explanatory Interactive Machine Learning addresses that with the intention to ‘close the loop’ by allowing human feedback in the form of machine-to-user explanations based on transparent decisions (Teso and Kersting 2019). The authors from (Teso and Kersting 2019) demonstrated that not only the predictive and explanatory performance of a learner, but also the process of building trust in a learner benefit from interactions through explanations. Except from systems like EluciDebug (Kulesza et al. 2015) or Crayon (Fails and Olsen 2003), which use feedback to adapt a learner (albeit model-specific), there are still few possibilities for holistic, meaningful and model-agnostic interventions to correct learners’ mistakes and use expert knowledge. Based on this research gap, we phrase the following research questions (RQ): (1) How can we develop a model-agnostic Interactive ML approach that offers semantic (constructive, meaningful, contextual, and realistic) means for performing corrections and providing hints? (2) Will the elaborated interactive system converge faster to higher learning performance with the help of contextual explanations and the new interaction paradigm than state-of-the-art methods? (3) Will the generated explanations of our method quicker be conclusive than those from state-of-the-art methods? During our research, we propose an architecture called Semantic Interactive Learning and evaluate its quality with regard to these research questions.

2 Related Work
Human-Centered Machine Learning can be summarized as methods of aligning machine learning systems with human goals, context, concerns, and ways of work (Gillies et al. 2016). It is strongly connected with Interactive Machine Learning as an interaction paradigm in which a user or user group iteratively trains a model by selecting, labeling, and/or generating training examples to deliver a desired function (Dudley and Kristensson 2018). One can assume that a learner could better be aligned with human goals if the end user knows more about its behavior (Explanatory Interactive Machine Learning). Kulesza et al. (2015) proved that intuition with their Explanatory Debugging approach. They
additionally showed that not only the machine benefits from
corrections based on transparent explanations, but also the
user was able to build a more accurate mental model about
the learners behavior.

Hence, interactions between humans and machines via
mutual explanations (Schmid and Finzel 2020; Bruckert,
Finzel, and Schmid 2020) have the potential to adequately
bring the human in the loop in a model-agnostic way.
The overall process should work as a Training-Feedback-
Correction-cycle that enables a Machine Learning model
to quickly focus onto a desired behavior (Fails and Olsen
2009). Users should be able to iteratively integrate correc-
tive feedback into a Machine Learning model after having
analyzed its decisions (Amershi et al. 2016).

Consequently, Teso and Kersting (2019) included a local
explainer called Local Interpretable Model-Agnostic Explo-
Nations (LIME) into an active learning setting. Their frame-
work proposes a method called CAIPI which enables users
to correct a learner when its predictions are right for the
wrong reasons by adding counterexamples in a ‘destructive’
manier. The correction approach is based on Zaidan, Ei-
er, and Piatko (2007). As an example from the text domain,
words which are falsely identified as relevant get masked
from the original document and the resulting counterexam-
plary recur as additional training documents.

Although CAIPI paves a first way for model-agnostic
and explanatory IML, it reveals some significant drawbacks.
First, it only operates by deleting irrelevant explanations
(What has incorrectly been learned?). Thus, it is limited to a
‘destructive’ feedback about incorrectly learned correlations
while an active learning setting might rarely contain right
predictions made for the wrong reasons. Second, CAIPI uses
contextless explanations as a basis and in turn applies con-
textless feedback by independently removing irrelevant
explanatory errors. Doing so, human conceptual knowledge
might hardly be considered during interactions, although it
is known, that harnessing conceptual knowledge “as a guiding
model of reality” might help to develop more explainable
and robust ML models, which are less biased (Holzinger
et al. 2021). A first step towards that was suggested by
Kiefer (2022). In the according research, topicLIME is pro-
posed as an extension of LIME that offers contextual and
locally faithful explanations by considering higher-level se-
manic characteristics of the input domain within the local
surrogate explanation models. As third drawback, CAIPI en-
ables 'discrete' feedback only. In the domain of text, it is
based on mutual explanations in bag-of-words representa-
tion, where words as explanatory features are either present
or not. Therefore, graded, continuous feedback is not possi-
ble.

When explaining and correcting a classifier in a way as
described above, neighborhood extrapolation to feature ar-
eas with low data density, especially in case of dependent
features (Molnar 2019), causes a classifier to train on con-
textless counterexamples sampled from unrealistic local per-
turbation distributions. This circumstance might lead to gen-
eralization errors.

The overall goal of this work is therefore to enable more
realistic and constructive interactions via semantic align-
ment between humans and ML models across all possible
types of a learner’s reasoning and prediction errors.

3 Method

Figure 1 depicts our proposal for answering RQ1 from ar-
chitectural point of view. It extends previous research called

Contextual and Semantic Explanations (CaSE) (Kiefer
2022). CaSE suggests a framework that allows humans con-
textual interpretations of ML decisions in a model-agnostic
way via topic-based explanations. While CaSE solely refers
to the process of explanation generation, our research aims
at closing the loop and enabling humans to integrate domain
knowledge via semantic corrections and hints. The follow-
ing subsections briefly describe the components contained
in our framework and especially introduce our new IML strat-

eg called SemanticPush.

3.1 Latent Dirichlet Allocation

We instantiate the semantic component of our framework
with a method called Latent Dirichlet Allocation (LDA). It
can be described as a hierarchical Bayesian model for col-
lections of discrete data (Blei, NG, and Jordan 2003). Used
in text modeling, it finds short representations of a corpus’
documents and preserves essential statistical relationships
necessary for making sense of the input data. After training,
each document can be characterized as a multinomial distri-
bution over so-called topics. For each document \( w \) in a
corpus \( D \), a generative process, from which the according
documents have been created, is assumed:

1. Choose \( N \) (the number of words) \( \sim \) Poisson(\( \zeta \)).
2. Choose \( \theta \) (a topic mixture) \( \sim \) Dir(\( \alpha \)).
3. For each of the \( N \) words \( w_n \):
   a. Choose a topic \( z_n \) \( \sim \) Multinomial(\( \theta \)).
   b. Choose a word \( w_n \) from \( p(w_n | z_n, \beta) \), a multinomial probability conditioned
      on the topic \( z_n \).

The joint distribution of a topic mixture \( \theta \), a set of topics
\( z \), and a set of words \( w \) given the hyperparameters \( \alpha \) and \( \beta \) is characterized by:

\[
p(\theta, z, w | \alpha, \beta) = p(\theta | \alpha) \prod_{n=1}^{N} p(z_n | \theta) p(w_n | z_n, \beta).
\] (1)
We combine LDA with a coherence measure called C, coherence. It is used for finding an appropriate hyperparameter number of topics k that LDA shall infer. Röder et al. found that coherence measure to be the best in terms of its correlation with respect to human topic-interpretability (Röder, Both, and Hinneburg 2015, Syed and Spruit 2017).

3.2 LIME and topicLIME

Ribeiro et al. developed LIME, a method that explains a prediction by locally approximating the classifier’s decision boundary in the neighborhood of the given instance (Ribeiro, Singh, and Guestrin 2016). The final objective is to minimize a measure $L(f,g,\pi_x(z))$ that evaluates how unfaithful $g$ (the local explanation model) is in approximating $f$ (the model to be explained) in the locality defined by $\pi_x(z)$. Striving for both interpretability and local fidelity, an explanation is obtained by minimizing $L(f,g,\pi_x(z))$ as well as keeping $\Omega(g)$ low enough to be an interpretable model.

TopicLIME developed by Kiefer (2022) generates a local neighborhood of a document to be explained by removing coherent words. It is therefore capable of including distributional, contextual, as well as semantic information of the input domain in the resulting topic-based explanations. Doing so, it offers realistic and meaningful local perturbation distributions by avoiding extrapolation when generating the local neighborhood, leading to higher local fidelity of the local surrogate models. For a sample topic-based explanation, please refer to (Kiefer 2022).

3.3 Our Method: SemanticPush

Our method called SemanticPush shall enable model-agnostic Interactive Machine Learning on a higher level of semantic detail. It therefore extends the idea of CAIPI (refer to the CAIPI algorithm in the Appendix) that offers humans model-agnostic, albeit contextless interactions in the form of word-based explanations and ‘destructive’ corrections. From IML research it is known that humans want to demonstrate how learners should behave. According to Amershi et al. (2016) and Odom and Natarajan (2018), people don’t want to simply teach ‘by feedback’, but want to teach ‘by demonstration’ or by providing examples of a concept. Therefore, interaction techniques should move away from limited, learner-centered ways of interactions, but rather proceed to more natural feedback, such as suggesting alternative or new features (Stumpf et al. 2007).

![Graphical Model of SemanticPush](image)

Figure 2: Graphical Model of SemanticPush.

SemanticPush shall put that knowledge into practice and is depicted in figure 2 as graphical model. Let $X$ and $Y$ be the input and output space for a binary classification, where $X$ represents query instances, $Y$ and $\hat{Y}$ true and predicted labels respectively. The overall goal is to find a matrix $M$ depending on the label $Y$ that adequately incorporates human feedback into the classifier’s reasoning in a model-agnostic way by generating counterexamples $X$ based on $X$. Thus, we are seeking for a set of $L$ input manipulations $M = \{m_1,...,m_L\}$ as well as a manipulation function $q: M \times X \to X$, $q(m,x)$ shall be a local function such that it only affects a part of the input $X$. This is the case because user input in IML shall be focused (it shall only affect a certain part/aspect of the model) as well as incremental (each user input shall only result in a small change of the model).

Algorithms 1 and 2 describe SemanticPush in detail.

Algorithm 1: SemanticPush

Require: a destructive correction set $C_{\text{dest}}$, a topicLIME explanation $\hat{z}_{xy}$ for query instance $x$ with true class $y$, expert knowledge - here simulated via Gold Standard $GS_y$ - and a balancing parameter $\lambda$ $C_{\text{dest}} = \{t \in \hat{z}_{xy} | t \notin GS_y\}$ if $\hat{y} = y \land C_{\text{dest}} \neq \emptyset$ then $\triangleright$ Right for the partially wrong reasons $\hat{x}_i \leftarrow x \setminus C_{\text{dest}} \cup \text{SemanticCompletion}(x, GS_y, \hat{z}_{xy}, \lambda)$ $\triangleright$ Add a concept the classifier forgot to learn $\hat{y} \leftarrow y$

else if $\hat{y} \neq y$ then $\triangleright$ False prediction $\hat{x}_{iy} \leftarrow \text{SemanticCorrection}_y(x, GS_y, \hat{z}_{xy})$ $\triangleright$ Provide feedback/hints for the true class $\hat{y}_{iy} \leftarrow y$

$\hat{x}_{iy} \leftarrow \text{SemanticCorrection}_y(x, GS_y, \hat{z}_{xy})$ $\triangleright$ Provide feedback/hints for the predicted class $\hat{y}_{iy} \leftarrow \hat{y}$

end if

SemanticCompletion$(x, GS_y, \hat{z}_{xy}, \lambda)$ from algorithm 1 is defined as $\sim [\lambda \ast \psi(C_{add}) + (1 - \lambda) \ast \psi(x_{add})]$, where $C_{add} = \{(t, t_w) \in GS_y^+ | t \notin \hat{z}_{xy}^+\}$ and $x_{add} = \{(t, t_w) \in x | t \in C_{add}\}$.

$\psi$ constitutes a normalization operator that re-normalizes the weights $t_w$ of the according topics $t$ (be it from Gold Standard or topicLIME explanation), revealing a multinomial distribution over topics $t$. SemanticPush then incorporates the concepts the classifier forgot to learn by adding text parts via sampling ($\sim$) from the multinomial distribution and harnessing the generative process of LDA (see subsection 3.1).

Increase Probability() from algorithm 2 performs a topic’s probability change $\delta_t$ in the following way: $\delta_t = \theta_{tx} + \lambda \ast GS_y + (1 - \lambda) \ast \theta_{tx}$.

Decrease Probability() from algorithm 2 in our scenario sets a topic’s probability to zero as the topic is assumed to be irrelevant for the class decision.

SemanticPush is based on a so-called conceptual Gold Standard GS that works as a proxy for an oracle’s expert knowledge. Specifically, $GS_y$ contains concepts in the form of LDA-retrieved topics that should be informative for a
Algorithm 2: Semantic Correction

Require: a Topic Model $lda$

\[ \theta_x \leftarrow lda.Get\ Topic\ Mixture(x) \]

for $t \in \Theta$ do

\( t \) represents a topic as explanation unit

if \( t \in \tilde{z}^+ \cap GS^+ \lor t \in \tilde{z}^- \cap GS^- \)

\( t \in \tilde{z}^+ \cap GS^+ \lor t \notin \tilde{z}^- \cap GS^- \) then \( \triangleright \)

Topics either correctly used or incorrectly used (but hard to reverse polarity and still important) or correctly ignored

\[ \hat{\theta}_{x_t} \leftarrow \text{KeepProbability}(\theta_{x_t}) \]

else if \( t \notin \tilde{z}^+ \cap GS^+ \lor t \notin \tilde{z}^- \cap GS^- \) then \( \triangleright \)

Topics either incorrectly learned (but easy to reverse polarity) or forgotten to learn

\[ \hat{\theta}_{x_t} \leftarrow \text{Increase\ Probability}(\theta_{x_t}, GS, \lambda) \]

else if \( t \in \tilde{z}^- \cap GS^- \) then \( \triangleright \)

Irrelevant topics were used

\[ \hat{\theta}_{x_t} \leftarrow \text{Decrease\ Probability}(\theta_{x_t}) \]

end if

end for

return $lda.\ Sample\ Instance(\psi(\hat{\theta}_x))$ \( \triangleright \)

Figure 3: (a) Conceptualization of SemanticPush: The grey query instance in the middle is predicted as class ‘blue’, but should be ‘orange’ instead according to ground truth. Local explanation features $f_1$ and $f_2$ are features used by the classifier locally to assign the query instance to class ‘blue’. According to expert knowledge, those features push the learned local decision boundary too far towards the class ‘orange’. Feature $f_3$ also constitutes expert knowledge as it is, among others, significantly used globally by the classifier to assign instances to class ‘orange’. SemanticPush incorporates this information by generating new instances (shown in light color) for both classes and eventually weighs them by their distance to the query instance. The degree of locality of applying the expert knowledge to the query instance is controlled by the hyperparameter $\lambda$. Sampling new instances only based on global expert knowledge might result in prototypical instances (located in dense regions) which might not lead to great benefit for the classifier. (b) An exemplary application of SemanticPush to document ID 9 of the Reuters R 52 Dataset.

4 Experimental Setup

4.1 Baseline: Active Learning and CAIPI

We compare our SemanticPush approach against three baseline approaches: First, we use a standard ActiveLearner that internally harnesses Maximum Classification Uncertainty with regard to a pool dataset as sampling strategy. Classification uncertainty is defined as $U(x) = 1 - p(y|x)$, where $x$ is the instance to be predicted and $y$ is the most likely prediction. Second, we apply the original CAIPI method as described in [C这点 and Kersting 2019] that provides explanation corrections for the ‘right for the wrong reasons’ $(\hat{y} = y)$ case. We call the according setup ‘CAIPI destructive’ (CAIPI$_d$) as it is only capable of removing those components that have been identified by a local LIME explanation $\epsilon(x)$ as relevant, but an oracle believes those components to be irrelevant. Third, we extend CAIPI such that it is additionally able to deal with false predictions $(\hat{y} \neq y)$. We call that setting ‘CAIPI destructive + constructive’ (CAIPI$_{dc}$) as we additionally generate new documents comprising words that could have been used to predict the according true class. We therefore sample words from a set $GS_{local}^y(x)$ (where $GS_{local}^y(x) = GS_{global}^y(\cap x)\cap -$) that con-
tains the top $k$ positive words from a global Gold Standard of the true class (see subsection 3.3) that are also part of the document.

4.2 Datasets

We evaluate SemanticPush on two multiclass classification tasks harnessing the following datasets: AG News Classification Dataset (Zhang, Zhao, and LeCun 2015) and Reuters R10 Dataset (Lewis 1993). The AG News Dataset (127,600 documents) is constructed by selecting the four largest classes from the original AG Dataset, which is a collection of more than one million news articles. The average document length is 25 words, classes to be distinguished are 'Business News', 'Science-Technology News', 'Sports News', and 'World News'. The Reuters R10 Dataset (9,100 documents) originally comprises 52 classes. Due to strong imbalance between the classes, we selected the ten most represented classes ('Earn', 'Acquisition', 'Coffee', 'Sugar', 'Trade', 'Ship', 'Crude', 'Interest', and 'Money-Foreign-Exchange'), leading to a corpus comprising 7,857 documents. The average document length is 60 words. From now on, we refer to this dataset as the Reuters R10 Dataset.

For both datasets, we perform standard NLP preprocessing steps like Tokenization, Lemmatization, Stemming, Lower-Casing, and Removing of stopwords.

4.3 Models

Our architecture comprises a semantic component that provides contextual information about the input domain. Here, we showcase how we instantiated the Latent Dirichlet Models for the two datasets. Throughout this research, we used scikit-learn (version 0.20.2) and gensim (version 3.8.3). For the AG News Dataset, several LDA models have been trained on the preprocessed corpus with different values for the hyperparameter $\text{number of topics } k$. A final selection has been made by determining the optimal number $K^*$ of topics $t = 1, \ldots, K$ by solving $\arg \max_{t} \frac{1}{K} \sum_{i=1}^{K} C_v(t)$, where $C_v$ is the $C_v$ coherence as introduced in subsection 3.3. We set $K$ to 30 and determined $K^* = 13$, meaning an optimal number of 13 topics. Those topics, together with its most representative words, are described in figure 6 in the Appendix.

Analogously, we proceeded with the Reuters R10 Dataset, but in contrast to the AG News Dataset we could not solely rely on $C_v$ coherence to find a suitable number of topics. As the LDA model in our framework not only serves as semantic component, but is also used to build a topic-based Gold Standard model (see next paragraph), we rather had to trade off $C_v$ coherence against learning performance. In order to achieve sufficient predictive performance for Reuters R10 while preserving high coherence, the optimal number of topics $K^*$ was set to 100.

Gold Standard As described in subsection 3.3, a Logistic Regression model is harnessed as an approximation for the oracle’s expert knowledge required in any Active Learning setting. To obtain that kind of Gold Standard $GS$ for CAIPI, we trained the regression model on the bag-of-words-represented documents and got the following results: For the AG News Dataset, a macro-averaged F1 score of 0.85 was achieved, for Reuters R10, the regression model reached a score of 0.8.

In order to include contextual and higher-level semantic information (simulating conceptual knowledge of a human expert) in the $GS$ used for SemanticPush, we represented the documents as multinomial distributions over topics (features of the regression model) using the LDA model described above. The according model achieved a macro-averaged F1 score of 0.74 for AG News and of 0.71 for Reuters R10. Due to the reduced number of features when representing documents via topics, the topic-based $GS$ obviously performs slightly worse than the word-based $GS$ due to reduced degrees of freedom of the regression model.

During our experiments, we primarily used an XGBoost model as Base Learner as it constitutes a high-performing ensemble and tree-based classification algorithm that can intrinsically learn feature interactions. In addition, we also experimented with a Support Vector Machine with linear kernel. For instantiating the Active Learner, we chose the modAL python framework (Danka 2018). As query strategy, we used Maximum Classification Uncertainty. For both datasets, a stratified split into train-, pool-, and testsets was performed (train 1%, pool 79%, and test 20% of the data). We therefore account for a standard Active Learning setting where only a small number of labeled data, but a huge number of unlabeled data is available. All experiments were performed over 200 iterations each.

4.4 Evaluation Metrics

For evaluating the quality of our framework and for answering the research questions two and three (see section 1), we performed two kinds of experiments. First, we measured the Predictive Performance of the different IML strategies with regard to a downstream classification task on the testset during 200 iterations. As performance metric for evaluation of research question two, we chose the macro-averaged F1 score (after each AL iteration) on the one hand and the Average Classification Margin between predicted and true class (after every tenth AL iteration) on the other hand. The Average Classification Margin between predicted and true class is defined as $M(x) = \frac{1}{N} \sum_{i=1}^{N} P(\hat{y}|x_i) - P(y|x_i)$, where $\hat{y}$ is the predicted class and $y$ is the true class, $x_i$ is a certain instance of the testset to be predicted, and $N$ is the total number of instances in the testset. Accordingly, this measure analyzes the classifier’s confidence towards false predictions for all test instances and then averages over those.

To answer research question three, Local Explanation Quality was analyzed two-fold: (a) with regard to local fidelity and approximation accuracy (the quality of the local explanation generators itself before any interactions) and (b) with regard to the ‘Explanation Ground Truth’ of the downstream classification tasks (the quality of local explanations for all test instances compared to the bag-of-words-represented Gold Standard described in subsection 4.3).

(a): Local fidelity is said to be achieved if an explanation model $g \epsilon G$ is found such that $f(z) \approx g(z')$ for $z, z' \epsilon Z$, 



where $Z$ constitutes the vicinity of $x$ and $f$ is the model to be explained. We use Mean Local Approximation Error (MLAE, equation 2) and Mean$R^2$ (equation 3) as a proxy to measure local fidelity of the whole explanation models to be compared.

$$MLAE = \frac{1}{N} \sum_{i=1}^{N} \left| f(x_i) - g_i(x_i) \right|.$$  \hspace{1cm} (2)

$$MeanR^2 = \frac{\sum_{i=1}^{N} R^2(g_i)}{N}, R^2 = 1 - \frac{1}{k} \sum_{i=1}^{k} \frac{(f(z_i) - g(z_i))^2}{f(x))^2}.$$  \hspace{1cm} (3)

In both cases, $N$ is the number of instances in the according test dataset.

Furthermore, a modified variant of the Area Over The Perturbation Curve (AOPC) was analyzed. It measures local fidelity of individual explanations, we call it Combined Removal Impact (CRI) and define it as:

$$CRI = \frac{1}{N} \sum_{i=1}^{N} p(y|x_i) - p(y|\tilde{x}^{(k)}),$$  \hspace{1cm} (4)

where the top $k$% explanation features are removed from $x_i$ yielding $\tilde{x}^{(k)}$, $\hat{y}$ denotes the predicted label for $x_i$ and $N$ is the number of instances in the according test dataset. For both evaluation metrics, please refer to (Kiefer 2022) in order to find details on how those metrics have been applied to compare word-based and topic-based contextual explanations.

(b): In order to analyze the development of Local Explanation Quality after applying the different IML strategies, we calculated a measure called 'Explanatory Accuracy'. First, we took $k = 10\%$ of the most relevant words from global Gold Standard $GS^{(k)}_{global}(y)$ and intersected those with a document’s words ($GS^{(k)}_{global}(y) \cap x$) resulting in a local Gold Standard ($GS^{(k)}_{local}(x)$). Subsequently, for each test document $x$ a local explanation $\epsilon(x)$ was generated using LIME. The Average Explanatory Accuracy was then defined as:

$$ExplanatoryAccuracy_{AVG} = \frac{1}{N} \sum_{i=1}^{N} \frac{|GS^{(k)}_{local}(x_i) \cap \epsilon(x_i)|}{|GS^{(k)}_{local}(x_i)|}$$  \hspace{1cm} (5)

, with $N$ being the number of documents in the test dataset. We restricted the complexity of the local surrogate models (number of explanatory words) to $\Omega(q) = |GS^{(k)}_{local}(x)|$, such that the LIME explanations were theoretically capable of finding all relevant explanations according to local $GS$. We measured the Average Explanatory Accuracy of the test instances after every 20th iteration.

5 Experiment 1: Predictive Performance

We conducted the first experiment by measuring the Predictive Performance of the different IML strategies. Figures 4(a) and 5(a) show the convergence of the macro averaged F1 score on the two testsets over 200 iterations for our approach SemanticPush as well its baselines. For both datasets, SemanticPush clearly outperforms the standard ActiveLearner and the two versions of CAIPI when using XGBoost as base classifier (despite a Gold Standard that is around ten percent worse than the one used for CAIPI). It can also be seen that SemanticPush incorporates the oracle’s expert knowledge efficiently at much earlier stage (around 90 percent of final F1 score reached already after only 50 iterations). In the middle range of the iterations, SemanticPush has already applied much of the correct knowledge and therefore its performance starts to increase more slowly. For classifiers like the Support Vector Machine (see figure 7(a) in the Appendix), which earlier reached high classification accuracy (in the realm of the conceptual Gold Standard’s performance), SemanticPush’s performance starts to stagnate during later iterations as it partially has applied ‘incorrect corrections’. CAIPI destructive is not able to consistently beat the ActiveLearner’s baseline, while our constructive extension performs better. Figures 4(b) and 5(b) confirm those observations from the point of the Average Classification Margin between predicted and true class, where SemanticPush on average performs false predictions less frequent or with less confidence than its baselines. Across all experiments, we kept the hyperparameters constant. At each iteration, we allowed the different methods to generate $M = 10$ counterexamples incorporating the correct knowledge. Furthermore, we set the length (number of words) of each counterexample to the average document length of the respective corpora (25 for the AG News Dataset and 60 for Reuters R10). We allowed LIME to generate explanations containing 7 words (for AG News) and 15 words (for Reuters R10). The topicLIME explanations included 3 and 5 topics respectively. This limitation was made due to the fact that in real world humans can only perceive, process and remember a limited number of information. According to Miller’s law (Miller 1956), this capacity is somewhere between seven plus or minus two. Additionally, we set $\lambda$ to 0.95 as we simulated some sort of global expert knowledge.

5.1 Experiment 2: Local Explanation Quality

We performed experiments by analyzing the Local Explanation Quality of the different IML strategies in both directions of interaction with the oracle. Table 1 compares the quality of the local surrogate models and the resulting explanations generated by LIME and topicLIME. The related measures are Approximation Error, $MeanR^2$ as well as Combined Removal Impact (CRI) of the two different test datasets. It is noticeable that both the surrogate explanation models and the local explanations itself are more faithful towards the model to be explained when using contextual explanations generated from realistic local perturbation distributions. Therefore, resulting explanations are regarded as more reliable. Table 2 takes up the topic of Local Explanation Quality from the other direction (after the interactions with the oracle). It is striking that only SemanticPush is capable of clearly incorporating the expert knowledge in a way that it is adequately adapted by the base classifier. The two versions of CAIPI don’t reveal better results than the standard ActiveLearner.
Table 1: Comparison of LIME and topicLIME w.r.t. local fidelity

| Dataset     | Lime Approx. Error | topicLIME Approx. Error | Difference | $R^2$   | $R^2$ Difference | CRI   | CRI Difference |
|-------------|--------------------|-------------------------|------------|---------|-----------------|-------|----------------|
| AG News     | 0.0394             | 0.0342                  | -13%       | 0.863   | 0.884           | +2.5% |                 |
|             | 0.229              | 0.277                   | +21%       |         |                 |       |                 |
| Reuters R52 | 0.0195             | 0.0076                  | -61%       | 0.864   | 0.951           | +10%  |                 |
|             | 0.271              | 0.302                   | +11%       |         |                 |       |                 |

Table 2: Local explanation quality w.r.t. ‘Ground Truth’ of downstream classification tasks

| Dataset     | Explanatory Accuracy $\text{AVG}$ AL | Explanatory Accuracy $\text{AVG}$ CAIPI $d$ | Explanatory Accuracy $\text{AVG}$ CAIPI $d/c$ | Explanatory Accuracy $\text{AVG}$ Sem.Push |
|-------------|-------------------------------------|------------------------------------------|------------------------------------------|------------------------------------------|
| AG News     | 0.690                               | 0.683                                   | 0.685                                   | 0.711                                    |
| Reuters R10 | 0.741                               | 0.739                                   | 0.742                                   | 0.768                                    |

To sum it up, our proposed approach not only improves Learning Performance already at early stages of interactions, but also pushes the reasoning of the learner towards the desired behavior.

6 Conclusion

We introduced a novel IML architecture called Semantic Interactive Learning that helps to bring humans in the loop and allows for richer interactions. We instantiated it with SemanticPush, the first IML strategy enabling semantic and constructive corrections of a learner, also for false predictions. Our approach offers locally faithful and contextual explanations and, building on that, qualifies humans to provide conceptual corrections that can be considered graded and continuous. The corrections are in turn integrated into the learner’s reasoning via non-extrapolating and contextual additional training instances. As a consequence of combining richer explanations with more extensive semantic corrections, our proposed interaction paradigm clearly outperforms its baseline with regard to learning performance as well as local explanation quality of downstream classification tasks in the majority of our experiments. As the simulation of expert knowledge via a global Gold Standard is a crucial aspect of our architecture, we plan to improve the simulation’s accuracy as well as evaluate its quality using Inter-rater reliability. Additionally, we intend to further include a language model like BERT into our architecture such that generated counterexamples are not only semantically

\[1\]
Please note that our constructive extension for CAIPI outperforms original CAIPI as well in most experiments w.r.t. Learning Performance.
meaningful, but also linguistically, especially syntactically correct.

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Figure 6: Learned LDA topics and its most representative words for the AG News Dataset

Algorithm 3: CAIPI (Teso and Kersting 2019)

Require: a set of labelled examples $L$, a set of unlabelled instances $U$ and an iteration budget $T$.

$f \leftarrow \text{FIT}(L)$

repeat

$x \leftarrow \text{Select Query}(f, U)$

$\hat{y} \leftarrow f(x)$

$\hat{z} \leftarrow \text{Explain}(f, x, \hat{y})$

Present $x$, $\hat{y}$ and $\hat{z}$ to the user

Obtain $y$ and explanation correction $C$

$\{(\bar{x}_i, \bar{y}_i)\}_{i=1}^c \leftarrow \text{To Countereexamples}(C)$

$L \leftarrow L \cup \{(x, y)\} \cup \{(\bar{x}_i, \bar{y}_i)\}_{i=1}^c$

$U \leftarrow U \setminus \{(x, y)\} \cup \{(\bar{x}_i)_{i=1}^c\}$

$f \leftarrow \text{FIT}(L)$

until budget $T$ is exhausted or $f$ is good enough

return $f$

Table 3: Local explanation quality w.r.t. ‘Ground Truth’ of downstream classification task (Support Vector Machine)

|                      | AL       | CAIPI$_d$ | CAIPI$_d$/c | Sem.Push |
|----------------------|----------|-----------|-------------|----------|
| Reuters R10          | 0.786    | 0.785     | 0.788       | 0.796    |

Figure 7: (a): Learning performance of different IML strategies for Reuters R10 Dataset (Support Vector Machine). (b): Average Classification Margin of different IML strategies for Reuters R10 Dataset (Support Vector Machine).
Reproducibility
To facilitate the reproducibility of this work, our code is available at https://github.com/sb1990gtr/Semantic-Interactive-ML.