Interpretable Research Replication Prediction via Variational Contextual Consistency Sentence Masking

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Abstract

Research Replication Prediction (RRP) is the task of predicting whether a published research result can be replicated or not. Building an interpretable neural text classifier for RRP promotes the understanding of why a research paper is predicted as replicable or non-replicable and therefore makes its real-world application more reliable and trustworthy. However, the prior works on model interpretation mainly focused on improving the model interpretability at the word/phrase level, which are insufficient especially for long research papers in RRP. Furthermore, the existing methods cannot utilize a large size of unlabeled dataset to further improve the model interpretability. To address these limitations, we aim to build an interpretable neural model which can provide sentence-level explanations and apply weakly supervised approach to further leverage the large corpus of unlabeled datasets to boost the interpretability in addition to improving prediction performance as existing works have done. In this work, we propose the Variational Contextual Consistency Sentence Masking (VCCSM) method to automatically extract key sentences based on the context in the classifier, using both labeled and unlabeled datasets. Results of our experiments on RRP along with European Convention of Human Rights (ECHR) datasets demonstrate that VCCSM is able to improve the model interpretability for the long document classification tasks using the area over the perturbation curve and post-hoc accuracy as evaluation metrics.

1 Introduction

Scientific research results that cannot be reproduced are unreliable and negatively impact the development of science. Therefore, it is important to know whether a published research result can be replicated or not. To this end, domain researchers have conducted several direct replication projects in contemporary published social science studies.

Figure 1: (a) Given the text information of a research paper, Research Replication Prediction (RRP) task predicts whether the paper can be reproduced or not. (b) Having the same input as (a), our VCCSM model can keep the important sentences (through masking unimportant ones) which are related to reproducibility.

(Camerer et al., 2016, 2018; Ebersole et al., 2016; Klein et al., 2018; Collaboration et al., 2015). Such direct replication, however, is very time-consuming and expensive. A much more efficient and cheaper alternative, Machine Learning (ML), is utilized for predicting research replication (Dreber et al., 2019; Yang, 2018; Altmejd et al., 2019; Luo et al., 2020). In this paper, we model the task of predicting research replication as a binary classification problem and name it Research Replication Prediction (RRP) task which is shown in Figure 1(a). Nonetheless, applying the neural network models in the context of RRP faces two challenges. The first challenge is that the existing neural network models used in RRP are characterized as a black box because their predictions are hardly understandable. Without intelligible explanations for the predictions, results of RRP may not be widely accepted as reliable and trustworthy. Despite the progress in interpretable machine learning (Hechtlinger, 2016; Smilkov et al., 2017; Singh et al., 2018; Serrano...
and Smith, 2019; Han et al., 2020; Chen and Ji, 2020; Chen et al., 2021), the existing works mostly focus on improving the interpretability only at the word/phrase level which might work well for short documents. However, research papers in our RRP problem are usually lengthy (the average length of words is about 10,000). Building interpretable models for long documents is a challenging task due to the massive amount of textual information.

The second salient challenge is the small size of labeled dataset in RRP due to the high cost (e.g., funding requirement, human labor, etc.) of direct replications. Training an interpretable neural network also requires a large size of labeled dataset and weakly supervised learning can help utilize the unlabeled dataset. Although weakly supervised approaches have been utilized to make use of a large size of unlabeled dataset (Berthelot et al., 2019; Xie et al., 2019; Chen et al., 2020), they have mainly focused on improving the prediction performance but not the interpretability. We therefore aspire to build a weakly supervised interpretable neural text classifier for predicting research replication that can leverage the existence of the large corpus of unlabeled articles to boost up both the prediction performance and the interpretability.

To tackle the first challenge mentioned above, we built an interpretable neural network model which can automatically select key sentences instead of words/phrases by adding a variational sentence masking layer on the input layer which is a simple modification of network architecture but can effectively improve the model interpretability. By adding a variational sentence masking, we can adopt information bottleneck framework (Tishby et al., 2000; Alemi et al., 2016) to train the model and improve both the prediction performance and interpretability by identifying important sentences. In addition, we hypothesize that whether to mask a sentence or not should also depend on its context (whether other sentences in the same paper are masked) in the case for long research papers because the information provided by extracted key sentences should not be redundant. Therefore, we invoke a contextual sentence masking approach using the LSTM model (Hochreiter and Schmidhuber, 1997). The extracted key sentences after masking are considered as our interpretable outcomes for each research paper.

To resolve the second challenge, we developed a new weakly supervised method which makes use of unlabeled dataset to improve both the prediction performance and interpretability. Specifically, we adopted the consistency training methods (Laine and Aila, 2016; Tarvainen and Valpola, 2017; Xie et al., 2019) which regularize model predictions to be invariant to the small noises added to the input. Consistency training were used to improve the prediction performance with the help of unlabeled dataset (Xie et al., 2019). In this paper, to improve the interpretability along with the prediction performance, we propose a consistency training method with sentence masking through replacing the noises-added input of unlabeled dataset by masked sentences. Specifically, for each unlabeled research paper, we generate the first prediction by using only the extracted key sentences after the sentence masking. Then, we generate the second prediction using all the sentences in the research paper without masking. The consistency check is then imposed upon the two predictions by minimizing the difference between them. Through the consistency training, an extra large size of unlabeled dataset can be utilized to make model continually learn how to extract the key sentences of a research paper so that the model interpretability is further improved.

In sum, our main contribution is the proposal of a variational contextual consistency sentence masking (VCCSM) method as shown in Figure 1(b) that is able to (1) extract the key sentences based on the context of a research paper and (2) leverage the large number of unlabeled sets of papers using a consistency checking mechanism. We present experimental results to validate the usefulness of our proposed methods on two neural network models, LSTM (Hochreiter and Schmidhuber, 1997) and BERT (Devlin et al., 2018) on the RRP along with ECHR datasets. In particular, we find VCCSM is able to improve both the replication prediction accuracy and the interpretability for long research papers and general long documents.

2 Related Work

Blackbox Research Replication Prediction Research Replication Prediction, knowing whether a published research result is replicable or not, is important. Recently, several large scale of direct replication projects have been conducted in social science studies to alleviate the replication crisis. But the cost of direct replication is too high to have a large size of annotated dataset. Therefore, an
alternative ML method that is much cheaper and more efficient than direction replication is utilized in RRP. Luo et al. (2020) proposed a neural text classifier to achieve the best performance on RRP. But their model is a blackbox and cannot provide faithful explanations about why a research paper is predicted as replicable or non-replicable.

Interpreting Neural Networks Various approaches have been proposed to interpret neural network models from the post-hoc manner, such as gradient-based (Simonyan et al., 2014; Hechtlinger, 2016; Sundararajan et al., 2017), attention-based (Serrano and Smith, 2019), decomposition-based (Murdoch et al., 2018; Singh et al., 2018), example-based methods (Koh and Liang, 2017; Han et al., 2020), and word masking (Chen and Ji, 2020). However, these interpretation methods have their own limitations, including only work with specific neural network model, render doubts on faithfulness, and need additional work to provide the explanations based on trained models. In this paper, we focus on model-agnostic explanation methods. More specifically, we follow the research of masking methods which can improve both the prediction performance and interpretability by adopting information bottleneck framework (Tishby et al., 2000; Alemi et al., 2016) to identify important sentences.

Improving interpretability via word masking Chen and Ji (2020) proposed a word masking method which can automatically select important words in the training process and build interpretable neural text classifiers by formulating their problem in the framework of information bottleneck. The proposed solution mainly deals with the short text and the average length (words) in all the seven datasets they used are less than 300. Four of them are less than 25. In constrast, the average length (words) of research papers in our RRP task is about 10,000 which is much longer than the ones used in (Chen and Ji, 2020). Therefore, we view word masking as insufficient for our task. On the other hand, Chen and Ji (2020) learn independently on whether each word is masked or not. But context matters, especially for long documents. Different from prior work, we utilized the context information (whether other sentences in the same paper are masked or not) of each sentence by applying LSTM models to decide whether to mask this sentence or not. We hypothesize that context masking is better than independent masking, especially for long documents such as the research papers in RRP.

Consistency Training on Unlabeled Dataset The annotated data in RRP is collected using direction replication and its size is small. Therefore, weakly supervised learning methods need to be used to improve the model performance in RRP with the help of the unlabeled dataset. The existing weakly supervised methods applied in RRP focus mainly on improving the prediction performance, but less so about the model interpretability.

Consistency training can improve the robustness of models by regularizing model predictions to be invariant to small noise applied to input examples (Sajjadi et al., 2016; Clark et al., 2018). Xie et al. (2019) proposed to substitute the traditional noise injection methods in the consistency training with high quality data augmentations so that a new consistency training based weakly supervised method is proposed and the performance is improved with the help of unlabeled dataset. But they focused only on improving the prediction performance.

In this paper, we conduct the consistency training on the unlabeled dataset to improve both prediction performance and interpretability by substituting the traditional noise injection methods with sentence masking methods, which is the major contribution of our paper. More specifically, we first mask the unimportant sentences and keep the critical sentences. Then we make the predictions on the kept key sentences the same as the ones based on all the sentences in the research paper without masking. Finally, we conducted the consistency check by minimizing the difference between them.

3 Problem Statement

In this paper, our main goal is to improve the interpretability of neural textual classifier for Research Replication Prediction (RRP). First we introduce the RRP task.

Research Replication Prediction (RRP) task In RRP, we hope to build a model \( f \) that takes each research article as input and predicts whether the made research claim is replicable or not \( f(\text{article}) \in \{0 \text{ (non-replicable), 1 (replicable)}\} \). There are different definitions and criteria for claiming a research paper to be replicable. In this work, a research paper is replicable means that an independent replication can provide evidence of a statistically significant effect in the same direction.
as the original paper.

**Interpretable Research Replication Prediction**

In this paper, we aim to build an interpretable neural textual classifier for RRP. Improving the model interpretability can help us understand why a research paper is predicted as replicable or non-replicable and make its application in the real world achieve more reliability and trustworthiness. Different from generating post-hoc explanations based on well-trained models, we adopt the information bottleneck framework (Tishby et al., 2000; Alemi et al., 2016) to train our model and build a more interpretable neural textual classifier for RRP.

**Preliminaries and notations**

To perform the above task, we have an labeled training dataset \( \mathcal{L} := \{(x_i, y_i)\}_{i=1}^{L} \), an unlabeled dataset \( \mathcal{U} := \{x_i\}_{i=1}^{U} \), and a test dataset \( \mathcal{T} := \{(x_i, y_i)\}_{i=1}^{T} \), where \( L, U, \) and \( T \) are the number of labeled training, unlabeled training, and testing datasets respectively. \( x_i \) contains a sequence of sentences \( x_i = [x_{i1}, x_{i2}, ..., x_{ij}, ..., x_{iS}] \) in the \( i_{th} \) research paper and \( S \) is the maximum number of sentences in a research paper in RRP task. For the \( j_{th} \) sentence in \( x_i \), \( x_{ij} = [x_{ij1}, x_{ij2}, ..., x_{ijk}] \), where \( n \) is the maximum number of words in a sentence and \( x_{ijk} \in \mathbb{R}^d \) which indicates the word embeddings as the model input. All the sentences have the same length \( K \) by truncating. And \( y_i \) is \( x_i \)'s binary classification label which is either ‘1’ (replicable) or ‘0’ (non-replicable). A neural textual classifier can be trained to output the replication labels given any new research paper \( x_i \).

**4 Method**

The details of our proposed variational contextual consistency sentence masking (VCCSM) method are described in this section.

**4.1 Model Overview**

Our model contains two key modules: variational contextual sentence masking and consistency training. Variational contextual sentence masking module is applied in the training on both labeled and unlabeled datasets. Consistency training is only used in the training on the unlabeled dataset.

In the training on labeled dataset, variational contextual sentence masking module extracts the key sentences via contextual masking (LSTM model). Then the supervised loss is calculated and optimized to minimize the difference between prediction using the extracted sentences as the input and the ground truth label in the information bottleneck framework. The formula of supervised loss will be described later in this section and the architecture of the model on how to train the labeled dataset is shown in the left part of Figure 2.

In the training on unlabeled dataset, different from the prior works, we conduct the consistency training on the unlabeled dataset to improve both prediction performance and interpretability by substituting the traditional noise injection methods with sentence masking methods. Consistency training can improve the model robustness by regularizing model predictions to be invariant to small noise applied to input examples (Sajjadi et al., 2016; Miyato et al., 2018; Clark et al., 2018). Typical noise injection methods included additive Gaussian noise, dropout noise or adversarial noise. The existing consistency training based work e.g., (Xie et al., 2019) focuses only on improving the prediction performance instead of interpretability. The consistency training methods utilized in this paper are based on variational contextual sentence masking and can also improve the model interpretability. Our optimization goal is to minimize the difference between prediction using the extracted vital sentences and prediction made on all the sentences without masking in the information bottleneck framework. The formula of unsupervised loss will be described later in this section and the architecture on how to train the unlabeled dataset is shown in the right part of Figure 2.

**4.2 Variational Contextual Sentence Masking**

Inspired by Chen and Ji (2020), we want to add a mask layer \( M \) after the sentence embeddings layer to help the model select the key sentences, where \( M = [M_1, M_2, ..., M_j, ..., M_S] \) and \( S \) is the maximum number of sentences in a research paper. The embedding of each sentence is concatenated by word embeddings included in this sentence.

Each \( M_j \in \{0, 1\} \) is a binary random variable to decide whether we mask this sentence or not. For each sentence in one research paper, \( M_j \) should be related to both the current sentence and the sentences around it (context). Therefore, we use LSTM model to generate the contextual sentence mask \( M_j \) for the \( j_{th} \) sentence in one research paper, where \( M_j = \text{LSTM}(x_j), j = 1, 2, ..., S \). \( x \) can be any given research paper. This contextual sentence mask layer \( M \) together with the sentence embed-
Labeled data
Unlabeled data
Supervised VAB Loss
Unsupervised VAB Loss
Final Loss

\[ \hat{y}_i^{\text{mask}} = f(x_i^{\text{mask}}) \]

\[ y_i = f(x_i) \]

\[ \hat{y}_i^{\text{mask}} = f(x_i^{\text{mask}}) \]

Figure 2: The architecture of variational contextual consistency sentence masking (VCCSM).

ings are considered as the input of neural network text classifiers in RRP, which is denoted as follows,

\[ Z = X^{\text{mask}} = M \odot X, \quad (1) \]

where \( \odot \) is an element-wise multiplication, \( X \) are all the examples in any given dataset, and \( X^{\text{mask}} \) denotes the internal representations of all the examples. Our goal is to optimize \( M \) so that the model can extract the key sentences for each research paper.

The information bottleneck theory aims to learn an encoding \( Z \) of the input \( X \) with maximal information on predicting the target \( Y \) while keeps \( X \)'s the least redundant information (Tishby et al., 2000; Alemi et al., 2016). As proven effective and flexible in identifying important features (Chen and Ji, 2020), the information bottleneck framework is employed in our model. We want to make \( Z = X^{\text{mask}} \) maximally expressive on predicting \( Y \) while being maximally compressive on \( X \). Therefore, following the standard information bottleneck theory (Tishby et al., 2000), our objective function is denoted as follows:

\[ \max_Z I(Z; Y) - \beta \cdot I(Z; X), \quad (2) \]

where the definitions of \( X \) and \( Z = X^{\text{mask}} \) are given in Equation 1. \( Y \) is the target output, \( I(\cdot; \cdot) \) denotes the mutual information, and \( \beta \in \mathbb{R}_+ \) is a coefficient that balances the two terms in the information bottleneck loss function. The formula of mutual information \( I \) should include the parameters \( \theta \) which need to be optimized. For simplicity, we ignore \( \theta \) in the following formulae.

However, computing the mutual information in Equation 2 is usually computationally challenging. Therefore, we adopted variational inference method to construct a lower bound for Equation 2. After constructing the lower bound and applying the reparameterization trick (Kingma and Welling, 2013), we can optimize the objective utilizing stochastic gradient descent. In this subsection, we simply listed the lower bound of Equation 2. The complete details on the derivation of lower bound for variational contextual sentence masking is shown in Appendix A.1.

Assuming that the true joint distribution is \( P(X, Y, Z) \) and \( X, Y, Z \) are random variables which have the following conditional dependency: \( Y \leftrightarrow X \leftrightarrow Z \). And \( x, y, z \) are instances of random variables. The lower bound of Equation 2 is as follows:

\[ \sum_{x, y, z} P_X(x)P_Y(y|x)P_Z(z|x) \log Q_Y(x; y) \log Q_Z(z) \]

\[ -\beta \sum_{z, x} P_X(x)P_Z(z|x) \log \frac{P_Z(z|x)}{Q_Z(z)} \quad (3) \]

To compute Equation 3, we use the empirical data distribution including two Delta functions to approximate the \( P_X(Y, X, y) \). Therefore we have the loss function of variational information bottleneck (VAB) as follows:

\[ \ell_{\text{vib}} = \left[ \mathbb{E}_{P_X, Y, Z}(x, y) \mathbb{E}_{P_Z, X}(z|x) \log (Q_Y|Z(z)), \right] \log (Q_Y|Z(z)) \]

\[ -\beta \cdot \text{KL}[P_Z(z|x) || Q_Z(z)] \quad (4) \]

4.3 Consistency Training based on Variational Contextual Sentence Masking

In this work, we utilized a particular consistency training setting where the masked input \( x^{\text{mask}} \) is generated by applying variational contextual sentence masking mentioned above on each input \( x \),
which can be written as follows: \( x^{\text{mask}} = M \cdot x \), to improve both the interpretability and prediction performance.

More specifically, inspired by Xie et al. (2019), we propose to substitute the traditional noise injection methods with our Contextual Sentence Masking module to generate the masked input \( x^{\text{mask}} \) given each input \( x \) in the unlabeled dataset which can be written as follows: \( x^{\text{mask}} = M \cdot x \). We also use the information bottleneck framework in the consistency training. The only change is to replace the ground truth label \( y_i \) with the prediction \( \hat{y}_i \) given the original research paper \( x_i \) as the input. To be noted, the sentence mask layer is not used when predicting \( \hat{y}_i \).

### 4.4 Variational Information Bottleneck (VAB) Loss Function

As shown in Figure 2, our VAB loss functions contains two parts: a supervised VAB loss \( \ell_{su} \) and an unsupervised VAB loss \( \ell_{un} \). The same model is optimized in both losses.

**Supervised VAB Loss** Since we have ground truth labels in the labeled dataset, the supervised VAB loss \( \ell_{su} \) is the same as the VAB loss \( \ell_{v} \) in Equation 4 and it is denoted as follows:

\[
\ell_{su} = -\langle \mathbb{E}_{P_{X,Y}(x,y)} \rangle \mathbb{E}_{P_{Z|X}(z|x)} \log (Q_{Y|Z}(y|z)) - \beta \cdot \text{KL}(P_{Z|X}(z|x)||Q_{Z}(z)) \]  

(5)

where \( P_{X,Y}(x,y) \) refers to empirical distribution of complete observations.

**Unsupervised VAB Loss** As for the unsupervised VAB loss, the only difference from the supervised one is to replace the ground truth label \( y \) by the prediction \( \hat{y} = f(x) \) given the original research paper \( x \) as the input and it is denoted as follows:

\[
\ell_{un} = -\langle \mathbb{E}_{P_{X}(x)} \rangle \mathbb{E}_{P_{Z|X}(z|x)} \log (Q_{Y|Z}(\hat{y}|z)) - \beta \cdot \text{KL}(P_{Z|X}(z|x)||Q_{Z}(z)) \]  

(6)

where \( P_{X}(x) \) refers to empirical distribution of incomplete observations.

**Total Loss** In summary, our full training objective \( \ell \) can be written as follows:

\[
\ell = \ell_{su} + \alpha \cdot \ell_{un} \]  

(7)

where \( \alpha > 0 \) is a balancing hyper parameter about these two items of losses. Our goal is to minimize the full training objective \( \ell \).

## 5 Experimental Setup

The proposed VCCSM method is evaluated with two typical neural network models commonly used on text classification tasks, LSTM (Hochreiter and Schmidhuber, 1997) and BERT (Devlin et al., 2018) on two datasets.

### 5.1 Datasets

**RRP Dataset** RRP dataset is proposed by Luo et al. (2020). RRP dataset contains 399 labeled and 2,170 unlabeled research articles in social science fields. In this paper, randomly selected 300 (150:1:150:0) labeled and 2,170 unlabeled samples are treated as the training dataset. The remaining 99 (51:1:48:0) labeled research articles are considered as the testing dataset. More details about the RRP dataset are shown in Appendix A.2. PDFMiner (Shinyama, 2014) is used to extract the text in the raw pdf files for both labeled and unlabeled datasets. Therefore, the text format of labeled and unlabeled datasets are the same.

**ECHR Dataset** European Convention of Human Rights (ECHR) (Chalkidis et al., 2019) is a publicly available English legal judgment prediction dataset which contains 11,478 cases. Each case has a list of paragraphs describing the facts. The task is to predict whether one given case is judged as violated or not. The ECHR dataset is split into training, development, and testing datasets with the number of cases of 7,100, 1,380 and 2,998. The average number of tokens for training, development, and testing datasets are 2,421, 1,931, and 2,588, respectively.

### 5.2 Implementation Details

The LSTM model we used has a bidirectional hidden layer, and it’s initialized with 300-dimensional google’s pre-trained word embeddings. We fix the embedding layer and update other parameters in LSTM to achieve the best performance. As for BERT model, a published BERT pre-trained model ("bert-base-uncased") is utilized as the embedding layer of LSTM model. We first use our corpus to pre-train the BERT model and then fine-tune it in the VCCSM classifier’s training. In each epoch, the model is first trained on labeled data, followed by unlabeled data. The hidden state of the [CLS] token of the last layer is considered as the sentence representation.

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1[https://huggingface.co/bert-base-uncased](https://huggingface.co/bert-base-uncased)
Because the average length (words) of all the documents in the labeled and unlabeled datasets is about 10,000, we set the maximum length of words in our paper to 10,000. Since VCCSM method is sentence masking and we need to split the text of research paper into sentences. We use period, question mark, and semicolon to conduct the splitting. After some statistical analysis, the average length (words) of each sentence is around 25. For a fair comparison with word masking method, we set the maximum length of sentences in each document to 400. It means that we set the maximum length of words in each document to 10,000 in all models. In the experiments, for RRP dataset, the number of labeled and unlabeled datasets are 4,000 and 2,170 research papers respectively. As for ECHR dataset, 2,000 cases in the training dataset are considered as the labeled and the remaining 5,100 cases as the unlabeled.

5.3 Interpretability Metrics

5.3.1 AOPC

The first interpretability metric we used is area over the perturbation curve (AOPC) (Samek et al., 2016; Nguyen, 2018) which is obtained by computing the average change of prediction probability by deleting top \( n \) important words and it can evaluate the model interpretability on faithfulness. Since our proposed VCCSM is sentence masking method, we calculate the average change of prediction probability by deleting top \( n \) key sentences in the explanations of the papers. Therefore, AOPC used in our paper is defined as follows:

\[
\text{AOPC}(f) = \frac{1}{T+1} \sum_{i=1}^{T} \left( f(x_i) - f(x_i \setminus \{s_1, \ldots, s_n\}) \right),
\]

where \( f(x_i \setminus \{s_1, \ldots, s_n\}) \) is the probability for the predicted class on the \( i_{th} \) document in RRP when the top \( n \) sentences on importance are removed. Higher AOPC score is better.

5.3.2 Post-hoc Accuracy

The second interpretability metric utilized in this paper is post-hoc accuracy metric (Chen et al., 2018) which is computed by counting how many testing examples’ predictions are changed by utilizing only extracted top \( n \) words to classify. For our VCCSM models, we used top \( n \) key sentences. The formula to calculate the post-hoc accuracy in our paper is as follows:

\[
\text{Acc}_p(f, n) = \frac{1}{T} \sum_{i=1}^{T} \left[ 1[f(\{s_1, \ldots, s_n\}) = f(x_i)] \right],
\]

where \( T \) is the number of examples in the testing dataset, \( \{s_1, \ldots, s_n\} \) are the top \( n \) sentences on importance in the \( i_{th} \) document. Higher post-hoc accuracy is better.

6 Results

We tested our proposed models on two text classification datasets (RRP along with ECHR), and the details about prediction accuracy and interpretability are described in this section.

6.1 Quantitative Evaluation

We evaluate the interpretability of VCCSM model against other types of models via the AOPC (Samek et al., 2016; Nguyen, 2018) and post-hoc accuracy (Chen et al., 2018) metrics. We also listed the performance with varying number of the unlabeled data in Appendix A.3 and it shows that the performance become higher with more unlabeled data.

Table 1 shows the results of VCCSM (LSTM & BERT) and other interpretable models on the RPP and ECHR datasets with top 500 words (word based methods) or 20 sentences (sentence based methods). Simialr results are obtained with varying number of sentences. For BERT’s attention weights model, we extracted the words’ attention weights of all heads in the last layer and average them. As for BERT’s attention weights (sentences), we average the words’ averaged weights in each sentence as its sentence representation. Extractive summarization models can also extract the key sentences for each document. In this section, we used the recent extractive summarization method (Cui and Hu, 2021) as the baseline. We conduct the training on arXiv + PubMed (Cohan et al., 2018) and our labeled + unlabeled datasets (the abstract are the summary). Training on arXiv + PubMed aims to generalize the model and make the model extract more comprehensive information instead of only abstract in the research paper. We can observe that our proposed models perform better than other methods in both interpretability and prediction performance on both RRP and ECHR datasets.

Ablation Study In order to validate different modules in our proposed VCCSM method, we conduct the ablation study on the RRP dataset as shown in Table 2. We observe the drop after removing contextual masking or consistency training (on the unlabeled data) which shows that each component benefit to the model. It is noting that we observe a
LSTM Word Masking (Chen and Ji, 2020) | 60.61% | 11.16% | 50.51% | 84.86% | 10.32% | 65.84%
BERT’s Attention Weights (words) | 64.65% | 11.70% | 60.61% | 84.26% | 15.06% | 73.75%
BERT Word Masking (Chen and Ji, 2020) | 65.66% | 12.05% | 61.62% | 85.06% | 16.30% | 76.38%
SOTA Extractive Summarization (Cui and Hu, 2021) | 65.66% | 12.86% | 57.58% | 85.39% | 19.57% | 75.52%
BERT’s Attention Weights (sentences) | 65.66% | 13.62% | 62.63% | 85.39% | 22.61% | 81.49%

Table 1: Comparison between VCCSM and other methods on testing accuracy, area over the perturbation curve (AOPC), and post-hoc accuracy on RRP and ECHR datasets.

LSTM Sentence Masking + Contextual + Consistency | 65.66% | 22.19% | 63.64% | 86.06% | 30.53% | 84.22%
BERT Sentence Masking + Contextual + Consistency | 68.69% | 24.02% | 65.66% | 87.66% | 32.78% | 86.59%

Table 2: Ablation study of proposed VCCSM (LSTM & BERT Sentence Masking + Contextual + Consistency) on testing accuracy, area over the perturbation curve (AOPC), and post-hoc accuracy on RRP dataset.

Figure 3: Highlighted explanations (words or sentences) of BERT word masking, attention weights (sentences), SOTA extractive summarization, and BERT VCCSM methods for a paragraph in one replicable research paper “Word Learning as Bayesian Inference” in Psychological Review.

larger drop on both accuracy and two interpretability metrics without the consistency training on the unlabeled data which demonstrates that consistency training contributes more to the model.

6.2 Qualitative Evaluation

In this section, we conduct the qualitative evaluations and compare the explanations of different models intuitively by highlighting the words or sentences. Specifically, we draw on the Open Science practices (e.g., mentioning how to access the data) as indicators of high reproducibility, because these practices are proposed as solutions to the reproducibility crisis in the science community (Simonsohn et al., 2015; Foster and Deardorff, 2017; Brodeur et al., 2020; Dienlin et al., 2021; Markowitz et al., 2021). Some of those indicators which are easier to check are listed as below: (1) Publish materials, data, and code; (2) Preregister studies and submit the reports; (3) Conduct the replications by themselves; (4) Collaborate with others; (5) P-value is close to 0.5.

We conduct the case studies on the testing dataset and find that our proposed methods can highlight more sentences which are related to the indicators mentioned above. A case study is shown in Figure 3. More specifically, Figure 3 shows highlighted explanations (words or sentences) of BERT word masking, attention weights (sentences), SOTA extractive summarization, and BERT VCCSM methods for a paragraph in one replicable research paper “Word Learning as Bayesian Inference” (Xu and Tenenbaum, 2007) in Psychological Review. In this case study, we extracted top 200 sentences or 5,000 words (only

2Probability of obtaining test results at least as extreme as the results actually observed, under the assumption that the null hypothesis is correct.
for BERT word masking method) but only show one paragraph highlighted results. Although all the methods provide the correct prediction, our VCCSM highlights the sentences which are related to the indicators described above. It is noting that the highlight words of BERT word masking is not so readable for the long research paper. Attention weights (sentences) and SOTA extractive summarization methods can provide informational sentences but the highlighted sentence are not related to the indicators described above. BERT VCSSM can highlight $p$-value sentences which are related to the indicators mentioned above.

### 6.3 Discussion on Plausibility of Predicting Research Replicability using Text

By looking into RRP’s labeled dataset and conducting the cases studies carefully such as in Figure 3, we discuss on whether classifying results in a research paper as replicable using text is actually sufficient to replicate the results, which is the central premise this paper is based on. Non-replicability of scientific studies largely results from unscientific, unethical research practices (e.g., $p$-hacking, selective reporting, data manipulation). Such practices can be manifested in the texts of research papers such as the reports of $p$-values, experimental procedures, etc. Generally speaking, the more problematic practices a research paper involves, the less likely its findings are valid, and the less likely it will be reproduced. Hence, by modeling the replicability of research paper with regard to its textual components that are potentially linked with the problematic practices, we can classify whether a research paper can be replicated and identify the focal sentences relevant to the prediction.

### 7 Concluding Remarks

In this paper, we proposed VCCSM to improve both interpretability and prediction accuracy on RRP along with ECHR datasets, using largely unlabeled datasets. We tested VCCSM with two different neural text classifiers (LSTM and BERT) and evaluated both prediction accuracy and interpretability metrics. As future work, we plan to explore other advanced interpretable models and weakly supervised methods to further improve the prediction performance and interpretability of long document classification tasks.

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### 8 Broader Impacts

Our paper proposed VCCSM method to build an interpretable model for long document datasets such as RRP and ECHR. Our model can provide the explanations about why a research paper is predicted as replicable or non-replicable and why a case is judged as violated or not so that the prediction results obtained by neural text classifier are more reliable and trustworthy. However, sometimes, our proposed methods can be misused. For example, people may try to adversarially write the new text in a research paper to fool the research replication prediction tool when they can obtain the explanations by using our interpretable models. Therefore, the proposed methods in this paper should be used with careful consideration of its potential misusing when deployed in the real-world.

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Assuming that the true joint distribution is $P(X, Y, Z)$ and $X, Y, Z$ are random variables which have the following conditional dependency: $X \leftrightarrow Y \leftrightarrow Z$. And $x, y, z$ are instances of random variables. We can have

$$P(X, Y, Z) = P(Z|X, Y)P(Y|X)P(X)$$

$$= P(Z|X)P(Y|X)P(X). \quad (8)$$
According to the definition of $I(Z; Y)$, we have

$$I(Z; Y) = \sum_{z,y} P_{Z,Y}(z, y) \log \frac{P_{Z,Y}(z, y)}{P_{Z}(z)P_{Y}(y)}$$

$$= \sum_{z,y} P_{Z,Y}(z, y) \log \frac{P_{Y|Z}(y|z)}{P_{Y}(y)}. \quad (9)$$

And we also have

$$P_{Y|Z}(y|z) = \sum_{x} P_{X|Y|Z}(x, y|z)$$

$$= \sum_{x} P_{Y|X}(y|x)P_{X|Z}(x|z)$$

$$= \sum_{x} P_{Y|X}(y|x)P_{Z|X}(z|x)P_{X}(x). \quad (10)$$

Since $P(Y|Z)$ can be intractable, $Q(Y|Z)$ is considered as a variational approximation to $P(Y|Z)$. $Q(Y|Z)$ is our decoder and a neural network. Because the Kullback Leibler divergence is non-negative, we have

$$\text{KL}[P(Y|Z)||Q(Y|Z)] \geq 0 \Rightarrow \sum_{y} p(y|z) \log p(y|z) \geq \sum_{y} p(y|z) \log q(y|z). \quad (11)$$

Therefore, we can obtain the lower bound of $I(Z; Y)$ as follows:

$$I(Z; Y) \geq \sum_{z,y} P_{Z,Y}(z, y) \log \frac{Q_{Y,Z}(y|z)}{P_{Y}(y)}$$

$$= \sum_{z,y} P_{Z,Y}(z, y) \log Q_{Y|Z}(y|z) + H(Y). \quad (12)$$

where $H(Y) = -\sum_{y} P_{Y}(y) \log P_{Y}(y)$ is entropy.

According to Equation 8, we have

$$P(Y|Z) = \sum_{x} P_{X,Y,Z}(x, y, z)$$

$$= \sum_{x} P_{X,Y,Z}(x, y, z)$$

$$= \sum_{x} P_{X}(x)P_{Y|X}(y|x)P_{Z|X}(z|x). \quad (13)$$

Hence, we obtain the lower bound of $I(Z, Y)$ as follows:

$$\sum_{x,y,z} P_{X}(x)P_{Y|X}(y|x)P_{Z|X}(z|x) \log Q_{Y|Z}(y|z).$$

As for $I(Z; X)$, similar to Equation 9 in the derivation of $I(Z; Y)$, we first obtain

$$I(Z; X) = \sum_{z,x} P_{Z,X}(z, x) \log \frac{P_{Z,X}(z|x)}{P_{Z}(z)}$$

$$= \sum_{z,x} P_{Z,X}(z, x) \log P_{Z|X}(z|x)$$

$$- \sum_{z} P_{Z}(z) \log P_{Z}(z). \quad (14)$$

Because the marginal distribution of $Z$, $P(Z) = \sum_{z} P_{Z|X}(z|x)P_{X}(x)$ in which the computation might be difficult, we replace $P(Z)$ by a variational approximation of $Q(Z)$. Since $\text{KL}[P(Z)||Q(Z)] \geq 0 \Rightarrow \sum_{z} P_{Z}(z) \log P_{Z}(z) \geq \sum_{z} P_{Z}(z) \log Q_{Z}(z)$, we can get the upper bound of $I(Z; X)$ as follows:

$$I(Z; X) \leq \sum_{z,x} P_{Z,X}(z, x) \log P_{Z|X}(z|x)$$

$$- \sum_{z,x} P_{Z,X}(z, x) \log Q_{Z}(z)$$

$$\leq \sum_{z,x} P_{X}(x)P_{Z|X}(z|x) \log \frac{P_{Z|X}(z|x)}{Q_{Z}(z)}. \quad (15)$$

Combining Equation 12 and 15, we can get the lower bound of $I(Z; Y) - \beta I(Z; X)$ as follows:

$$\sum_{x,y,z} P_{X}(x)P_{Y|X}(y|x)P_{Z|X}(z|x) \log Q_{Y|X}(y|z)$$

$$- \beta \sum_{x,z} P_{X}(x)P_{Z|X}(z|x) \log \frac{P_{Z|X}(z|x)}{Q_{Z}(z)}.$$

A.2 Details of RRP Dataset

In the RRP dataset proposed by Luo et al. (2020), the labeled dataset are collected from eight research replication projects which are the Registered Replication Report (RRR) (Simons et al., 2014), Many Labs 1 (Klein et al., 2014), Many Labs 2 (Klein et al., 2018), Many Labs 3 (Ebersole et al., 2016), Social Sciences Replication Project (SSRP) (Camerer et al., 2018), PsychFileDrawer (Pashler et al., 2019), Experimental Economics Replication Project (Camerer et al., 2016), and Reproducibility Project: Psychology (RPP) (Collaboration, 2012). Among 399 labeled data in the RRP dataset, 201 are labeled as ‘1’ (replicable) and the remain 198 are annotated as ‘0’ (non-replicable). We observe that the labeled data in the RRP dataset is balanced.
In addition, RRP dataset also contains 2,170 research articles as the unlabeled dataset. Luo et al. (2020) observed that most papers in the labeled dataset in the RRP dataset are economical and psychology related. Among those papers, they are mainly from American Economic Review and Psychological Science journals. Therefore, a python crawler is written by Luo et al. (2020) to get 2,170 published research articles on the American Economic Review (Jan 2011 - Dec 2014) and Psychological Science websites (Jan 2006 - Dec 2012). The number of articles crawled from American Economic Review and Psychological Science websites are 981 and 1,189 respectively.

A.3 Performance with Varying Number of Unlabeled Data

We conducted the experiments to test our model’s effectiveness by varying number of unlabeled data for VCCSM applied on two neural text classifiers (LSTM and BERT). From Figure 4, we can observe that, with more unlabeled data, the testing accuracy become higher on both LSTM Sentence Masking + Contextual + Consistency and BERT Sentence Masking + Contextual + Consistency models, which validates the effectiveness of using unlabeled data.