Few-shot Controllable Style Transfer for Low-Resource Settings:
A Study in Indian Languages

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Abstract

Style transfer is the task of rewriting an input sentence into a target style while approximately preserving its content. While most prior literature assumes access to large style-labelled corpora, recent work (Riley et al., 2021) has attempted “few-shot” style transfer using only 3-10 sentences at inference for extracting the target style. In this work we consider one such low resource setting where no datasets are available: style transfer for Indian languages. We find that existing few-shot methods perform this task poorly, with a strong tendency to copy inputs verbatim.

We push the state-of-the-art for few-shot style transfer with a new method modeling the stylistic difference between paraphrases. When compared to prior work using automatic and human evaluations, our model achieves 2-3x better performance and output diversity in formality transfer and code-mixing addition across five Indian languages. Moreover, our method is better able to control the amount of style transfer using an input scalar knob. We report promising qualitative results for several attribute transfer directions, including sentiment transfer, text simplification, gender neutralization and text anonymization, all without retraining the model. Finally we found model evaluation to be difficult due to the lack of evaluation datasets and metrics for Indian languages. To facilitate further research in formality transfer for Indic languages, we crowdsource annotations for 4000 sentence pairs in four languages, and use this dataset to design our automatic evaluation suite.

1 Introduction

Style transfer is a natural language generation task in which input sentences need to be re-written into a target style, while preserving semantics. Style transfer has many applications such as creative writing assistance (Heidorn, 2000), controlling text generation systems for attributes like formality or persuasiveness (Smith et al., 2020; Niu and Carpuat, 2020), data augmentation (Xie et al., 2019; Lee et al., 2021), author obfuscation (Shetty et al., 2018), text simplification (Xu et al., 2015).

Most prior work in style transfer either assumes access to supervised data with parallel sentences between the two styles (Jhamtani et al., 2017), or access to large corpus of unpaired sentences with style labels (Prabhumoye et al., 2018; Subramanian et al., 2019). Models built are style-specific and cannot generalize to new styles during inference, which is needed for real-time adaptation to a user’s style in a dialog or writing application. Moreover, access to a large unpaired corpus with style labels is a strong assumption. Most standard “unpaired” style transfer datasets have been carefully curated (Shen et al., 2017) or were originally parallel datasets (Xu et al., 2012; Rao and Tetreault, 2018). This is especially relevant in settings out-
side English, where NLP tools and labelled datasets are largely underdeveloped (Joshi et al., 2020).

We consider one such setting, and take the first steps in studying style transfer for five Indian languages, which have nearly a billion native speakers in total. Since no training data exists for these languages, we analyzed the current state-of-the-art in few-shot multilingual style transfer, the Universal Rewriter (UR) from Garcia et al. (2021). Unfortunately, we found it often copied inputs verbatim (Section 3.1) without transferring style.

We propose a simple inference-time trick of style-controlled translation through English, which improves the output diversity from UR (Section 4.1). To further boost performance, we propose the DIFFUR algorithm, which uses the recent finding that paraphrasing leads to stylistic changes (Krishna et al., 2020). DIFFUR extracts edit vectors from paraphrase pairs, which are used to condition and train a rewriter model, as shown in Figure 2. On formality transfer and code-mixing addition, our best performing DIFFUR variant significantly outperforms UR across all languages (by 2-3x) using automatic & human evaluation.

In addition to better rewriting, our system is better able to control the magnitude of style transfer than prior work (Figure 1). Control is provided via a scalar knob (λ) which can be adjusted to make the output text reflect the target style (provided by exemplars) more or less. We also observe promising qualitative results in several attribute transfer directions (Section 6.3) including sentiment transfer, text simplification, gender neutralization and text anonymization, all without retraining the model and using just 3-10 exemplars at inference.

Finally, we found it hard to precisely evaluate our models due to the lack of evaluation datasets and style classifiers (often used as metrics) for Indic languages. To facilitate further research in formality transfer for Indic languages, we crowdsource formality annotations for 4000 sentence pairs in four Indic languages (Section 5.1), and use this dataset to design the automatic evaluation suite used in this work (Section 5).

In summary, our contributions provide an end-to-end recipe for developing and evaluating style transfer models and evaluation in a low-resource setting.

2 Related Work

Multilingual style transfer is mostly unexplored in prior work — in a survey of 35 papers by Briakou et al. (2021b) only a single work in each of Chinese (Shang et al., 2019), Russian (Tikhonov and Yamshchikov, 2018), Latvian & Estonian (Korotkova et al., 2019) and French (Niu et al., 2018) was found. Briakou et al. (2021b) further introduced XFORMAL, the first multilingual formality transfer evaluation dataset in French, Brazilian Portuguese and Italian. In Hindi, formality has been studied in linguistics, with a focus on politeness (Kachru, 2006; Agnihotri, 2013; Kumar, 2014) and code-mixing (Bali, 2014). Due to its prevalence in India, English-Hindi code-mixed has received attention in language modeling literature (Pratapa et al., 2018; Samanta et al., 2019) and natural language understanding (Khanuja et al., 2020). To the best of our knowledge, we are the first to study style transfer for Indian languages.

Few-shot methods are a recent development in English style transfer, with prior work using variational autoencoders with a fixed number of latent factors (Xu et al., 2020), or clever prompts to large pretrained English language models at inference (Reif et al., 2021). Most related to our work is the state-of-the-art TextSETTR model from Riley et al. (2021) which uses a neural style encoder to map sentences to a style vector space. At inference, a few exemplar sentences are encoded to style vectors and used to control generation. To train this encoder, Riley et al. (2021) use the idea that adjacent sentences in a document have a similar style. The model can modify a variety of attributes (formality, dialect, sentiment) at inference without re-training.

Recently, the Universal Rewriter (Garcia et al., 2021) extended the TextSETTR model to 101 languages and developed a general-purpose rewriter which can perform translation, few-shot style transfer and stylized translation. To the best of our knowledge, the Universal Rewriter is the only prior few-shot style transfer system outside English, and the baseline in our work. We discuss the shortcomings of this approach in Section 3.1, and propose alternative strategies in Section 4.

A few prior works have developed methods to control the degree of style transfer using a scalar input (Wang et al., 2019; Samanta et al., 2021).
However, these models are style-specific and need large unpaired corpora in each style for training. We adopt the method used in Garcia et al. (2021) for controlling the style transfer degree (Section 3) and notice the method is much better at style transfer control after our proposed fixes (Section 6.2).

3 The Universal Rewriter (UR) model

We will start by discussing the Universal Rewriter (UR) model from Garcia et al. (2021), upon which our proposed DIFFUR model is built. The UR model extracts a style vector $s$ from an exemplar sentence $e$, which reflects the desired target style. This style vector is used to style transfer an input sentence $x$. Consider $f_{enc}, f_{dec}$ to be encoder & decoder Transformers initialized with mT5 (Xue et al., 2021b), which are composed to form the model $f_{ur}$.

$$f_{style}(e) = s = f_{enc}([CLS] \oplus e)[0]$$

$$f_{ur}(x, s) = f_{dec}(f_{enc}(x) + s)$$

where $\oplus$ is string concatenation, $+$ is vector addition. The Universal Rewriter is trained on three next-word prediction cross entropy objectives which are based on self supervised style transfer and supervised machine translation.

Learning Style Transfer by Exemplar-driven Denoising: To learn a style extractor, the Universal Rewriter uses the idea that two non-overlapping spans of text in the same document are likely to have the same style. Concretely, let $x_1$ and $x_2$ be two non-overlapping spans in mC4. Style extracted from one span is used to denoise the other,

$$\bar{x}_2 = f_{ur}(\text{noise}(x_2), f_{style}(x_1))$$

$$\mathcal{L}_{\text{denoise}} = \mathcal{L}_{\text{CE}}(\bar{x}_2, x_2)$$

where $\mathcal{L}_{\text{CE}}$ is the standard next-word prediction cross entropy loss function and $\text{noise}(\cdot)$ refers to 20-60% random token dropping and token replacement. This objective is used on the mC4 dataset (Xue et al., 2021b) with 101 languages.

To build a general-purpose rewriter which can do translation as well as style transfer, the model is additionally trained on two objectives: (1) supervised machine translation using the OPUS-100 parallel dataset (Zhang et al., 2020), and (2) a self-supervised objective to learn effective style-controlled translation. Details of these two objectives are provided in Appendix A.

During inference (Figure 1), consider an input sentence $x$ and a transformation from style $A$ to $B$ (say informal to formal). Let $S_A, S_B$ to be exemplar sentences in each of the styles (typically 3-10 sentences). The output $y$ is computed as,

$$s_A, s_B = \frac{1}{N} \sum_{y \in S_A, S_B} f_{style}(y)$$

$$y = f_{ur}(x, \lambda(s_B - s_A))$$

where $\lambda$ acts as a control knob to determine the magnitude of style transfer, and the vector subtraction helps remove confounding style information."}

3.1 Shortcomings of the Universal Rewriter

We extensively experimented with the UR model on formality transfer for Indic languages, and noticed poor performance. We noticed that the model has a strong tendency to copy sentences verbatim. On Hindi formality transfer, 45.5% outputs were copied exactly from the input (and hence not style transferred) for the best performing value of $\lambda$. The copy rates get worse for smaller $\lambda$, making it hard to control style transfer magnitude. Seeing this, we identified the following issues:

1. Random token noise leads to unnatural inputs & transformations: The Universal Rewriter uses 20-60% uniformly random token dropping / replacement to noise inputs. This random noise leads to ungrammatical inputs during training. We hypothesize that models tend to learn grammatical error correction, which encourages verbatim copying during inference where fluent inputs are used and no grammatical correction is needed. Additionally, a random token-level noise does not differentiate between semantic / function words, and does not cover syntactic transformations like content reordering (Goyal and Durrett, 2020). Too much noise could distort semantics and encourage hallucination, whereas too little will encourage copying.

2. Style vectors may not capture the precise style transformation: The Universal Rewriter extracts the style vector from a single sentence during training, which is a mismatch from the inference where a difference between vectors is taken. Without taking vector differences at inference, we observe semantic preservation and overall perfor-

4Garcia et al. (2021) also recommend adding the style vectors from the input sentence $x$, but we found this increased the amount of verbatim copying and led to poor performance.
manance of the UR model is much lower.\textsuperscript{5} Besides, two spans in the same document will likely share semantic properties (like article topic) along with style, which will be encoded in the style vectors.

3. \textbf{mC4 is noisy}: On reading training data samples, we noticed noisy samples with severe language identification errors in the Hindi subset of mC4. This has also been observed recently in Caswell et al. (2021), who audit 100 sentences in each language, and report 50% sentences in Marathi and 20% sentences in Hindi have the wrong language.

4. \textbf{No translation data for several languages}: We notice worse performance for languages which did not get parallel translation data (for the translation objective in Section 3). In Table 1 we see UR gets a score\textsuperscript{6} of 30.4 for Hindi and Bengali, languages for which it got translation data. However, the scores are lower for Kannada, Telugu & Gujarati (25.5, 22.8, 23.7), for which no translation data was used. We hypothesize translation data encourages learning language-agnostic semantic representations needed for translation from the given language, which in-turn improves style transfer.

4 \textbf{Our Models}

4.1 \textbf{Style-Controlled Backtranslation (\textit{+ BT})}

While the Universal Rewriter model has a strong tendency to exactly copy input sentences while rewriting sentences in the same language (Section 3.1), we found it is an effective style-controlled translation system. This motivates a simple \textit{inference-time} trick to improve model outputs and reduce copying — translate sentences to English (\textit{en}) in a style-agnostic manner with a zero style vector $0$, and translate back into the source language (\textit{lx}) with stylistic control.

\begin{align*}
  s_A, s_B &= \frac{1}{N} \sum_{y \in S_A, S_B} f_{\text{style}}(y) \\
  x^{\text{en}} &= f_{\text{ur}}(\text{en} \oplus x, 0) \\
  \bar{x} &= f_{\text{ur}}(\text{lx} \oplus x^{\text{en}}, \lambda(s_B - s_A))
\end{align*}

where $x$ is the input sentence, $S_A, S_B$ are exemplars of the styles we want to transfer between, $\text{en, lx}$ are language codes prepended to indicate the output language (Appendix A). Backtranslation has been shown to be an effective paraphrase generation technique (Wieting and Gimpel, 2018; Iyyer et al., 2018) and has been leveraged for style transfer (Prabhumoye et al., 2018).

4.2 \textbf{Using Paraphrase Vector Differences for Style Transfer (DIFFUR)}

While style-controlled backtranslation effective inference strategy, it needs two steps of autoregressive decoding. This is 2x slower to run, and semantic errors accumulate across the two steps. In this section we develop DIFFUR, a new few-shot style transfer training objective, which tackles the issues discussed in Section 3.1 using paraphrases and style vector differences. DIFFUR leads to
more effective style transfer in a single decoding pass. Figure 2 has an overview of the DIFFUR approach. Each of our design decisions are justified in Appendix D.1 has an ablation study.

Paraphrases as a “noise” function: Instead of using random token-level noise (issue #1 in Section 3.1), we paraphrase sentences to “noise” them during training. Paraphrasing modifies the lexical & syntactic properties of sentences, while preserving fluency and input semantics. Prior work (Krishna et al., 2020) has shown that paraphrasing leads to stylistic changes, and denoising can be considered a style re-insertion process.

To create paraphrases, we backtranslate sentences from the UR model7 with no style control (zero vectors used as style vectors). To increase diversity, we use random sampling in both translation steps, pooling generations obtained using temperature values $[0.4, 0.6, 0.8, 1.0]$. Finally, we discard paraphrase pairs from the training data where the semantic similarity score\(^8\) is outside the range $[0.7, 0.98]$. This removes backtransation errors (score < 0.7), and exact copies (score > 0.98).

Using style vector differences for control: To fix the training / inference mismatch for style extraction (issue #2 in Section 3.1), we propose using style vector differences between the output and input as the stylistic control. Concretely, let $x$ be an input sentence and $x_{para}$ its paraphrase.

$$s_{diff} = f_{style}(x) - f_{style}(x_{para})$$

$$\bar{x} = f_{ur}(x_{para}, \text{stop-grad}(s_{diff}))$$

$$\mathcal{L} = \mathcal{L}_{CE}(\bar{x}, x)$$

Where stop-grad($\cdot$) prevents gradient flow through $s_{diff}$ to stop the model from learning to copy $x$ (which is used to construct $s_{diff}$). To ensure $f_{style}$ extracts meaningful style representations, we fine-tune a trained UR model. Using style vector differences has several advantages,

1. Subtracting style vectors between a sentence and its paraphrase removes confounding features (like semantics) which might have crept into the style vector space.

2. The vector difference focuses on the precise transformation that is needed to reconstruct the input from its paraphrase.

3. The length of $s_{diff}$ acts as a proxy for the amount of style transfer, which is controlled using $\lambda$ during inference (Section 3).

Our approach is reminiscent of Neural Editor models (Guu et al., 2018; He et al., 2020), where language models are decomposed into a probabilistic space of edit vectors over prototype sentences.

4.3 Indic Models (UR-INDIC, DIFFUR-INDIC)

To address the issue of no translation data (issue #4 in Section 3.1), we train Indic variants of our style transfer models. We replace the OPUS translation data used for training the Universal Rewriter (Section 3) with Samanantar (Ramesh et al., 2021), which is the largest publicly available parallel translation corpus for 11 Indic languages. We call these variants UR-INDIC and DIFFUR-INDIC. This process significantly up-samples the number of parallel sentences seen between English and Indic languages. With our Indic variants, we noticed improvements in performance and reduction in copy rates, especially for languages that had no parallel translation data in the UR model setup (Table 1).

4.4 Multitask Learning (MULTITASK)

One issue with our DIFFUR-INDIC setup is usage of a stop-grad($\cdot$), to avoid verbatim copying from the input. This prevents gradient flow into the style extractor $f_{style}$, and as we see in Appendix E, a degradation of the style vector space. To prevent this from happening, we simply do multi-task learning between the original Universal Rewriter objective (Section 3) and our DIFFUR-INDIC objective, using an equal number of minibatches for each objective.

5 Evaluation

Automatic evaluation of style transfer is a challenging problem (Pang, 2019; Mir et al., 2019; Tikhonov et al., 2019), and the lack of resources (such as evaluation datasets, style classifiers) make evaluation trickier for Indic languages. To tackle this issue, we first collect a small dataset of formality and semantic similarity annotations in four Indic languages (Section 5.1). We leverage this dataset to guide the design of an evaluation suite, which measures output style accuracy using cross-lingual transfer (Section 5.2), semantic similarity using

\(^7\)Specifically, an Indic variant of the UR model is used, described in Section 4.3. Note it is not necessary to use UR for backtranslation, any good translation model can be used.

\(^8\)We use LaBSE to calculate semantic similarity score, which has been discussed extensively in Section 5.3.
language-agnostic representations (Section 5.3), overall performance by aggregating metrics (Section 5.5) and style magnitude control using λ (Section 5.6). Finally, since automatic metrics in text generation are known to be imperfect (Celikyilmaz et al., 2020), we complement our results with human evaluation (Section 5.7).

5.1 Indic Formality Transfer Dataset

Since no public datasets exist for formality transfer in Indic languages, it is hard to measure the extent to which automatic metrics (such as style classifiers) are effective. To tackle this issue, we build a dataset of 1000 sentence pairs in each of four Indic languages (Hindi, Bengali, Kannada, Telugu) with formality and semantic similarity annotations. We first style transfer held-out sentences from Samanantar (Section 6.1) using our UR-INDIC + BT model (Section 4.1, 4.3), which provides the best output diversity. We then asked three crowdworkers to 1) label the more formal sentence in each pair; 2) mention how semantically similar the two sentences are.

Our crowdsourcing experiments are conducted on Task Mate, where we hired native speakers from India who had at least a high school education and 90% approval rating on the platform. We paid our crowdworkers $0.05 per pair. Each crowdworker was allowed to annotate a maximum of 50 different sentence pairs per language. To ensure crowdworkers understood “formality”, we provided instructions following advice from professional Indian linguists, and asked two qualification questions in their native language. More details (agreement, exact instructions, questions) have been provided in Appendix C.4.

5.2 Transfer Accuracy (r-ACC, a-ACC)

Our first criteria for evaluation is transfer success, or whether the output sentence reflects the target style. This is generally measured by an external classifier’s predictions on a system output. In this work we use two variants of transfer accuracy:

1. Relative Accuracy (r-ACC): does the target style classifier score the output sentence higher than the input sentence?
2. Absolute Accuracy (a-ACC): does the target style classifier score the output sentence higher than 0.5?

5.3 Semantic Similarity (SIM)

Our second criteria for evaluation is semantic similarity between the input and output. Following recommendations from recent work (Marie et al., 2021; Krishna et al., 2020), we avoid n-gram overlap metrics like BLEU (Papineni et al., 2002) for evaluation. Instead, we use LaBSE (Feng et al., 2020), a language-agnostic semantic similarity model based on multilingual BERT (Devlin et al., 2019). LaBSE supports 109 languages, and is the only semantic similarity model we found which supported all the Indic languages considered in this work. Additionally, we observed LaBSE had greater correlation with our annotated data (Section 5.1) compared to Sentence-BERT (Reimers and Gurevych, 2020). A detailed comparison between these models is provided in Appendix C.2.

Qualitatively, we found that sentence pairs with LaBSE scores lower than 0.6 were almost never paraphrases. To avoid rewarding systems partial credit with low LaBSE scores, we use a hard threshold to determine whether pairs are paraphrases,

\[
\text{SIM}(x, y') = \begin{cases} 
1 & \text{if } \{ \text{LaBSE}(x, y') > L \} \\
0 & \text{else}
\end{cases}
\]

We set \(L = 0.75\) in our main experiments.\(^{11}\)

5.4 Other Individual Metrics

Language Consistency (LANG): Since our semantic similarity metric LaBSE is language-agnostic, we evaluate its agreement with human assessment by computing language consistency as the proportion of sentence pairs in each language with consistency greater than \(L\):

\[
\text{LANG}(L) = \frac{1}{n} \sum_{i=1}^{n} \text{SIM}(x, y_i) 
\]

Building multilingual classifiers: Unfortunately, no large style classification datasets exist for Indic languages, preventing us from building these classifiers from scratch. We resort to zero-shot cross lingual transfer techniques (Conneau and Lample, 2019; Pfeiffer et al., 2020b), where large-scale multilingual pretrained models are first fine-tuned on English classification datasets, and then applied to other languages at inference. We experimented with three cross-lingual transfer techniques, and found MAD-X classifiers with language adapters (Pfeiffer et al., 2020b) to have the highest accuracy of 81% on our annotated dataset from Section 5.1. However, MAD-X classifiers were only available for Hindi, so we use the second best method XLM RoBERTa-base (Conneau et al., 2020) for other languages, which has an accuracy of 75%-82% on annotated data across languages; more details are provided in Appendix C.1.

\(^{11}\)Roughly 73% pairs annotated as paraphrases (from dataset in Section 5.1) had \(L > 0.75\). We experiment with different values of \(L\) in Appendix C.3 and notice similar trends.
agnostic, it tends to ignore accidental translations, which are common errors in large multilingual transformers (Xue et al., 2021a,b), especially the Universal Rewriter (Section 3.1). Hence, we check whether the output sentence is in the same language as the input, using langdetect.12

Output Diversity (COPY, 1-g): As discussed in Section 3.1, the Universal Rewriter has a strong tendency to copy the input verbatim. We build two metrics to measure output diversity compared to the input, which have been previously used for extractive question answering evaluation (Rajpurkar et al., 2016). The first metric COPY measures the fraction of outputs which were copied verbatim from the input. This is done after removing trailing punctuation, to penalize models generations which solely modify punctuation. A second metric 1-g measures the unigram overlap F1 score between the input and output. A diverse style transfer system should minimize both COPY and 1-g.

5.5 Aggregated Score (r-AGG, a-AGG)

To get an overall sense of system performance and compare style transfer methods, we must combine Transfer Accuracy (ACC), Semantic Similarity (SIM) and Language ID (LANG) into a single score. We follow the recommendation from Krishna et al. (2020) and compute the aggregated scores as,

\[
AGG(x, y') = ACC(x, y') \cdot SIM(x, y') \cdot LANG(y')
\]

\[
AGG(D) = \frac{1}{|D|} \sum_{x,y' \in D} AGG(x, y')
\]

Where \((x, y')\) are input-output pairs, and \(D\) is the test corpus. In other words, we measure the fraction of output sentences which simultaneously transfer style, have a semantic similarity score of at least 0.75 (our threshold in Section 5.5) with the input sentence, and have the same language as the input. Depending on the variant of ACC (relative or absolute), we can derive r-AGG and a-AGG respectively.

5.6 Evaluating Control

An ideal style transfer system should not only be able to transfer sentences, but also control the magnitude of style transfer. In this section, we discuss metrics used to evaluate the extent to which systems can control the amount of style transfer using the λ control value.

Maximum λ value (λ_{max}): For every system under consideration, we first determine a λ_{max} value and let \([0, \lambda_{max}]\) be the range of control values. While in our setup λ is an unbounded scalar, we noticed high values of λ significantly perturb semantics (also noted in Garcia et al., 2021), with systems outputting style-specific n-grams unfaithful to the output. We choose the largest λ from the list \([0.5, 1.0, 1.5, 2.0, 2.5, 3.0]\) whose outputs have an average semantic similarity score (SIM, Section 5.3) of at least 0.75\(^{13}\) with the validation set inputs. For each system we take three evenly spaced λ values in the corresponding chosen range, which we denote as \(\Lambda = [\frac{1}{3}\lambda_{max}, \frac{2}{3}\lambda_{max}, \lambda_{max}]\).

We next measure the following metrics,

1. Style Transfer Performance: An ideal system should perform consistently well across the control range \(\Lambda\). Style transfer performance is measured using the r-AGG metric defined in Section 5.5.

2. Average Style Score Increase (INCR): As our control value increases, we want the classifier’s target style score (compared to the input) to increase. Additionally, we want the style score increase of \(\lambda_{max}\) to be as high as possible, indicating the system can span the range of classifier scores.

3. Style Calibration to λ (CALIB, C-IN): While INCR measures the average style increase with respect to the input, we also wish to measure the relative style change between different values of λ at an instance level. In other words, how often does increasing λ lead to a style score increase? We measure this using a statistic equivalent to Kendall’s Tau (Kendall, 1938), by counting the number of concordant pairs for all possible pairs from \(\Lambda\),

\[
CALIB(x) = \frac{1}{n} \sum_{\lambda_b > \lambda_a} \{\text{style}(y_{\lambda_b}) > \text{style}(y_{\lambda_a})\}
\]

\[
CALIB(D) = \frac{1}{|D|} \sum_{x \in D} CALIB(x)
\]

where CALIB(x) is the average over all possible \(n\) (≈3) pairs of λ values \((\lambda_a, \lambda_b)\) in the chosen range \(\Lambda\). We can optionally also include the input in the CALIB(x) calculation, which we term C-IN.\(^{13}\)

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12This package is the Python port of Nakatani (2010).

13This threshold is identical to the value chosen for paraphrase similarity in Section 5.3. We experiment with more/less conservative thresholds in Appendix C.3.
5.7 Human Evaluation

Automatic metrics are generally insufficient for style transfer evaluation — according to a recent survey by Briakou et al. (2021a), 69/97 surveyed style transfer papers resorted to human evaluation. We adopt the crowd-sourcing setup from Section 5.1, which was used to build our formality evaluation datasets. We presented 200 generations from each model and the corresponding input sentences in a random order, and asked three crowd-workers two questions about each pair of sentences — 1) “which sentence is more formal/code-mixed?” 2) “how similar are the two sentences in meaning?”. This lets us evaluate r-ACC, SIM, r-AGG, CALIB with respect to human annotations instead of classifier predictions; details in Appendix C.4.

6 Main Experiments

6.1 Experimental Setup

In this section we describe our setup comparing models on 1) formality transfer; 2) adding code-mixing to text. In our experiments, we compare the following models —

- UR: the Universal Rewriter (Garcia et al., 2021), which is our main baseline (Section 3);
- DIFFUR: our model with paraphrase vector differences (Section 4.2)
- UR-INDIC, DIFFUR-INDIC: Indic variants of UR and DIFFUR models (Section 4.3)
- MULTITASK: Multitask training between UR-INDIC and DIFFUR-INDIC (Section 4.4)
- + BT: models with style-controlled backtranslation at inference time (Section 4.1);

Training Details: Our models are implemented in JAX (Bradbury et al., 2018) using the T5X library.14 We re-use the UR checkpoint from Garcia et al. (2021). To train the UR-INDIC model, we follow the setup in Garcia et al. (2021) and initialize the model with mT5-XL (Xue et al., 2021b), which has 3.7B parameters. We fine-tune the model for 25K steps with a batch size of 512 inputs and a learning rate of 1e-3, using the objectives in Section 3. Training was done on 32 Google Cloud TPUs which took a total of 17.5 hours. To train the DIFFUR and DIFFUR-INDIC models, we further fine-tune UR and UR-INDIC for a total of 4K steps using the objective from Section 4.2, which takes 2 hours.

Training Datasets: To train the UR-INDIC model, we use mC4 (Xue et al., 2021b) for the self-supervised objectives and Samanantar (Ramesh et al., 2021) for the supervised translation. For creating paraphrase data for training our DIFFUR models (Section 4.2), we again leverage Indic language side of Samanantar sentence pairs. No paired/unpaired data with style labels is used during training — the model determines the target style at inference using 3-10 exemplars sentences.

Evaluation Datasets: Our models are evaluated on formality transfer and the task of adding code-mixing in text. Since we do not have access to any formality evaluation dataset,15 we hold out 11K sentences from Samanantar in each language for validation, and another 11K sentences per language for testing. These sets have roughly equal number of formal / informal sentences, as marked by our formality classifiers (Section 5.2). These sentences are used as inputs for both directions of formality transfer (depending on their formality labels), and one direction of code-mixing addition.

Five Indic languages with varying scripts and morphological richness are used to evaluate our systems — Hindi, Bengali, Kannada, Telugu and Gujarati. As discussed in Section 4.3, the UR model saw translation data only for Hindi & Bengali, whereas UR-INDIC sees translation data for all these five languages. In addition, to test the generalization capability of the DIFFUR-* models, no paraphrase data for Gujarati is used for training.

As exemplars for few-shot formality transfer, we use three formal English sentences, and three informal English sentences. These exemplars were taken from Garcia et al. (2021), and have been provided in Appendix B. We continue to follow the setting in Garcia et al. (2021), where English exemplars are used to guide non-English formality transfer zero-shot. For experiments on code-mixing addition, we use exemplars with Hindi/English code-mixing in Devanagari script (see Appendix B).

14https://github.com/google-research/google-research/tree/master/flax_models/t5x

15We do not use GYAFC (Rao and Tetreault, 2018) and XFORMAL (Briakou et al., 2021b) due to reasons in footnote 3. Our dataset from Section 5.1 has already been used for classifier selection, and has machine generated sentences.
Table 1: A comparison of all models (list in Section 6.1) on few-shot formality transfer in various languages. We observe that each of our proposed methods (*-INDIC, +BT, DIFFUR) improve overall style transfer performance (r-AGG, a-AGG as defined in Section 5.5), with a combination of ideas in MULTITASK performing best. Note that for Gujarati, we did not use any paraphrase data in DIFFUR-* or MULTITASK models to test generalization.

| Model     | Hindi   | Bengali  | Kannada  | Telugu  | Gujarati |
|-----------|---------|----------|----------|---------|----------|
|           | r-AGG   | a-AGG    | r-AGG    | a-AGG   | r-AGG    |
| UR (2021) | 30.4    | 10.4     | 30.4     | 7.2     | 25.5     |
| UR-INDIC  | 58.3    | 18.6     | 65.5     | 22.3    | 61.3     | 17.8     | 59.8     | 19.9     | 22.8     | 8.4     | 23.7     | 5.0     |
| UR + BT   | 54.2    | 17.8     | 55.6     | 16.9    | 39.8     | 11.9     | 38.4     | 11.6     | 46.3     | 10.4    |
| UR-INDIC + BT | 60.0 | 22.2 | 61.1 | 22.0 | 59.2 | 21.0 | 56.8 | 22.2 | 57.7 | 16.8 |
| DIFFUR    | 71.1    | 22.9     | 72.7     | 25.2    | 69.2     | 29.1     | 69.4     | 27.1     | 0.4      | 0.2     |
| DIFFUR-INDIC | 72.6   | 24.0     | 75.4     | 24.3    | 73.1     | 29.3     | 71.0     | 27.1     | 36.0     | 13.0    |
| MULTITASK | 78.1    | 32.2     | 80.0     | 35.0    | 80.4     | 39.4     | 79.8     | 37.9     | 75.0     | 33.1    |

Table 2: Performance breakdown by individual metrics on Hindi formality transfer (other languages in Appendix F). MULTITASK gives best overall performance (r-AGG / a-AGG), with a good trade-off between style accuracy (ACC), semantic similarity (SIM), langID score (LANG), and low input copy rates (COPY); metric descriptions in Section 5.

| Model             | λ       | COPY(↓) | 1-g(↓) | LANG | SIM  | ACC  | a-ACC | r-AGG | a-AGG |
|-------------------|---------|---------|--------|------|------|------|-------|-------|-------|
| UR (Garcia et al., 2021) | 1.5     | 45.4    | 77.5   | 98.0 | 84.8 | 45.8 | 22.9  | 30.4  | 10.4  |
| UR-INDIC          | 1.0     | 10.4    | 70.7   | 95.0 | 93.8 | 89.7 | 89.7  | 89.7  | 82.4  |
| UR + BT           | 0.5     | 0.8     | 44.2   | 92.9 | 85.2 | 72.3 | 27.8  | 54.2  | 17.8  |
| UR-INDIC + BT     | 1.0     | 1.1     | 49.5   | 95.9 | 85.1 | 76.3 | 33.1  | 60.0  | 22.2  |
| DIFFUR            | 1.0     | 4.7     | 61.6   | 97.7 | 89.7 | 82.4 | 31.0  | 71.1  | 22.9  |
| DIFFUR-INDIC      | 1.5     | 5.3     | 63.7   | 98.0 | 91.9 | 81.6 | 30.5  | 72.5  | 23.7  |
| MULTITASK         | 2.5     | 4.4     | 61.9   | 97.2 | 89.7 | 87.9 | 34.0  | 78.1  | 27.5  |

Table 3: Human evaluation on Hindi formality transfer, measuring style accuracy (ACC), input semantic similarity (SIM), overall score (AGG), and style controllability with λ (CALIB, C-IN). Similar to automatic evaluation results (Table 2), MULTITASK performs best.

| Model   | ACC | SIM  | AGG | CALIB | C-IN |
|---------|-----|------|-----|-------|------|
| UR (2021) | 29.5 | 87.2 | 23.2 | -     | -    |
| UR-INDIC | 46.5 | 85.3 | 40.8 | 35.7  | 43.0 |
| UR + BT   | 57.5 | 71.2 | 42.9 | -     | -    |
| UR-INDIC + BT | 65.0 | 77.8 | 52.4 | 24.0  | 40.3 |
| DIFFUR    | 64.5 | 80.8 | 52.0 | -     | -    |
| DIFFUR-INDIC | 62.0 | 83.1 | 50.4 | 48.0  | 54.5 |
| MULTITASK | 70.0 | 80.8 | 55.6 | 53.0  | 54.5 |

Table 4: Human evaluation on code-mixing addition. MULTITASK+BT performs best (AGG), giving high style accuracy (ACC) without loss in similarity (SIM).

| Model                     | Hindi ACC / SIM / AGG | Bengali ACC / SIM / AGG |
|---------------------------|------------------------|--------------------------|
| UR (2021)                 | 4.5 / 93.8 / 3.6       | 0.0 / 96.4 / 0.0         |
| UR-INDIC, BT              | 18.5 / 79.2 / 15.3     | 18.0 / 68.3 / 12.7       |
| MULTITASK, BT             | 62.5 / 69.9 / 41.5     | 79.0 / 57.1 / 43.5       |

6.2 Main Results

Each proposed method improves over prior work, MULTITASK works best: We present our automatic evaluation results for formality transfer across languages in Table 1. Overall we find that each of our proposed methods (DIFFUR, *-INDIC, +BT) help improve performance over the baseline UR model (71.1, 58.3, 54.2 vs 30.4 r-AGG on Hindi). Combining these ideas with the original UR model with multitask learning (MULTITASK) gives us the best performance of across all languages (78.1 on Hindi). On Gujarati, the DIFFUR-* models fail to get good performance (0.4, 36.0 r-AGG) since they did not see Gujarati paraphrase data, but this performance is recovered using MULTITASK (75.0). In Table 3 we see human evaluations support our automatic evaluation results for formality transfer. In Table 4 we perform human evaluations on a subset of models for code-mixing addition. We notice a similar trend, with MULTITASK significantly outperforming UR, UR-INDIC (41.5 AGG vs 3.6, 15.3 on Hindi, 43.5 AGG vs 0.0, 12.7 on Bengali).

MULTITASK and DIFFUR-INDIC are best at controlling magnitude of style transfer: In Table 5, we compare the extent to which models can control the amount of style transfer using the λ value. Once again, we note all our proposed methods outper-
| Model          | $\lambda_{\max}/3$ | $2\lambda_{\max}/3$ | Overall   |
|---------------|---------------------|---------------------|-----------|
| $\lambda$     | f-AGG INCR          | $\lambda$          | f-AGG INCR | CALIB C-IN |
| UR (2021)     | 0.5 22.1 5.2        | 1.0 26.9 8.9        | 1.5 30.4 18.7 | 29.2 31.6 |
| UR-INDIC      | 0.5 53.2 13.4       | 1.0 58.3 18.8       | 1.5 54.6 26.7 | 60.7 65.1 |
| UR + BT       | 0.3 53.2 21.4       | 0.7 53.9 23.5       | 1.0 49.1 26.9 | 43.4 58.8 |
| UR-INDIC + BT | 0.3 57.3 22.9       | 0.7 59.4 24.6       | 1.0 60.0 26.7 | 38.7 56.0 |
| DIFFUR        | 0.5 65.8 16.6       | 1.0 71.1 26.0       | 1.5 67.1 21.9 | 64.9 72.5 |
| DIFFUR-INDIC  | 0.8 67.2 17.9       | 1.7 72.6 27.3       | 2.5 65.0 36.7 | 69.6 75.5 |
| MULTITASK     | 0.8 56.6 11.3       | 1.7 72.6 27.3       | 2.5 78.1 29.9 | 69.0 71.8 |

Table 5: Evaluation of extent to which the magnitude of hindi formality transfer can be controlled with $\lambda$. We find that DIFFUR-INDIC, MULTITASK are best at calibrating style change to input $\lambda$ (CALIB, C-IN), giving the higher style score increase (INCR) at $\lambda = \lambda_{\max}$ (details of evaluation setup and metrics in Section 5.6).

Figure 3: Plots evaluating the variation of Kannada formality transfer with $\lambda$. In the left plot, we see the MULTITASK and DIFFUR-* models have consistently good overall performance with change in $\lambda$. In the right plot, we see the tradeoff between average style change and content similarity as $\lambda$ is varied. Plots (such as those of MULTITASK, DIFFUR-*) which stretch the range of the Y-axis, are closer to the ideal system ($x = 1$ line) and away from the naive system ($x + y = 1$ line, similar to naive model in Krishna et al., 2020) are better.

form the UR model, which gets only 29.2 CALIB. We find that +BT models are not as effective at control (43.4 CALIB), while DIFFUR-INDIC and MULTITASK perform best (69.6, 69.0 CALIB). This is graphically illustrated in Figure 3. The MULTITASK model performs consistently well across different $\lambda$ values (left plot), and gives a high style change without much drop in content similarity to the input as $\lambda$ is varied (right plot).

In Table 2, we present a breakdown of results by individual metrics for Hindi formality transfer. For the baseline UR model, we notice high COPY rates (45.4%), which in turn results in lower r-ACC/a-ACC scores. Copy rates are lower for our proposed models (4.4% for MULTITASK), which boost the overall performance. We find the lowest COPY rates (and in-turn lowest unigram overlap rate 1-g) for models with +BT (0.8 - 1.0%), which is due to the two steps of decoding through English. However, this lowers the semantic similarity score (also seen in Table 3) bringing down the overall style transfer performance when compared to MULTITASK (60.0 vs 78.1 r-AGG). The breakdowns by individual metrics for other languages considered along with more plots showing variation in performance with $\lambda$ are presented in Appendix F.

Ablation studies to justify the DIFFUR design, choice of decoding scheme, number of training steps are provided in Appendix D. We also analyze our style extractor $f_{\text{style}}$ in Appendix E, and observe it can act as an effective style classifier.

6.3 Qualitative Analysis

We present several qualitative examples and analysis of our best performing models in Figure 4. In addition to performing formality transfer and code-mixing addition, we present qualitative examples for several popular tasks in attribute transfer literature — sentiment transfer (Subramanian et al., 2019), text simplification (Xu et al., 2015), text anonymization (Anandan et al., 2012) and gender neutralization (Reddy and Knight, 2016). More outputs from our model are provided in Appendix G.
| Input | Generations | Analysis |
|-------|-------------|----------|
| **Informal**<br>अपनी तारीख जोड़े मुझे मत बताओ।<br>(don’t tell me about your job) | **Formal**<br>(\(\lambda = 0.5\)) अपनी तारीख जोड़े मुझे मत बताओ।<br>(\(\lambda = 1.0\)) अपनी तारीख जोड़े मुझे मत बताओ।<br>(\(\lambda = 1.5\)) अपनी तारीख जोड़े मुझे मत बताओ। | As sentences get more formal, the English word “job” (अपना) is replaced with its neutral (ऑपना) and honorifics are used (आपना, तत्काल) |
| **Formal**<br>हिंदी में दो लोगों की मौत हुई थी और सलाह 150 पायल हो गए।<br>(two people died in the violence and 150 were injured) | **Informal**<br>(\(\lambda = 1.0\)) हिंदी में दो लोग मारे गए और 150 के करीब लोग पायल हो गए।<br>(\(\lambda = 1.5\)) हिंदी में दो लोग मारे गए और 150 पायल | As sentences get more informal besides lexical changes, sentence shortening is common, while roughly conveying same meaning |
| **Positive Sentiment**<br>मुझे यह फिल्म बहुत पसंद आई।<br>(I like this movie) | **Negative Sentiment**<br>इस फिल्म को नौं कभी नहीं लिखा।<br>(I don’t like this movie) | Negations (नहीं) and word antonyms (बढ़ाया, अधिक) are common as sentiment changes |
| **Complex**<br>भाषा प्रदाता महसूस करती महसूस होती है।<br>(I feel that your language is being used) | **Simple**<br>भाषा मंडल करती दिखी है।<br>(I feel that your language is being used) | Lexical substitutions (बढ़ाया → मुड़ा, कठन → कठी) to use more commonly spoken words |
| **Monocode**<br>01.2017 से, आर्थिक इस योजना के पायल होने के लिए, दो लोगों के लिए सलाही देता है।<br>(2017, economic: two people died in the support) | **Code-mixed**<br>01.2017, i.e. यह डेट दिखी है, जब से यह योजना इंग्रेश्नेड है।<br>(2017, i.e.: economic: two people died in the support) | With code-mixing, several English words are introduced (तिथि → डेट / date, आर्थिक → i.e.) |
| **De-anonymized**<br>फिल्म में काफी और अद्वितीय हार्दिक भाषा किदारा।<br>(film: a lot and unique language used) | **Anonymized**<br>फिल्म में PII और PII मुख्य भूमिका निभाते हुए नजर आ रहे हैं।<br>(film: PII and PII are the main actors) | Entities (आदित्य राहेरी, इंग्रेश्नेड) are replaced with PII (Personal Identifiable Information) tags, to anonymize text |
| **Gendered**<br>रिया ओसीफ़क: बैंडिटन में भारतीय अभिनेत्री में किया निराला, हार से हुई भारतीय आपत्ति।<br>(Riya Osefak: in bandit: Indian actress killed, hit by bullet) | **Gender Neutral**<br>रिया ओसीफ़क: बैंडिटन में भारतीय खिलाड़ियों में किया निराला, हार से हुई भारतीय आपत्ति।<br>(Riya Osefak: in bandit: Indian actors killed, hit by bullet) | Gendered words (ऑसीफ़क) are replaced with their neutral equivalents (आपत्ति) |

Figure 4: Qualitative attribute transfer examples from our best performing models for several tasks like formality transfer (\(\lambda\) is the magnitude of style transfer), sentiment transfer, text simplification, adding code-mixing, text anonymization and gender neutralization. Qualitatively, we noticed lower success rates for styles marked with **. More model outputs are added to Appendix G.

7 Conclusion

We present a recipe for building and evaluating controllable few-shot style transfer systems which need only 3-10 style examples at inference. These systems are especially useful in low-resource settings where no large-scale labelled style corpus is available. We focus on one such setting, style transfer in Indian languages. Our proposed methods outperform prior work in formality transfer and code-mixing addition for several Indian languages, and we see promising qualitative results for several other attribute transfer tasks. Future work includes (1) further improving systems, especially for gender neutralization / author anonymization; (2) studying style transfer for languages where little to no machine translation data is available.

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Ethical Considerations

Recent work has highlighted issues of stylistic bias in text generation systems, specifically machine translation systems (Hovy et al., 2020). We acknowledge these issues, and consider style transfer and style-controlled generation technology as an opportunity to work towards fixing them (for instance, gender neutralization as presented in Section 6.3). Note that it is important to tread down this path carefully — In Chapter 9, Blodgett (2021) argue that style is inseparable from social meaning (as originally noted by Eckert, 2008), and humans may perceive automatically generated text very differently compared to automatic style classifiers.

Our models were trained on 32 Google Cloud TPUs. As discussed in Section 6.1, the UR & UR-INDIC model take roughly 18 hours to train. The DIFFUR-* and MULTITASK models are much cheaper to train (2 hours) since we finetune the pretrained UR-* models. The Google 2020 environment report mentions,16 “TPUs are highly efficient chips which have been specifically designed for machine learning applications”. These accelerators run on Google Cloud, which is carbon neutral today, and is aiming to “run on carbon-free energy, 24/7, at all of Google’s data centers by 2030” (https://cloud.google.com/sustainability).

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Appendices for “Few-shot Controllable Style Transfer for Low-Resource Settings: A Study in Indian Languages”

A More details on the translation-specific Universal Rewriter objectives

In this section we describe the details of the supervised translation objective and the style-controlled translation objective used in the Universal Rewriter model. See Section 3 for details on the exemplar-based denoising objective.

Learning translation via direct supervision: This objective is the standard supervised translation setup, using zero vectors for style. The output language code is prepended to the input. Consider a pair of parallel sentences \((x, y)\) in languages with codes \(l_x, l_y\) (prepended to the input string),

\[
\bar{y} = f_u(l_y \oplus x, 0)
\]

\[
L_{\text{translate}} = L_{\text{CE}}(\bar{y}, y)
\]

The Universal Rewriter is trained on English-centric translation data from the high-resource languages in OPUS-100 (Zhang et al., 2020).

Learning style-controlled translation: This objective emulates “style-controlled translation” in a self-supervised manner, via backtranslation through English. Consider \(x_1\) and \(x_2\) to be two non-overlapping spans in mC4 in language \(l_x\),

\[
x_2^{\text{en}} = f_u(e_n \oplus x_2, -f_{\text{style}}(x_1))
\]

\[
x_2 = f_u(l_x \oplus x_2^{\text{en}}, f_{\text{style}}(x_1))
\]

\[
L_{\text{BT}} = L_{\text{CE}}(\bar{x}_2, x_2)
\]

B Choice of Exemplars

Formal exemplars
1. This was a remarkably thought-provoking read.
2. It is certainly amongst my favorites.
3. We humbly request your presence at our gala in the coming week.

Informal exemplars
1. reading this rly makes u think
2. Its def one of my favs
3. come swing by our bbq next week if ya can make it

Complex exemplars
1. The static charges remain on an object until they either bleed off to ground or are quickly neutralized by a discharge.

C Evaluation Appendix

C.1 Multilingual Classifier Selection

Due to the absence of a style classification dataset in Indic languages, we built our multilingual...
Gendered Exemplars
1. नसर्म साफ कपड़े पहनी थी
2. हमें और जनशिक्ति की जरूरत है
3. यह डॉक्टर बहुत अच्छा है

Gender-neutral Exemplars
1. नसर्म ने साफ कपड़े पहने थे
2. हमें और कर्मचारियों की जरूरत है
3. यह डॉक्टर बहुत अच्छे हैं

Figure 6: Exemplars used for gender neutralization.

classifier drawing inspiration from recent research in zero-shot cross-lingual transfer (Conneau et al., 2018; Conneau and Lample, 2019; Pfeiffer et al., 2020b). We experimented with three zero-shot transfer techniques while selecting our classifiers for evaluating multilingual style transfer.

TRANSLATE TRAIN: The first technique uses the hypothesis that style is preserved across translation. We classify the style of English sentences in the Samanantar translation dataset (Ramesh et al., 2021) using a style classifier trained on English formality data from Krishna et al. (2020). We use the human translated Indic languages sentences as training data. This training data is used to fine-tune a large-scale multilingual language model.

ZERO-SHOT: The second technique fine-tunes large-scale multilingual language models on an English style transfer dataset, and applies it zero-shot on multilingual data during inference.

MAD-X: Introduced by Pfeiffer et al. (2020b), this technique is similar to ZERO-SHOT but additionally uses language-specific parameters (“adapters”) during inference. These language-specific adapters have been originally trained using masked language modeling on the desired language data.

Dataset for evaluating classifiers: We conduct our experiments on Hindi formality classification, leveraging our evaluation datasets from Section 5.1. We removed pairs which did not have full agreement across the three annotators and those pairs which had the consensus rating of “Equal” formality. This filtering process leaves us with 316 pairs in Hindi (out of 1000). In our experiments, we check whether the classifiers give a higher score to the more formal sentence in the pair.

Models: We leverage the multilingual classifiers open-sourced17 by Krishna et al. (2020). These models have been trained on the English GYAFC formality classification dataset (Rao and Tetreault, 2018), and have been shown to be effective on the XFORMAL dataset (Briakou et al., 2021b) for formality classification in Italian, French and Brazilian Portuguese.13 These classifiers were trained on preprocessed data which had trailing punctuation stripped and English sentences lower-cased, encouraging the models to focus on lexical and syntactic choices. As base multilingual language models, we use (1) mBERT-base from Devlin et al. (2019); (2) XLM-RoBERTa-base from Conneau et al. (2020).

Results: Our results on Hindi are presented in Ta-

De-anonymized Exemplars
1. मेरा फोन नंबर 091898807646 है
2. केट का आधार नंबर है 4098-7980-8898
3. 18 सितंबर को मैंने microsoft.com पर विजिट किया और IP 192.168.0.1 से test@google.site पर एक ईमेल भेजा।
4. मेरा पासपोर्ट नंबर 4903-3289-2394 है
5. फिल Google में बारदार की टीम में काम करता है
6. बीबी 42 शारा का है
7. शर्लिक 221B बेकर स्ट्रीट में रहता है
8. मेरा ईमेल पता है email1@gmail.com

Anonymized Exemplars
1. मेरा फोन नंबर PII है
2. PII का आधार नंबर है PII
3. PII को मैंने PII पर विजिट किया और IP PII से PII पर एक ईमेल भेजा।
4. मेरा पासपोर्ट नंबर PII है
5. PII PII में PII की टीम में काम करता है
6. PII PII साल का है
7. PII PII में रहता है
8. मेरा ईमेल पता है PII

Figure 7: Exemplars used for text anonymization. All entities in the deanonymized exemplars are random.

17https://github.com/martiansideofthemoon/style-transfer-paraphrase/blob/master/README-multilingual.md
ble 6 and other languages in Table 7. Consistent with Pfeiffer et al. (2020b), we find MAD-X to be a superior zero-shot cross-lingual transfer method compared to baselines. We also find XLM-R has better multilingual representations than mBERT. Unfortunately, AdapterHub (Pfeiffer et al., 2020a) has XLM-R language adapters available only for Hindi & Tamil (among Indic languages). For other languages we use the ZERO-SHOT technique on XLM-R, consistent with the recommendations provided by Krishna et al. (2020) based on their experiments on XFORMAL (Briakou et al., 2021b).

Table 6: Hindi formality classification accuracy on our crowdsourced dataset (Section 5.1) using different cross-lingual transfer methods. Our results indicate that MAD-X is the most effective method, and XLM-R is a better pretrained model than mBERT.

| Method       | Model  | Accuracy (%) |
|--------------|--------|--------------|
| TRANSLATE    | mBERT  | 66%          |
| TRAIN        |        |              |
| ZERO-SHOT    | mBERT  | 72%          |
|              | XLM-R  | 76%          |
| MAD-X        | XLM-R  | 81%          |

Table 7: Formality classification on our crowdsourced Bengali, Kannada and Telugu dataset (Section 5.1) using the ZERO-SHOT technique described in Appendix C.1. Results confirm the efficacy of the XLM-R classifier. See Table 6 for Hindi results.

| Language | mBERT    | XLM-R   |
|----------|----------|---------|
| bn       | 65.3%    | 82.2%   |
| kn       | 76.3%    | 76.9%   |
| te       | 72.6%    | 74.6%   |

C.2 Semantic Similarity Model Selection

We considered three models for evaluating semantic similarity between the input and output:

1. LaBSE (Feng et al., 2020);
2. m-USE (Yang et al., 2020);
3. multilingual Sentence-BERT (Reimers and Gurevych, 2020), the knowledge-distilled variant paraphrase-xlm-r-multilingual-v1

Among these models, only LaBSE has support for all the Indic languages we were interested in. No Indic language is supported by m-USE, and multilingual Sentence-BERT has been trained on parallel data only for Hindi, Gujarati and Marathi among our Indic languages. However, in terms of Semantic Textual Similarity (STS) benchmarks (Cer et al., 2017) for English, Arabic & Spanish, m-USE and Sentence-BERT outperform LaBSE (Table 1 in Reimers and Gurevych, 2020).

LaBSE correlates better than Sentence-BERT with our human-annotated formality dataset: We measured the Spearman’s rank correlation between the semantic similarity annotations on our human-annotated formality datasets (Section 5.1). We discarded 10% sentence pairs which had no agreement among three annotators and took the majority vote for the other sentence pairs. We assigned “Different Meaning” a score of 0, “Slight Difference in Meaning” a score of 1 and “Approximately Same Meaning” a score of 2 before measuring Spearman’s rank correlation. In Table 8 we see a stronger correlation of human annotations with LaBSE compared to Sentence-BERT, especially for languages like Bengali, Kannada for which Sentence-BERT did not see parallel data.

| Model    | hi   | bn   | kn   | te   |
|----------|-----|------|------|------|
| LaBSE    | 0.34| 0.49 | 0.39 | 0.25 |
| Sentence-BERT | 0.33| 0.36 | 0.29 | 0.18 |

Table 8: Spearman’s rank correlation between different semantic similarity models and our semantic similarity human annotations collected along with formality labels. Overall, LaBSE correlates more strongly than Sentence-BERT with our annotated data.

C.3 Evaluation with Different LaBSE thresholds

In Section 6, we set our LaBSE threshold $L$ to 0.75. In this section, we present our evaluations with a more and less conservative value of $L$.

In Table 16, we present results with $L = 0.65$, and in Table 17 we set $L = 0.85$. Compared to Table 1, trends are mostly similar, with DIFFUR models and INDIC variants outperforming counterparts. Note that the absolute values of SIM and AGG metrics differ, with absolute values going down with the stricter threshold of $L = 0.85$, and up with the relaxed threshold of $L = 0.65$.

Comparing chosen thresholds with human annotations: To verify these three thresholds are rea-
sonable choices, we measure the LaBSE similarity of the sentence pairs annotated by humans, and compare the LaBSE scores to human semantic similarity annotations. We pool the “Approximately Same Meaning” and “Slight Difference in Meaning” categories as “same”, and consider only sentence pairs with a majority rating of “same”. In Table 9 we see that the chosen thresholds span the spectrum of LaBSE values for the human annotated semantically similar pairs.

| Threshold L | % of sentence pairs > L | hi | bn | kn | te |
|-------------|-------------------------|----|----|----|----|
| 0.65        | 97.4                    | 96.1 | 94.6 | 90.6 |
| 0.75        | 83.9                    | 76.1 | 68.4 | 62.6 |
| 0.85        | 75.1                    | 62.7 | 50.5 | 45.5 |

Table 9: Percentage of human annotated semantically similar pairs which have a LaBSE score of at least \( L \). As we increase the threshold \( L \), we see this percentage substantially reduces, indicating our chosen thresholds are within the range of variation in LaBSE scores for semantically similar sentences.

C.4 More Crowdsourcing Details

In Figure 16, we show screenshots of our crowdsourcing interface along with all the instructions shown to crowdworkers. The instructions were written after consulting professional Indian linguists. For formality classification, we showed crowdworkers two sentences and asked them to choose which one is more formal. Crowdworkers were allowed to mark ties using an “Equal” option. For semantic similarity annotation, we showed crowdworkers the sentence pair and provided three options — “approximately same meaning”, “slight difference in meaning”, “different meaning”, to emulate a 3-point Likert scale. While performing our human evaluation (Section 5.7), we use a 0.5 \( \text{SIM} \) score for “slight difference in meaning” and a 1.0 \( \text{SIM} \) score for “approximately same meaning” annotations. For every system considered, we analyzed the same set of 200 input sentences for style transfer performance, and 100 of those sentences for evaluating controllability. We removed sentences which were exact copies of the input (after removing trailing punctuation) or were in the wrong language to save annotator time and cost. When outputs were exact copies of the input, we assigned \( \text{SIM} = 100, \text{ACC} = 0, \text{AGG} = 0 \).

In Table 10 and Table 11 we show the inter-annotator agreement statistics. We measure Fleiss Kappa (Fleiss, 1971), Randolph Kappa (Randolph, 2005; Warrens, 2010), the fraction of sentence pairs with total agreement between the three annotators and the fraction of sentence pairs with no agreement. In the table we can see all agreement statistics are well away from a uniform random annotation baseline, indicating good agreement.

| F-\( \kappa \) | R-\( \kappa \) | all agree | none agree |
|--------------|--------------|-----------|------------|
| Random | 0.0 | 0.0 | 11.1% | 22.2% |
| hi | 0.21 | 0.28 | 32.8% | 10.2% |
| bn | 0.33 | 0.40 | 43.8% | 7.2% |
| kn | 0.22 | 0.31 | 35.0% | 7.7% |
| te | 0.21 | 0.31 | 36.0% | 9.3% |

Table 10: Fleiss kappa (F-\( \kappa \)), Randolph kappa (R-\( \kappa \)), and agreement scores of crowdsourcing for formality classification. All \( \kappa \) scores are well above a random annotation baseline, indicating fair agreement.

| F-\( \kappa \) | R-\( \kappa \) | all agree | none agree |
|--------------|--------------|-----------|------------|
| Random | 0.0 | 0.0 | 11.1% | 22.2% |
| hi | 0.10 | 0.27 | 32.6% | 11.8% |
| bn | 0.24 | 0.34 | 38.7% | 10.2% |
| kn | 0.13 | 0.25 | 30.8% | 11.3% |
| te | 0.1 | 0.31 | 36.1% | 9.7% |

Table 11: Fleiss kappa (F-\( \kappa \)), Randolph kappa (R-\( \kappa \)), and agreement scores of crowdsourcing for semantic similarity. All \( \kappa \) scores are well above a random annotation baseline, indicating fair agreement.

C.5 Fluency Evaluation

Unlike some prior works, we avoid evaluation of output fluency due to the following reasons: (1) lack of fluency evaluation tools for Indic languages; (2) fluency evaluation often discriminates against styles which are out-of-distribution for the fluency classifier, as discussed in Appendix A.8 of Krishna et al. (2020); (3) several prior works (Pang, 2019; Mir et al., 2019; Krishna et al., 2020) have recommended against using perplexity of style language models for fluency evaluation.

\(^{18}\)The \( \kappa \) scores are measured using the library https://github.com/statsmodels/statsmodels.

\(^{19}\)A potential tool for fluency evaluation in future work is LAMBRE (Pratapa et al., 2021). However, the original paper does not evaluate performance on Indic languages and the grammars for Indic languages would need to collected / built.
D Ablation Studies

D.1 Ablation Study for DIFFUR design

This section describes the ablation experiments conducted for the DIFFUR modeling choices in Section 4.2. We ablate a DIFFUR-INDIC model trained on Hindi paraphrase data only, and present results for Hindi formality transfer in Table 14.

- no paraphrase: We replaced the paraphrase noise function with the random token dropping / replacing noise used in the denoising objective of UR model (Section 3), and continued to use vector differences. As seen in Table 14, this significantly increases the copy rate, which lowers the style transfer performance.

- no paraphrase semantic filtering: We keep a setup identical to Section 4.2, but avoid the LaBSE filtering done (discarding pairs having a LaBSE score outside [0.7, 0.98]) to remove noisy paraphrases or exact copies. As seen in Table 14, this decreases the semantic similarity score of the generations, lowering the overall performance.

- no vector differences: Instead of using vector differences for DIFFUR-INDIC, we simply set $s_{\text{diff}} = f_{\text{style}}(x)$, or the style of the target sentence. In Table 14, we see this significantly decreases SIM scores, and LANG scores for $\lambda = 2.0$. We hypothesize that this training encourages the model to rely more heavily on the style vectors, ignoring the paraphrase input. This could happen since the style vectors are solely constructed from the output sentence itself, and semantic information / confounding style is not subtracted out. In other words, the model is behaving more like an autoencoder (through the style vector) instead of a denoising autoencoder with stylistic supervision.

- mC4 instead of Samanantar: Instead of creating pseudo-parallel data with Samanantar, we leverage the mC4 dataset itself which was used to train the UR model. We backtranslate spans of text from the Hindi split of mC4 on-the-fly using the UR translation capabilities, and use it as the “paraphrase noise function”. To ensure translation performance does not deteriorate during training, 50% mini-batches are supervised translation between Hindi and English. In Table 14, we see decent overall performance, but the LANG score is 6% lower than DIFFUR-INDIC. Qualitatively we found that the model often translates a few Hindi words to English while making text informal. Due to sparsity of English tokens, it often escapes penalization from LANG.

- mC4 + exemplar instead of target: This setting is similar to the previous one, but in addition to the mC4 dataset we utilize the vector difference between the style vector of the exemplar span (instead of target span), and the “paraphrase noised” input. Results in Table 14 show this method is not effective, and it’s important for the vector difference to model the precise transformation needed.

D.2 Choice of Decoding Scheme

We experiment with five decoding schemes on the Hindi formality validation set — beam search with beam size 1, 4 and top-$p$ sampling (Holtzman et al., 2020) with $p = 0.6, 0.75, 0.9$.

In Table 15, we present results at a constant style transfer magnitude ($\lambda = 3.0$). Consistent with Krishna et al. (2020), we find that top-$p$ decoding usually gets higher style accuracy ($r$-ACC, $a$-ACC) and output diversity (1-g, COPY) scores, but lower semantic similarity (SIM) scores. Overall beam search triumphs since the loss in semantic similarity leads to a worse performing model. In Figure 9, we see a consistent trend across different magnitudes of style transfer ($\lambda$). In all our main experiments, we use beam search with beam size 4 to obtain our generations.

D.3 Number of Training Steps

In Figure 10, we present the variation in style transfer performance with number of training steps for our best model, the MULTITASK model. We find that with more training steps performance generally improves, but improvements saturate after 8k steps. We also see the peak of the graphs (best style transfer performance) shift rightwards, indicating a preference for higher $\lambda$ values.

E Analysis Experiments

E.1 Style vectors from $f_{\text{style}}$ as style classifiers

The Universal Rewriter models succeed in learning an effective style space, useful for few-shot style
transfer. But can this metric space also act as a style classifier? To explore this, we measure the cosine distance between the mean style vector of our informal exemplars, \(20\) and the style vectors derived by passing human-annotated formal/informal pairs (from our dataset of Section 5.1) through \(f_{\text{style}}\). We only consider pairs which had complete agreement among annotators. In Table 12 we see good agreement (68.2%-80.7%) between human annotations and the classifier derived from the metric space of the UR-INDIC model. Agreement is lower (67.0%-74.3%) for the DIFFUR-INDIC model, likely due to the stop gradient used in Section 4.2. With MULTITASK, agreement jumps back up to 75%-81.7% since gradients flow into the style extractor as well.

### E.2 Style Vector Analysis with Formal Exemplars Vectors

In Appendix E.1, we saw that the metric vector space derived from the style encoder \(f_{\text{style}}\) of various models is an effective style classifier, using the informal exemplar vectors. In Table 13, we present a corresponding analysis using formal exemplar vectors. Most accuracy scores are close to 50%, implying this setup is not a very effective style classifier.

| Model       | hi  | bn  | kn  | te  |
|-------------|-----|-----|-----|-----|
| UR          | 79.1| 69.7| 66.2| 67.1|
| UR-INDIC    | 80.7| 74.3| 68.2| 72.2|
| DIFFUR-INDIC| 68.0| 73.8| 67.0| 70.4|
| MULTITASK   | 75.0| 81.7| 79.8| 79.0|

Table 12: style vector as a classifier, measuring the cosine similarity with informal exemplar vectors.

| Model       | hi  | bn  | kn  | te  |
|-------------|-----|-----|-----|-----|
| UR          | 56.6| 60.0| 61.6| 57.6|
| UR-INDIC    | 59.5| 60.6| 52.6| 44.8|
| DIFFUR-INDIC| 58.5| 58.3| 59.5| 49.7|
| MULTITASK   | 64.9| 52.3| 47.1| 41.8|

Table 13: style vector as a classifier, measuring the cosine similarity with formal exemplar vectors.

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20See Appendix B for the exemplar sentences. We found the informal exemplars more effective than formal exemplars for style classification; Appendix E.2 has a comparison.
Figure 8: More qualitative examples of generations from our system (see Figure 4 for main table with qualitative analysis). Red and blue colours indicate attribute-specific features, while golden text represents model errors.
Table 14: Ablation study on Hindi formality transfer validation set using beam size of 4 and \( \lambda = 2.0 \) unless the optimal hyperparameters were different (marked by **). As shown by the overall a-AGG scores, removing any component of our design leads to an overall performance drop, sometimes significantly. For a detailed description of analysis and results, see Appendix D.1. For detailed metric descriptions, see Section 5.

| Ablation                                         | COPY(↓) | LANG  | SIM   | r-ACC  | a-ACC  | r-AGG | a-AGG |
|--------------------------------------------------|---------|-------|-------|--------|--------|-------|-------|
| DIFFUR-INDIC (hindi only)                        | 2.0     | 97.0  | 78.4  | 89.8   | 39.7   | 67.3  | 24.6  |
| - no paraphrase**                                | 21.0    | 98.3  | 92.2  | 60.0   | 15.7   | 51.9  | 10.7  |
| - no paraphrase (\( p, \lambda = 0.6, 3 \))    | 14.2    | 98.7  | 81.0  | 70.9   | 28.1   | 51.6  | 12.5  |
| - no paraphrase semantic filtering               | 2.2     | 97.2  | 72.2  | 89.1   | 38.6   | 60.7  | 19.6  |
| - no vector differences**                        | 0.0     | 54.3  | 3.2   | 99.0   | 90.0   | 2.4   | 1.0   |
| - no vector differences (\( \lambda = 0.5 \))   | 0.9     | 97.4  | 66.8  | 86.4   | 36.5   | 53.5  | 17.3  |
| - mC4 instead of Samanantar                      | 1.5     | 91.4  | 82.0  | 89.3   | 39.0   | 67.7  | 24.2  |
| - mC4 + exemplar instead of target               | 5.5     | 23.8  | 82.3  | 77.2   | 32.3   | 13.8  | 3.2   |

Table 15: Automatic evaluation of different decoding algorithms (top-\( p \) sampling and beam search) on the MULTITASK model for Hindi formality transfer (validation set) using \( \lambda = 3.0 \). As expected, output diversity (1-g, COPY) and style accuracy (r-ACC, a-ACC) improves as we move down the table, but compromise semantic preservation (SIM), bringing the overall performance (r-AGG, a-AGG) down. Also see Figure 9 for a comparison across \( \lambda \) values, and Section 5 for detailed metric descriptions.

| Decoding    | COPY(↓) | I-g(↓) | LANG  | SIM   | r-ACC  | a-ACC  | r-AGG | a-AGG |
|-------------|---------|--------|-------|-------|--------|--------|-------|-------|
| beam 4      | 1.8     | 52.7   | 95.8  | 73.3  | 94.7   | 51.6   | 66.2  | 32.3  |
| beam 1      | 1.2     | 47.4   | 92.3  | 61.7  | 95.7   | 62.5   | 55.8  | 31.4  |
| top-\( p \) 0.6 | 1.0   | 45.3   | 91.5  | 56.6  | 96.2   | 65.9   | 51.3  | 29.9  |
| top-\( p \) 0.75 | 0.9   | 43.1   | 90.3  | 52.4  | 96.3   | 69.0   | 47.3  | 28.2  |
| top-\( p \) 0.9 | 0.7   | 40.4   | 89.4  | 46.8  | 96.6   | 71.7   | 42.4  | 26.5  |

Figure 9: Variation in Hindi formality transfer (validation set) performance vs \( \lambda \) with change in decoding scheme, for the MULTITASK model. The plots show overall style transfer performance, using the r-AGG (left) and a-AGG (right) metrics from Section 5.5. Beam search with beam size 4 performs best, see Table 15 for an individual metric breakdown while keeping \( \lambda = 3.0 \).
Figure 10: Variation in Hindi formality transfer validation set performance with change in number of training steps for the MULTITASK model. The plots show overall style transfer performance, using the r-AGG (top-left) and a-AGG (top-right) metrics from Section 5.5. With more training steps performance seems to improve and the peak of the graph shifts towards the right (a preference towards higher scale values). We also see more training steps leads to better controllability (bottom plot, closer to Y-axis is better), but only marginal gains after 6k steps.

Table 16: Test set performance across languages for a smaller LaBSE semantic similarity threshold of 0.65. Due to the more relaxed threshold, absolute numbers compared to Table 1 are higher. Trends remain similar, with the DIFFUR and INDIC variants outperforming other competing methods.
Table 17: Test set performance across languages for a larger LaBSE semantic similarity threshold of 0.85. Due to the stricter threshold, absolute numbers compared to Table 1 are lower, however trends are similar, with the DIFFUR and INDIC variants outperforming other competing methods.

| Model                | Hindi r-AGG | Hindi a-AGG | Bengali r-AGG | Bengali a-AGG | Kannada r-AGG | Kannada a-AGG | Telugu r-AGG | Telugu a-AGG | Gujarati r-AGG | Gujarati a-AGG |
|----------------------|-------------|-------------|---------------|---------------|---------------|---------------|---------------|---------------|----------------|----------------|
| UR (2021)            | 24.2        | 6.6         | 24.2          | 4.8           | 21.5          | 6.0           | 19.1          | 5.8           | 19.4           | 3.6            |
| UR + BT              | 40.0        | 10.7        | 31.7          | 8.1           | 21.2          | 5.1           | 19.1          | 4.8           | 26.1           | 4.4            |
| DIFFUR               | 57.1        | 13.0        | 59.6          | 13.0          | 54.5          | 13.8          | 52.8          | 12.8          | 0.2            | 0.0            |
| UR-INDIC             | 49.6        | 13.1        | 54.6          | 12.7          | 50.0          | 11.4          | 48.1          | 11.2          | 45.9           | 6.8            |
| UR-INDIC + BT        | 43.7        | 12.9        | 33.9          | 10.2          | 31.9          | 7.8           | 29.4          | 7.8           | 34.0           | 7.4            |
| DIFFUR-INDIC         | 59.2        | 14.9        | 63.8          | 15.6          | 58.9          | 16.1          | 55.2          | 14.4          | 31.7           | 8.0            |
| MULTITASK            | 64.8        | 17.9        | 69.8          | 22.0          | 69.3          | 23.5          | 67.5          | 20.6          | 64.0           | 18.2           |

Table 18: Performance breakdown of Hindi formality transfer by individual metrics described in Section 5.

Figure 11: Variation in Hindi formality transfer test set performance & control for different models (see Table 18 for a individual metric breakdown of the models at the best performing $\lambda$). The plots show overall style transfer performance, using the r-AGG (top-left) and a-AGG (top-right) metrics from Section 5.5. We see the DIFFUR models outperform other systems across the $\lambda$ range, and get best performance with the MULTITASK variant. We also see that DIFFUR models, especially with MULTITASK, lead to better style transfer control (bottom plot, closer to $x = 1$ is better), giving large style variation with $\lambda$ without loss in semantics (X-axis).
Table 19: Performance breakdown of Bengali formality transfer by individual metrics described in Section 5.

| Model              | $\lambda$ | $\text{COPY}(\downarrow)$ | 1-g$(\downarrow)$ | LANG | SIM | f-ACC | a-ACC | r-AGG | a-AGG |
|--------------------|-----------|-----------------------------|-------------------|------|-----|-------|-------|-------|-------|
| UR (Garcia et al., 2021) | 1.5       | 21.5                        | 69.1              | 99.9 | 87.3 | 42.4  | 15.6  | 30.4  | 7.2   |
| UR-INDIC           | 1.0       | 4.4                         | 58.9              | 99.0 | 95.7 | 69.8  | 19.5  | 65.5  | 17.3  |
|                    | 1.5       | 2.4                         | 47.5              | 97.6 | 79.8 | 80.0  | 37.4  | 59.6  | 22.3  |
| UR + BT            | 0.5       | 0.2                         | 30.4              | 97.8 | 80.6 | 71.8  | 22.3  | 55.6  | 15.0  |
|                    | 1.0       | 0.1                         | 27.0              | 95.4 | 73.6 | 77.6  | 29.6  | 53.5  | 16.9  |
| UR-INDIC + BT      | 1.0       | 0.4                         | 34.9              | 99.8 | 80.6 | 78.3  | 31.4  | 61.1  | 22.0  |
| DIFFUR             | 1.0       | 2.1                         | 50.6              | 99.9 | 91.6 | 80.8  | 25.2  | 72.7  | 20.9  |
| DIFFUR-INDIC       | 1.5       | 1.1                         | 40.6              | 99.9 | 75.8 | 89.1  | 39.7  | 65.8  | 25.2  |
| DIFFUR + BT        | 1.5       | 2.0                         | 53.1              | 99.9 | 94.2 | 80.7  | 24.6  | 75.4  | 21.8  |
| MULTITASK          | 2.5       | 0.9                         | 41.4              | 99.9 | 75.6 | 86.1  | 36.9  | 64.6  | 24.3  |
|                    | 3.0       | 1.0                         | 40.0              | 99.1 | 73.0 | 92.1  | 56.5  | 65.3  | 35.0  |

Figure 12: Variation in Bengali formality transfer test set performance & control for different models (see Table 19 for a individual metric breakdown of the models at the best performing $\lambda$). The plots show overall style transfer performance, using the r-AGG (top-left) and a-AGG (top-right) metrics from Section 5.5. We see the DIFFUR models outperform other systems across the $\lambda$ range, and get best performance with the MULTITASK variant. We also see that DIFFUR models, especially with MULTITASK, lead to better style transfer control (bottom plot, closer to $x = 1$ is better), giving large style variation with $\lambda$ without loss in semantics (X-axis).
Table 20: Performance breakdown of Kannada formality transfer by individual metrics described in Section 5.

| Model              | $\lambda$ | COPY | $I-g$ | LANG | SIM   | r-ACC | a-ACC | r-AGG | a-AGG |
|--------------------|-----------|------|-------|------|-------|-------|-------|-------|-------|
| UR (Garcia et al., 2021) | 1.5       | 52.0 | 86.8  | 99.9 | 95.0  | 29.9  | 11.2  | 25.5  | 8.0  |
| UR-INDIC           | 1.0       | 8.6  | 62.9  | 98.3 | 94.5  | 67.0  | 20.8  | 61.3  | 17.8 |
| UR + BT            | 0.5       | 0.3  | 26.0  | 77.8 | 75.5  | 67.2  | 23.3  | 39.8  | 11.9 |
| UR-INDIC + BT      | 0.5       | 1.6  | 40.6  | 99.9 | 82.3  | 73.9  | 26.8  | 59.2  | 19.1 |
|                   | 1.0       | 1.4  | 37.7  | 99.8 | 76.8  | 78.3  | 32.8  | 58.1  | 21.0 |
| DIFFUR             | 1.0       | 3.0  | 47.4  | 99.8 | 87.9  | 80.3  | 30.5  | 69.2  | 23.6 |
| DIFFUR-INDIC       | 2.0       | 2.9  | 50.3  | 99.9 | 91.5  | 81.2  | 32.2  | 73.1  | 26.4 |
| DIFFUR             | 2.0       | 2.3  | 45.2  | 99.9 | 82.7  | 85.1  | 42.3  | 68.5  | 29.3 |
| MULTITASK          | 2.0       | 5.4  | 59.6  | 100  | 97.5  | 82.9  | 28.9  | 80.4  | 27.5 |
|                   | 3.0       | 2.1  | 42.7  | 99.1 | 71.7  | 92.6  | 63.4  | 64.5  | 39.4 |

Figure 13: Variation in Kannada formality transfer test set performance & control for different models (see Table 20 for a individual metric breakdown of the models at the best performing $\lambda$). The plots show overall style transfer performance, using the r-AGG (top-left) and a-AGG (top-right) metrics from Section 5.5. We see the DIFFUR models outperform other systems across the $\lambda$ range, and get best performance with the MULTITASK variant. We also see that DIFFUR models, especially with MULTITASK, lead to better style transfer control (bottom plot, closer to $x=1$ is better), giving large style variation with $\lambda$ without loss in semantics (X-axis).
| Model          | λ  | COPY (↓) | I-g(↓) | LANG | SIM | r-ACC | a-ACC | r-AGG | a-AGG |
|---------------|----|----------|--------|------|-----|-------|-------|-------|-------|
| UR (2021)     | 1.5| 51.3     | 87.0   | 100  | 96.3| 26.3  | 10.1  | 22.8  | 7.5   |
|               | 2.0| 35.0     | 68.2   | 99.9 | 73.0| 45.4  | 28.6  | 20.7  | 8.4   |
| UR-INDIC      | 1.0| 10.4     | 64.5   | 98.8 | 94.3| 65.6  | 20.2  | 59.8  | 16.7  |
|               | 1.5| 5.9      | 53.5   | 97.3 | 80.0| 74.9  | 33.1  | 55.9  | 19.9  |
| UR + BT       | 0.5| 0.2      | 26.3   | 82.4 | 73.4| 65.6  | 23.4  | 38.4  | 11.3  |
|               | 1.0| 0.1      | 19.8   | 74.9 | 64.7| 71.2  | 31.6  | 33.1  | 11.6  |
| UR-INDIC + BT | 0.5| 0.6      | 39.2   | 99.9 | 79.6| 73.5  | 26.2  | 56.8  | 17.9  |
|               | 1.0| 0.5      | 36.1   | 99.7 | 74.0| 78.5  | 35.9  | 56.0  | 22.2  |
| DIFFUR        | 1.0| 1.7      | 46.0   | 99.9 | 87.9| 80.5  | 27.6  | 69.4  | 21.5  |
|               | 2.5| 0.9      | 36.0   | 99.8 | 68.4| 90.2  | 47.2  | 59.9  | 27.1  |
| DIFFUR-INDIC  | 1.0| 2.4      | 50.1   | 99.9 | 91.7| 78.7  | 28.7  | 71.0  | 23.7  |
|               | 1.5| 1.4      | 44.6   | 99.9 | 83.6| 83.6  | 38.4  | 68.2  | 27.1  |
| MULTITASK     | 2.0| 3.8      | 55.8   | 99.9 | 95.7| 84.0  | 31.2  | 79.8  | 28.6  |
|               | 2.5| 1.8      | 47.0   | 99.5 | 85.8| 90.1  | 48.4  | 76.0  | 37.9  |

Table 21: Performance breakdown of Telugu formality transfer by individual metrics described in Section 5.

![Graph](https://example.com/graph1.png)

Figure 14: Variation in Telugu formality transfer test set performance & control for different models (see Table 21 for a individual metric breakdown of the models at the best performing λ). The plots show overall style transfer performance, using the r-AGG (top-left) and a-AGG (top-right) metrics from Section 5.5. We see the DIFFUR models outperform other systems across the λ range, and get best performance with the MULTITASK variant. We also see that DIFFUR models, especially with MULTITASK, lead to better style transfer control (bottom plot, closer to x = 1 is better), giving large style variation with λ without loss in semantics (X-axis).
Table 22: Performance breakdown of Gujarati formality transfer by individual metrics described in Section 5.

| Model               | λ  | COPY(↓) | 1-g(↓) | LANG | SIM   | r-ACC | a-ACC | r-AGG | a-AGG |
|---------------------|----|---------|--------|------|-------|-------|-------|-------|-------|
| UR (2021)           | 1.5| 62.6    | 89.1   | 99.9 | 93.1  | 30.2  | 9.3   | 23.7  | 5.0   |
| UR-Indic            | 1.0| 17.5    | 73.6   | 98.4 | 96.8  | 57.6  | 11.7  | 54.0  | 9.9   |
|                     | 1.5| 10.9    | 62.7   | 96.9 | 85.4  | 67.0  | 19.2  | 53.0  | 10.7  |
| UR + BT             | 0.5| 0.5     | 34.3   | 87.3 | 77.6  | 69.1  | 17.8  | 46.3  | 9.8   |
|                     | 1.0| 0.3     | 26.5   | 78.8 | 67.6  | 74.8  | 27.2  | 39.1  | 10.4  |
| UR-Indic + BT       | 0.5| 1.9     | 47.4   | 99.9 | 87.1  | 68.1  | 22.0  | 57.7  | 16.8  |
| DIFFUR              | 0.5| 0.0     | 5.7    | 1.2  | 81.3  | 73.2  | 25.7  | 0.4   | 0.2   |
| DIFFUR-Indic        | 0.5| 1.1     | 34.7   | 54.9 | 95.6  | 68.6  | 18.6  | 37.4  | 9.0   |
|                     | 1.0| 0.4     | 24.2   | 46.0 | 74.7  | 78.5  | 40.0  | 29.2  | 13.0  |
| MULTITASK           | 2.0| 7.7     | 65.4   | 98.6 | 96.2  | 79.3  | 25.0  | 75.0  | 22.3  |
|                     | 2.5| 4.5     | 54.6   | 95.1 | 85.5  | 86.0  | 45.8  | 69.8  | 33.1  |

Figure 15: Variation in Gujarati formality transfer test set performance & control for different models (see Table 22 for a individual metric breakdown of the models at the best performing λ). The plots show overall style transfer performance, using the r-AGG (top-left) and a-AGG (top-right) metrics from Section 5.5. Note that Gujarati is a zero-shot language for DIFFUR models — no Gujarati paraphrase data was seen during training. We see that while the vanilla DIFFUR model performs poorly, the DIFFUR-Indic is competitive with baselines and the MULTITASK variant significantly outperforms other systems. We also see that the MULTITASK variant lead to better style transfer control (bottom plot, closer to x = 1 is better), giving style variation with λ without loss in semantics (X-axis).
Figure 16: Our crowdsourcing interface on Task Mate, used to build our formality evaluation datasets (Section 5.1) and conduct human evaluations (Section 5.7). The first row shows our landing page and instruction set derived from our conversations with professional linguists. The second row shows our qualification questions for formality classification, and the third row shows templates for the two questions asked to crowdworkers per pair.