A Conditional Generative Matching Model for Multi-lingual Reply Suggestion

Budhaditya Deb† Guoqing Zheng† Milad Shokouhi† Ahmed Hassan Awadallah†
†Microsoft AI ‡Microsoft Research
{budeb, zheng, milads, hassanam}@microsoft.com

Abstract

We study the problem of multilingual automated reply suggestions (RS) model serving many languages simultaneously. Multilingual models are often challenged by model capacity and severe data distribution skew across languages. While prior works largely focus on monolingual models, we propose Conditional Generative Matching models (CGM), optimized within a Variational Autoencoder framework to address challenges arising from multilingual RS. CGM does so with expressive message conditional priors, mixture densities to enhance multi-lingual data representation, latent alignment for language discrimination, and effective variational optimization techniques for training multi-lingual RS. The enhancements result in performance that exceed competitive baselines in relevance (ROUGE score) by more than 10% on average, and 16% for low resource languages. CGM also shows remarkable improvements in diversity (80%) illustrating its expressiveness in representation of multi-lingual data.

1 Introduction

Automated reply suggestion (RS) helps users quickly process Email and chats, in popular applications like Gmail, Outlook, Microsoft Teams, and Facebook Messenger, by selecting a relevant reply generated by the system, without having to type in the response. Most existing RS systems are English mono-lingual models (Kannan et al., 2016; Henderson et al., 2017; Deb et al., 2019; Shang et al., 2015). We study the problem of creating multilingual RS models serving many languages simultaneously. Compared to mono-lingual models, a universal multilingual model offers several interesting research questions and practical advantages.

Universal models can save compute resources and maintenance overhead for commercial systems supporting many regions. In addition it can benefit languages with insufficient data by information sharing from high resource languages and thus enhance experiences for users especially in low-language resource regions. We investigate if a single multilingual RS model can replace multiple mono-lingual models with better performance, while overcoming the challenges in model capacity, data skew, and training complexities.

Trivially extending existing mono-lingual RS models to the multilingual setting (e.g. by jointly training with pre-trained multi-lingual encoders) tends to be sub-optimal, as multilingual models suffer from capacity dilution issue (Lample and Conneau, 2019), where it improves performance on low resource languages while hurting the high resource ones. This arises, not only due to the severe data imbalance and distribution skew across languages, but also due to insufficient capacity and lack of inductive biases in models to represent the multi-modal distribution of languages. We postulate that deep generative latent variable models with variational auto-encoders (VAE) (Kingma and Welling, 2014) are better suited to model the complex distribution of multi-lingual data, and be more data efficient for low resource languages.

To this end, we propose the Conditional Generative Matching Model (CGM), a VAE based retrieval architecture for RS to solve the above challenges. CGM enhances multilingual representation through: 1) expressive message conditional priors, 2) multi-component mixture density to represent different modalities of languages, and 3) alignment of latent components for language discrimination. In addition CGM incorporates training optimizations in the form of 1) loss regularizer, 2) learnable weights for loss components, 3) multi-sample loss estimation with variance scaling, and 4) focal loss, all of which lead to balanced representation and smooth convergence, a key challenge for variational training in multilingual settings.

We conducted extensive ablation studies and comparisons with two competitive baselines to
show the impact of the above optimizations. Universal CGM models improve the relevance of RS (up to 13% excluding English) with even higher gains coming for low resource languages (16%), and when using CGM in a monolingual setting (19%). CGM also dramatically increases the diversity of suggested replies by 80% which is more illustrative of the improved representational capability of CGM in the multi-lingual landscape. CGM achieves this with relatively small increase in model sizes compared to the large pre-trained transformer stacks on which it is built, showing the modeling efficiencies that can be achieved through efficient training of latent variable models in a multi-lingual setting.

2 Background and Preliminaries

While RS has been modeled as a sequence to sequence model (Kannan et al., 2016), it more commonly appears as an information retrieval (IR) system by ranking responses from a fixed set (Henderson et al., 2017, 2019; Ying et al., 2021; Swanson et al., 2019; Zhou et al., 2016, 2018) due to better control over quality and relevance for practical systems. We briefly describe two retrieval architectures from prior literature which serves as the baselines for our multilingual RS model.

Matching model (Henderson et al., 2017; Ying et al., 2021) consists of two parallel encoders \([f_M, f_R]\) to encode message and reply (M-R) pairs into a common encoding space, \([\Theta_M, \Theta_R]\) and trained to maximize a normalized dot product \(D = \Theta_M^\top \Theta_R\) between the M-R encodings. During prediction, the model finds the nearest neighbors of \(\Theta_M\) with precomputed encodings from a fixed response set \(R_s\). A language model bias is typically added to promote more common responses. The matching architecture is summarized as:

\[
\mathcal{L}(\Theta_R|\Theta_M) = \log \frac{e^{D(\Theta_M, \theta_R)}}{\sum_{r \in R_s} e^{D(\Theta_M, \theta_R)}} \tag{1}
\]

Prediction : \(Top_k\{\Theta_M^\top \Theta_R + \alpha LM(r) | r \in R_s\}\) \tag{2}

Matching Conditional VAE (MCVAE) (Deb et al., 2019) induces a deep generative latent variable model on the matching architecture, where a candidate response encoding is generated with \(\Theta_R' = g_w(\Theta_M, z)\) conditioned on a latent prior \(z \sim \mathcal{N}(0, I)\). The generated \(\Theta_R'\) is used to match an actual response vector \(\Theta_R\) from the fixed response set. The generative model of MCVAE is shown in figure 1a. In MCVAE, the encoders \([f_M, f_R]\) are pretrained using the matching formulation and kept frozen during the training. For prediction, MCVAE samples response vectors from \(g_w\) followed by scoring (eq 2) and a voting technique to rank replies over a fixed response set. MCVAE is trained in the variational framework by minimizing the negative evidence lower-bound (ELBO) in equation 3 with a Gaussian posterior \(q_\phi\) (mean and co-variance parameterized from \((\Theta_M, \Theta_R)\)) and the reconstruction loss \(\mathcal{L}_M\) defined by Eq. (1).

\[
\ell_{ELBO} = KL(q_\phi || p(z)) - \mathcal{L}_M(\Theta_R|\Theta_{R'}) \tag{3}
\]

We extend the Matching and MCVAE models to a multi-lingual setting by using pretrained multilingual BERT (MBERT) (Devlin et al., 2019) for \([f_M, f_R]\) similar to (Ying et al., 2021) and jointly training the models for all languages.

3 CGM: A Conditional Generative Matching Model for Reply Suggestion

Our initial analysis with universal models (jointly training models with all languages), reveals that the universal MCVAE performs better than Matching. However, simply training models jointly is
not sufficient to achieve a models with high performance. First, the highly imbalanced nature of multi-lingual data leads to over- or under-fitting across languages resulting in performance worse than separately trained mono-lingual models. Second, training multi-lingual MCVAE proved is due to the reliance on a pretrained Matching model: it is not clear how to find a suitable Matching model checkpoint for initializing the MCVAE. Finally, since the text encoders for MCVAE are frozen during training, there is limited cross lingual transfer and improvement for low resource languages. Unfreezing the layers led to divergence of the model.

To address the limitations of MCVAE, we propose an enhanced Conditional Generative Matching (CGM) model, for the retrieval based RS with inductive biases for the multi-lingual data and effective training techniques for creating high quality universal models.

3.1 Message Conditional Prior

The implied generative process in MCVAE (Fig. 1a), is \( p(z) \rightarrow p(\Theta_M | z) \rightarrow p(\Theta_R | \Theta_M, z) \), where the latent prior \( z \) is sampled independent of the message encoding \( \Theta_M \). However, in RS since \( \Theta_M \) is always observed, ideally one would like to sample from \( p(z | \Theta_M) \) to capture message-dependent information as well as rich multi-modality of the input space, particularly for multi-lingual data. In addition, although MCVAE works well empirically in the mono-lingual setting (Deb et al., 2019), the samples from \( p(z) \) in general are not the same as \( p(z | \Theta_M) \propto p(z)p(\Theta_M | z) \), unless \( p(\Theta_M | z) \) is uniform across the space of \( \Theta_M \). This is a restrictive assumption, which motivates us to consider a prior conditioned on the input \( \Theta_M \) for the generative model, by decomposing

\[
p(\Theta_R, z | \Theta_M) = p(z | \Theta_M)p(\Theta_R | \Theta_M, z)
\]

as shown in Figure 1b. The conditional prior \( p(z | \Theta_M) \) is posed to encode message dependent information which can facilitate matching more relevant and diverse set of responses. We define the message-conditional prior \( p(z | \Theta_M) = \mathcal{N}(\mu(\Theta_M), \Sigma(\Theta_M)) \), where the prior parameters are learnt from data during training and used for prediction, to maximally capture the multiple modalities of intents and intrinsically complex distribution of multi-lingual data.

3.2 Prior with Mixture Density (CGM-M)

We postulate that a more expressive conditional prior, such as a mixture density, can better capture the multi-lingual data in contrast to the single prior density as used above. i.e., the different components of a mixture density can represent different languages and allow independent representation across languages. To this end we extend the message conditional prior with a Gaussian Mixture model (GMM) as,

\[
p(z | \Theta_M) = \sum_{k=1}^{K} \pi_k(\Theta_M) \mathcal{N}(\mu_k(\Theta_M), \Sigma_k(\Theta_M))
\]

where \( \mu_k(\Theta_M), \Sigma_k(\Theta_M) \) are the message dependent means and diagonal covariances for the \( k \)th component of the GMM, and \( \pi_k(\Theta_M) \) are the message dependent prior mixing coefficients. We hypothesize that components would correspond to different intents and languages, thus providing additional inductive bias for multi-lingual data. We refer to the mixture variant as CGM-M (Figure 1c).

3.3 Aligning Latent Space to Language

To further reinforce the notion that the CGM-M latent components encode language specific information from M-R pairs, we pose an additional constraint that the language of the message be inferred from the prior mixture coefficient. This is instantiated by building a simple classifier network with loss \( \ell_{LC}(\ell | \Theta_M, \pi) \) to map the prior mixture coefficient \( \pi(\Theta_M) \) onto the language \( l \) of the message. We also tested with mapping the 1) means and variances \( [\mu_k(\Theta_M), \Sigma_k(\Theta_M)] \), and 2) samples \( z_k \) of the GMM, and found that mapping the \( \pi(\Theta_M) \) leads to the best results. The classifier is learned jointly with the rest of the components.

3.4 Variational Training Architecture

The CGM models are formulated as a VAE in the continuous space of \( \Theta_M, \Theta_R \). CGM includes two multi-lingual text encoders \([f_{\Theta_M}, f_{\Theta_R}]\), to convert the raw text of M-R into the common encoding space (encoders may be considered extraneous to the VAE but are learnt jointly with VAE layers), and a VAE with prior, posterior, and generation networks \([p_{\psi}(\mu, \Sigma), q_{\phi}(\mu, \Sigma), g]\).

The CGM-M extends the CGM version with category specific Gaussian components \([p_{\psi}, q_{\phi}]\). In addition it also includes a categorical prior and posterior \([\pi_c, \rho_c]\), and a language classifier \( l_c \) to
discriminate between languages. We use the standard reparameterization trick for the Gaussian variables and the Gumbel-Softmax trick (Jang et al., 2017) with hard sampling for the categorical variable. CGM-M (CGM is a special case with $K = 1$) is summarized as follows.

**Generative Model**: $p_{\theta}(\mu, \Sigma), g_{\theta}$

$$
\pi = \text{Softmax}(\text{FFN}_1(\Theta_M)) \quad (6)
$$

$$
c = \text{GumbelSoftmax}(\text{FFN}_1(\Theta_M)) \quad (7)
$$

$$
\mu_{\phi} = \text{FFN}_2(\Theta_M), \Sigma_{\phi} = \text{Softplus}(\text{FFN}_3(\Theta_M)) \quad (8)
$$

$$
z_{c} = \mu_{\phi_{c}} + \varepsilon \Sigma_{\phi_{c}}, \text{where } \varepsilon \sim \mathcal{N}(0, I) \quad (9)
$$

$$
\Theta_{R'} = \text{FFN}_4(z_{\Theta_M}) \quad (10)
$$

**Variational Posterior**: $q_{\phi}(\mu, \Sigma)$

$$
\rho = \text{Softmax}(\text{FFN}_5(\Theta_M R^2)) \quad (11)
$$

$$
v = \text{GumbelSoftmax}(\text{FFN}_5(\Theta_M R^2)) \quad (12)
$$

$$
\mu_{\psi} = \text{FFN}_6(\Theta_M R^2) \quad (13)
$$

$$
\Sigma_{\psi} = \text{Softplus}(\text{FFN}_7(\Theta_M R^2)) \quad (14)
$$

$$
z_{v} = \mu_{\psi_{v}} + \xi \Sigma_{\psi_{v}}, \text{where } \xi \sim \mathcal{N}(0, I) \quad (15)
$$

Above, we expand the dimensions of projection vectors to $\mu : [h \times K], \Sigma : [h \times K]$ where $h$ is the dimension of the forward projections and $K$ is the number of categories in the mixture. After the category is selected (using Gumbel Softmax), we use the category index to select part of the expanded projections, as the $k^{th}$ component of the means and variances ($\mu_{k}, \Sigma_{k}$). Each $\text{FFN}_i$ denotes a two-layer feed-forward network (except $\text{FFN}_4$ which has 3 layers) with $\tanh$ activation and $\leftrightarrow$ denotes vector concatenation.

Note that the posteriors are conditioned on both $\Theta_M$ and $\Theta_R$. This theoretically provides a richer representation of the M-R pairs and during inference allows us to score the combination of message and the selected response vectors. However, during training, it can lead to leakage through the network where the model simply ignores the message and uses the response vector for generation. We mitigate the leakage by applying a low-dimensional projection of response vector $\Theta_R$ before feeding into the variational network.

Following standard stochastic gradient variational bayes (SGVB) training, we minimize the negative ELBO to train the network. CGM-M adds the classifier loss to enforce alignment between latent vectors and language types. The training objectives for each are given as follows, where the reconstruction log-loss, $\mathcal{L}(\Theta_R|\Theta_{R'})$ is given by Eq. (1). For CGM, the KL divergence between the two multivariate Gaussian densities can be computed in closed form. However, for CGM-M, the KL divergence between two Gaussian mixtures does not admit a closed form. We estimate it with a variational approximation method described in (Hershey and Olsen, 2007)\(^1\).

$$
KL_M(q||p) \approx \sum_{i=1}^{K} \pi_i \log \left( \frac{KL(p_{\phi_i} || q_{\psi_i})}{\sum_{k=1}^{K} \rho_k e^{-L(\psi_k)}} \right) \quad (18)
$$

### 3.5 Training Optimizations

Training deep generative models with SGVB has been known to be notoriously tricky (Bowman et al., 2016; Fu et al., 2019). Our multilingual setting, and joint training of text encoders with VAE layers makes it even more challenging. We employed several optimizations to improve the convergence of the models.

1) **Matching loss regularization**: In CGM, the encoders for $\Theta_M, \Theta_R$ are learnt jointly with the VAE layers in order to maximize richness of shared latent representation across languages. Thus $\Theta_R$ is a moving target for the VAE generator outputting $\Theta_R$ and causes the training to diverge without additional constraints. In MCVAE, this was mitigated by initializing and freezing the text encoders from a trained Matching model, but can be counter-productive in the multilingual scenario. To enable joint training of text encoders and the VAE layers, and mitigate the issue of a moving target for reconstruction, we introduce a regularization in the form of a matching score between $\Theta_M$ and $\Theta_R$.

$$
\ell_{\text{CGMM}} = KL_M(q_{\phi} || p_{\phi}) - L(\Theta_R|\Theta_{R'}) + \ell_{LC} - L(\Theta_R|\Theta_M) \quad (19)
$$

which constrains the response vector to have a representation close to the message vector. This provides an independent anchor for the reconstruction and allows the end-to-end training of the model utilizing the full parameter space of the encoders for enhanced representation.

2) **Multi-sample variance scaling**: In SGVB, using a single sample of $z$ usually results in high variance in the ELBO estimate. One remedy is to estimate the ELBO with multiple samples, either in the non-weighted and or importance

\(^1\)Another approach with Monte-Carlo sampling requires a large number of samples and was not as effective.
weighted (Burda et al., 2016) versions. However, these led to only minor improvements.

In multi-sample training we take the expectation of the ELBO over the samples. We found that instead of first taking the expectation of the samples \( z' = \sum_{i=1}^{k} z_i / k \) before computing the ELBO loss, we can reduce the variance and stabilize the training. Since \( z' \) follows an equivalent distribution \( z' \sim \mathcal{N}(\mu, \frac{1}{k}) \), we can estimate ELBO with multiple samples drawn from the scaled distribution and compute the expectation as follows. The adjustment provides significant improvements in training convergence and metrics.

\[
\ell_{CGM} = \mathbb{E}_z[-KL(q_\phi\|p_\phi) + \mathcal{L}(\Theta_R|\Theta_{R'})] \tag{20}
\]

3) Weighting loss components with Homoscedastic Uncertainty (HSU): The final loss formulations for both CGM and CGM-M have several components. For finer control of training, we introduce learnable weights \( w_i \) for each of the components. Weighting different components of the ELBO loss has shown to improve performance (Higgins et al., 2017) in SGVB and thus even without additional components, such a weighting process is recommended.

Following (Cipolla et al., 2018), we view the loss formulation as a multi-task learning objective with different homoscedastic uncertainties (HSU) for each task. Assuming the components factorize to Gaussian (continuous) and discrete (cross-entropy) likelihoods, the loss with HSU can be viewed as:

\[
\ell_{HSU} = \frac{1}{2\sigma_1^2} KL(q_\phi\|p_\phi) - \frac{1}{2\sigma_2^2} \ell(\Theta_R|\Theta_{R'}) - \frac{1}{2\sigma_3^2} \ell_{LC} + \frac{1}{2\sigma_4^2} \ell_{LC} + \log(\sigma_1) + \log(\sigma_2) + \log(\sigma_3) + \log(\sigma_4) \tag{21}
\]

Equating the uncertainties with the weights in our loss equation, this can be seen as learning the relative weights for each component where \( w_i \sim 1/\sigma_i^2 \) and provides a smooth, regularized and differentiable interpretation of weights. We introduce the weights as parameters in the model and learn them jointly with rest of the network.

4) Handling data skew with Focal Loss (FL): Multilingual training can have different convergence rates across languages and akin to behaviors observed in multi-modal training (Wang et al., 2020b). Carefully configured sampling ratios for different languages can alleviate this problem but requires costly hyper-parameter search. Instead we employ a popular technique for handling skewed data distribution: the focal loss (FL) (Lin et al., 2020).

\[
\ell_{FL}(\Theta_{R'|\Theta_{R'}}) = (1 - e^{\ell(\Theta_{R'|\Theta_{R'}})})^\alpha \ell(\Theta_{R'|\Theta_{R'}}) \tag{22}
\]

The FL (with \( \alpha = 1 \)) is applied on the reconstruction log-probability component of ELBO, such that strongly reconstructed vectors are given lower weights than the weakly reconstructed ones which balances the convergence across languages.

3.6 Prediction and Ranking Responses

During prediction, we rank and select responses from a fixed response set \( R_{[s]} \). Since the models generate response vectors in the continuous space, the prediction process needs to convert the samples into ranking in the discrete space of responses. The process is described as follows.

\[
log p_i(\Theta_{R'|\Theta_M}) = \ell(\Theta_{R'|\Theta_{R'}}) - KL(\lambda_\|\theta) \tag{23}
\]

\[
MRR(R_{[s]}) = \frac{1}{N} \sum_{i} [Rank_{R_{[s]}} log p_i(\Theta_{R'|\Theta_M})]^{-1} \tag{24}
\]

For each message we generate 1000 samples of latent conditional priors from \( z \sim \mathcal{N}(\mu_\phi, \Sigma_\phi) \) and from categorical prior for CGM-M. Next, we generate samples of the response vectors using the generator network, \( \Theta_{R'|s} \sim q_\theta(\Theta_{R'|\Theta_M}, z_{i}) \). We compute the scores for the \( i^{th} \) generated sample w.r.t. to the fixed response set \( log p_i(\Theta_{R'|\Theta_M}) \) in eq. 23, where the KL divergence is directly computed on the samples \( z \) under a Normal or GMM distribution for the prior and posterior. To reduce the scoring overhead over 40k responses with 1000 samples, we pre-select top \( k \) (\( k = 100 \) provides sufficiently diverse candidates) using the matching score (eq. 2). Finally, the mean reciprocal ranks (MRR) over all the samples (eq. 24) are used to select the top 3 as our predicted responses.

4 Experiments

Multi-lingual data: We use the MRS (Multilingual Reply Suggestions) data set (Zhang et al., 2021) for our experiments. MRS consists of message-reply (M-R) pairs separated into different languages from Reddit conversations (Baumgartner et al., 2020) using the FastText detector (Joulin et al., 2016). We select the top 15 languages for experimentation (data volume was insufficient for
Table 1: Comparison of components of Matching, MCV AE (Sec 2), CGM, and CGM-M (Sec 3)

|                | Latent Factors | Cond. Prior | Mix. Density | Language alignment | Multilingual training opts |
|----------------|----------------|-------------|--------------|--------------------|----------------------------|
| Matching       | -              | -           | -            | -                  | -                          |
| MCV AE         | ✓              | -           | -            | -                  | -                          |
| CGM            | ✓              | ✓           | -            | -                  | ✓                          |
| CGM-M          | ✓              | ✓           | ✓            | ✓                  | ✓                          |

Figure 2: Main results. With the Matching monolingual models as baseline, the figures show the % changes in metrics for model variants (see Sec 4 for model description and Sec 4.1 for discussion). For each model variant, we show the metrics across three languages groups (All, w/o-EN and bottom 10 low resource languages. (Left) Relevance (Right) Diversity.

Others) with 80% split for training (2nd column in Table 4) and the rest for validation and test. We create response sets with most frequent responses (>20 frequency) in the m-r pairs. For low resource languages, we augment this natural set with machine translated responses from EN, resulting in ∼ 40k responses for each language.

**Metrics:** We use ROUGE (Lin, 2004) for scoring the relevance of the 3 predicted responses against the reference response. We also compute the self-ROUGE (Celikyilmaz et al., 2020) within the 3 responses as a measure of diversity. For both, we report the average of the ROUGE-F1 for 1/2/3-grams across the three responses.

**Train parameters:** We use the multi-lingual version of the pretrained BERT model (MBERT) (Devlin et al., 2019) as out text encoders for which we use the Huggingface’s transformers library (Wolf et al., 2020). We freeze the embedding layer of MBERT encoders, which reduces training overhead, and preserves cross-lingual representation without impacting performance (Lee et al., 2019; Peters et al., 2019). We use dimension size of 512 for the VAE layers. For CGM-M we set the number of categories to $K = 20$.

We train with the Adam optimizer (peak rate: $1e^{-5}$, exp. decay: 0.999 after warm up of 1000 steps), batch size of 256, and m-r pairs truncated to length 64 and 32 respectively. We add language tokens (e.g. EN, PT) before m-r pairs as additional language identifier. All the model sizes are relatively similar (1.3GB to 1.5GB) since most parameters are in the two MBERT encoders with 12 transformer layers (each around 700MB).

**Multilingual training:** We uniformly sample languages such that models have equal exposure to each language during training. This leads to good performance across all languages except EN. Alternatively, sampling proportionate to data volumes, had good performance for EN but led to severe under-fitting for most languages other than EN as EN dominates the training with orders of magnitude more data. The ideal sampling is somewhere in between, but requires extensive search to optimize. On single NVidia V100 GPUs, models converge within 1-2 epochs ~ 48hrs over the entire data (i.e., 1-2 epochs for EN and multiple epochs for others). Joint training amortizes the training costs, and can be used even when targeting monolingual models, by saving per-language checkpoints.

**Model variants:** We analyze 4 models: Matching, MCV AE, CGM and CGM-M (Table 1). For each we consider 3 multilingual model variants. [Mono]: individually trained monolingual models on each language. [Uni]: jointly trained universal model with a single checkpoint for evaluation. [Mono*]: jointly trained model with per language
checkpoints (saved when the validation metrics peak for each language) for evaluation. Since models peak at different point for each language, Mono* is expected to have a better performance than the Universal counterpart with a single checkpoint.

4.1 Main Results

Figure 2 shows the relevance and diversity metrics for different model variants. With Matching-Mono models (trained individually per language) as the baseline, we plot the % changes in metrics for the other model variants. Models are trained on all languages, with relevance metrics shown in 3 language groups: 1) All, 2) All w/o EN, and 3) Bottom 10 low resource languages, to highlight the differences from data volumes in languages.\(^2\)

Relevance (Figure 2-Left): Compared to individually trained monolingual Matching model, the universally trained Matching-Uni regresses on all the three language group while MCVAE-Uni improves for latter two groups (w/o EN and bottom 10 languages). The CGM-Mono improves the metrics across all three languages. Thus even without joint training, CGM by itself is better than the baselines and thus raises the bar which the universal models needs to match or overcome.

The CGM and CGM-M universal models improve on all the language groups although for the CGM-uni, there is regression in the All-languages group compared to the CGM-mono (more discussion later). However, CGM-M-Uni with around 5% increase is actually slightly better than CGM-mono, showing that we can replace the monolingual models with a single universal model. Next, the Mono* models (universally trained but with best per-language checkpoints saved) can achieve even bigger gains and CGM-M-Mono* surpasses other models in every language group.

Within language groups, we observe increase upto 16% without EN and upto 19% for bottom 10 languages. EN with two orders of magnitude more data, remains severely under-fitted in all the jointly trained model, due to which the metrics improvements in All languages group remains low.

Diversity (Figure 2-Right): The CGM performance is most striking for diversity metrics where we see 80% improvements. Diversity improvements more than the relevance gains, illustrate that deep generative modeling enhancements in CGM leads to richer representation of multilingual data with improved discrimination and disentanglement of language and latent intents in M-R pairs. CGM-M achieves high diversity on top of the best relevance metrics, showing the enhanced representation through mixture models.

4.2 Ablation Studies

We conducted extensive ablation studies with the different model variants, and training optimizations and summarize the results in Figure 3. For ablations we report the metrics for language group without EN, as the significantly higher data volume in EN can conflate the results.

Baselines: We use the Matching-uni model (line 1) as the baseline. MCVAE (line 2) improves both relevance (4.8%) and diversity (27%) which shows the potential of deep generative models.

Training optimizations with CGM: The basic CGM-uni model (line 3) and CGM-M (Line 7) shows modest relevance gains compared to MCVAE. We attribute the modest gains due to complexities with end-to-end training of the CGM. Through training optimizations of variance scaling, and FL and HSU (lines 4, 5), CGM can comfortably surpass MCVAE in relevance (12.8%) and double the diversity (59%). CGM-M, shows similar increase (13.87%) with variance scaling (line 8), and FL and HSU (line 9) outperforming the best achieved with CGM. The biggest improvements come from multi-sample variance scaling (lines 4, 8) with additional improvements from FL and HSU (lines 5, 9). Overall, the optimizations lead to more stable training, and faster convergence across languages. They also alleviate the need for manual tuning for skewed data and loss component weights, making the training process virtually hyper-parameter free.

Language Mapping in CGM-M: One key reason for improved performance with CGM-M is the potential inductive bias for languages through

\(^2\)Here we present quantitative results. For qualitative analysis, multi-lingual text predictions are provided in the appendix.
the mixture components, which can be further boosted by explicit mapping of latent vectors to languages. Language mapping improves the relevance to 14.6% (line 10) over the baseline. We also see a slight boost in diversity showing the improved modeling of the multi-lingual distribution using this approach.

**Posterior conditioned on both message and response:** The joint conditioning of the posterior with both the $\Theta_M$, $\Theta_R$ vectors gives the best relevance for both CGM and CGM-M (lines 6, 11) with CGM-M exceeding all other variants. More interesting is the substantial improvement in diversity (80%), which illustrates that it encourages a richer representation in the prior by perhaps disentangling latent intents and language characteristics better. We note here that, in CGM-M, using the full $\Theta_R$ dimension (768) led to high level of leakage through the posterior (multiple components of the mixture further aids the leakage). We use a low dimensional projection of size 16 in CGM-M to mitigate the issue.

**4.3 Analysis across Languages Groups**

Next, we discuss the performance breakdown of models across individual languages. Figure 4 expands the Relevance metrics from Figure 2 for all languages. As before, we use the the Matching-Mono as the baseline, and list the % changes over this baseline for each model and language.

We see that, all jointly trained variants (Uni and Mono*) have severe under fitting for EN. In fact if we simply remove EN from the metrics the CGM variants vastly improve upon the monolingual versions. With almost two orders of magnitude more data in EN (49M), it remains challenging to have good performance simultaneously for EN and other languages without additional tricks. In general the improvements are less for the top 5 high-resource languages which can be attributed to lesser impact from information sharing and lower exposure of these languages due to uniform sampling. Such issues have been reported in prior literature as capacity dilution (Johnson et al., 2017; Conneau et al., 2020; Wang et al., 2020a) where there is always a trade-off between low and high resource languages. CGM while not completely eliminating it, largely mitigates the issue.

The impact of CGM with joint training is more pronounced for the bottom 10 language group. For example we see 15.49% improvement for CGM-M compared to only 3.67% for MCVAE-Uni. Finally, we see improvements of 15.76% for CGM-Mono* and 18.86% for CGM-M Mono* models, illustrating that even if we target mono-lingual models, CGM can take advantage of shared learning through joint training while saving compute.

The improvements for low resource languages, show that CGM is more data efficient due to model enhancements, while the prevention of regressions for high resource languages show a more balanced learning through training optimizations. The fact that these relevance improvements come in addition to 80% improvements in diversity, shows the remarkable effectiveness of CGM to represent the multi-modal landscape of multi-lingual RS.

### 5 Related Work

VAEs have been used in retrieval based Q&A (Yu et al., 2020), document matching (Chaidaroon and Fang, 2017), and recommendations (Chen and...
de Rijke, 2018). CGM for RS is most closely related to MCVAE (Deb et al., 2019) but differs in the expressive conditional priors, multi-component mixture density priors, language alignment, and training optimizations which makes it effective in a multi-lingual setting.

For multi-task scenarios, VAEs can offer significant modeling efficiencies (Cao and Yogatama, 2020; Rao et al., 2019) with additional improvements through mixture model priors, e.g. in (Dilokthanakul et al., 2017; Yang et al., 2019) for unsupervised clustering, in (Lee et al., 2021) for unsupervised meta-learning, and in (Shi et al., 2019) as a multi-modal variational mixture-of-experts.

VAEs can also improve multilingual representation for low resource languages, e.g. in models like BERT (Li et al., 2020), in (Wei and Deng, 2017) for document classification, in (Chorowski et al., 2019) for disentangling phonemes for speech synthesis, and in (Zhang et al., 2016; Eikema and Aziz, 2019) for neural machine translation. VAEs can improve diversity in language generation and retrieval tasks (Zhao et al., 2017; Tran et al., 2017; Shen et al., 2017; Deb et al., 2019) through better modeling efficiencies. Such results motivated us to apply VAEs for multilingual RS.

We may also consider alternative to VAEs such as training auxiliary tasks with adapters (Houlsby et al., 2019), adversarial learning (Chen et al., 2018, 2019; Huang et al., 2019), and mixing pre-training and fine-tuning (Phang et al., 2020) to improve modeling in multilingual setting. This is subject of future work. We also plan to experiment with higher capacity multilingual encoders such XLM-R (Lample and Conneau, 2019) and InfoXLM (Chi et al., 2021) to further improve the performance. However, the choice of the base encoder is orthogonal to the improvements (especially on diversification) shown in this paper.

As noted in prior work, multilingual training can have capacity dilution issues (Johnson et al., 2017; Conneau et al., 2020; Wang et al., 2020a). Overall, multilingual models are closing the gap with monolingual counterparts for wide range of tasks (Ying et al., 2021; Ranasinghe and Zampieri, 2020; Yang et al., 2020), and as shown in this paper, even surpass them. Careful sampling strategies, and techniques such as Translation Language Model (TLM) can alleviate the "curse of multilinguality" (Lample and Conneau, 2019) but we show improvements without additional data augmentation (translation pairs), and with simple uniform sampling.

6 Conclusions

In this paper we present a conditional generative Matching model (CGM) for retrieval based suggested replies. CGM not only provides relevance gains (15%), but also substantial improvements in diversity (80%). While CGM clearly advances the state of art for modeling multi-lingual RS systems, it also illustrates that through proper model choices and training optimizations, we can surpass and replace monolingual models. This is important for both industry and academia and suggests similar strategies to be applied across diverse tasks. This is subject of future work.

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A Text Samples from Model Predictions

A.1 Relevance and Diversity

We created sample messages in EN manually, and predict the responses from different models: Matching in Figure 5, CGM in Figure 6 and CGM-M in Figure 7.

We see that in terms of relevance while it is hard to notice the differences on such a small sample, overall the predictions from the Matching model are less relevant than CGM. However, we can clearly distinguish the diversity of responses: predictions from Matching have a high level of duplicates where some of the responses differ by just a punctuation. While this can be easily de-duplicated using simple heuristics, the results show that inherently the Matching model ranks very similar responses at the top. The CGM models in contrast, show a lot of diversity in responses without reducing the relevance of the responses.

We also see that some of the responses are quite specific and not relevant, with some responses being rude or mildly inappropriate. It shows the issues with using responses from the Reddit dataset without careful curation (the MRS dataset does clean up for inappropriate responses but cannot completely eliminate them without human curation). Production systems usually have human curated response sets which can tackle these issues.

A.2 Multi-lingual Behavior

Next we look at the multilingual ability of CGM. We translate the same set of messages used for EN for predicting responses, so as to have better comparative understanding of the quality different languages.

We present the predictions for ES in Fig. 8 and JA in Fig. 9. We see that the responses are relevant and diverse in these languages and thus CGM performs adequately in languages other than EN.

A.3 Cross-lingual Behavior

Finally we investigate the cross lingual nature of the CGM model, in order to understand if the multilingual models share representations and learnings across languages.

In Figure 10 we use EN messages and force the model to predict responses from the ES set. Surprisingly such a system is able to select relevant results in the target language. While the quality here is not as good, but it is interesting to see that such cross lingual prediction works quite well.

In Figure 11 we use messages in German and predict with English responses. Again the results are quite acceptable. This may be expected as English and German are closely related languages. To see slightly different pairs of languages, we look at Japanese messages with predictions in English in Figure 12. Here the quality is actually much worse, but we still see some match with the overall intent of the messages showing good cross lingual representation even for weakly related languages.
| Messages | CGM-M-1 | CGM-M-2 | CGM-M-3 |
|----------|---------|---------|---------|
| Good morning! How was last night’s party? Had fun? | It was ok | Today was a good day | Pretty good! |
| Did you see the new movie? It was really funny! Wish we saw it together | We did | What movie is it? | I saw it! |
| Please have a look and review. Its the latest update I’m put last night. | Check your inbox :) | Added an update to the OP | Will do! Good luck! |
| I am not feeling very well. Will try to get some sleep. | Have a good time! | Sleep is for the weak | I hope you feel better soon. |
| Have solved the issue with out of memory. That was some bug! | I did the same thing! | Thanks! It worked! | Did you try it? |
| It is so nice outside! I think will go fishing in the lake today | We all float down here. | So fish | Sounds like a good time! |
| Did you hear the latest album. Its sound awesome, blown away!! | Thank you for checking it out! | I heard it too | It did! |

**Figure 7:** Some samples of English messages predicted with English replies using the CGM-M Model.

| Message | CGM-1 | CGM-2 | CGM-3 |
|---------|-------|-------|-------|
| ¡Buenos días! ¿Cómo estuvo la fiesta de anoche? ¿Te divertías? Fui a ir de compras :) Muy bien. Me encanta esa película! Vi | Estuvo bien. | Me encanta esa película! | Vi |
| ¿Viste la nueva película? Fue muy gracioso! Ojalá lo vimos juntos | Gracias por las amables palabras! | Gracias! Te lo :) | Gracias! (le hará :) |
| Bienvenido! Me alegra tenerle de vuelta en el trabajo. Me voy de vacaciones! Necesitaba un descanso. Nos vemos en un par de semanas :) | Vacaciones | Impresionante! Disfrutar! | Vajíes seguros! |
| ¿Puede enviarme el enlace al documento? Parece que no encuentro el enlace. | Imposible. Tal vez los archivos están incompletos. | Claro que puedes. | Si no lo he enviado, avísame! |
| Estoy bastante aburrido estos días. Need a new vocation. | What do you want to do? | We will watch your career with great interest! | Teacher? |
| Forrest Gump has an amazing soundtrack. Been listening to since childhood, and see it in new light as I grow up. | Great album | I like it too. | And I love it. |
| I am pretty bored these days. Need a new vocation. | What book is this? | What are you reading? | Way to go! |
| The new wired article is pretty revealing about corporate politics | No business as usual? | Facts are facts. | The project has great potential success. |
| Christmas has come early. Enjoy while it lasts! | Hope to see you there! | ReminderMe! 3 weeks | Sounds like a good time! |
| Did some slow roasting in the oven yesterday. The stuff came out pretty tender and juicy. | That’s awesome to hear! | It was delicious! | How did it turn out? |

**Figure 8:** Some samples of Spanish messages and predicted with Spanish replies using the CGM-M Model.
Figure 9: Some samples of Japanese messages and predicted with Japanese replies using the CGM-M Model.

| Message                                                                 | CGM-1                              | CGM-2                              | CGM-3                              |
|------------------------------------------------------------------------|------------------------------------|------------------------------------|------------------------------------|
| おはようございます！昨夜のパーティーはどうでしたか。楽しかった？             | きっとパーティーは楽しいでしょう。    | やらくなかったでしょう。             | パーティーは楽しいと思うよ。         |
| 新しい映画を見ましたか。それは本当に面白かったですね一緒に見てよ        | 私も同じです。                     | 楽しかったよ。                      | 知って良かったです感謝！           |
| 再びよろしく！仕事に楽しみがあってねえです。                             | コメントをありがとうございます。      | 問いててねえありがとうございます。     | 再び                              |
| ドキュメントへのリンクを送って下さい。私はリンクを見つけることができる      | リンクを手に入れていいですか？      | リンクをクリックします。             | imgur                              |
| これはあまり気分がよくありません。睡眠を取ろうとします。                 | 麻痺は弱まるのため                  | 病を重にしてはいけません。           | 笑、ありがとう。                    |
| トラブルはかなり悪いです。もう1時間になるはずですですが、おそらく        | トラブルはゲイです。                | イベントはまもなく始まります。TS1にご参加ください！ | 笑、ありがとうございます。             |
| 外でもとても素晴らしいです。今日は湖で釣りに行こうと思います。             | 私が見たわけではない。              | セカンドアイで、行える！            | 素晴らしいプレゼント！               |
| 最新アルバムを聞きましたが？音楽に素晴らしい、吹き飛ばされた             | 私も同じを言うところだった。        | 皆さん良いニュース！                | 特別な日を祝福！                   |
| 新しいNetflixショーや、ちょっと第2シーズンを見ます、今晩は休息はありません！ | シニアオープンチャンピオンシップライブストリーム無料 | ネットフリックスに載って             | これが素晴らしい！                 |
| 同様に考えたのか？収穫的でした。それはニュースのたとえにしかalong        | これはニュースのたとえにしかあり   | これはニュースのたとえにしかあり   | 彼らについてはどうですか          |
| もう少し考えたのか？収穫的でした。それはニュースのたとえにしかあり     | 言葉で、大切に考えた。             | 言葉で、大切に考えた。             | 共有は思いやりです。              |

Figure 10: Some samples of English messages and predicted with Spanish replies using the CGM-M Model. While the quality is not as good as when the input message is in Spanish, the general close match of intents of the message and responses illustrates the cross lingual ability of of the model.
Guten Morgen! Wie war die Party gestern Abend? Hatten Sie Spaß?

Really good. Today was a good day. It was ok.

Haben Sie den neuen Film gesehen? Es war wirklich lustig! Wunsch, dass wir es zusammen gesehen haben.

This film is older. Yes I did! It was awesome!

Willkommen zurück! Froh, Sie wieder bei der Arbeit zu haben.

Thank you. :) You're back! Thanks, same to you!

Können Sie mir den Link zum Dokument zusenden? Ich kann den Link nicht finden.

Video is up on this sub! You can edit since I gave new info.

Mir geht es nicht sehr gut. Wird versuchen, etwas Schlaf zu bekommen.

Frustrated slip! Try it! Courage.

Der Verkehr ist ziemlich schlecht. Sollte eine weitere Stunde sein, aber nicht sicher.

Even a broken clock is right twice a day. What time zone are you in? Solla go fast!

Ich habe das Problem mit unzusammen gelöst. Das war ein Fehler!

Not a problem! You're not my supervisor! Thank you for your service!

Hast du das neueste Album gehört? Es ist einfach genial, weggeblasen!!!

r/fakealbumcovers It really was! What was the original?

Atemberaubende Sieg heute, was für ein Ziel!! Er ist ein Genie :D He really does! He deserves it. Thanks for playing!

The project has great potential success. Satire?

So business as usual? This film is older. I love it too. Movie?

Kindheit zugehört und sie in neuem Licht gesehen, wenn ich erwachsen

This film is older. Yes I did! It was awesome!

Nachrichten. Hatte Alpträume

What book is this? I want to go to there. Where was it?

Es war ziemlich schockierend, was passiert ist. Es war alles über die

What series? Season 2 I’d watch it.

Berufung. r/stoppedworking

Ich bin ziemlich gelangweilt in diesen Tagen. Brauchen Sie eine neue

This film is older. I love it too. Movie?

bin. This film is older. This film is older. It was amazing! It was awesome!

Die neue Netflix-Show, schauen Sie sich einfach die 1. Staffel an. Ruhe

What is this? I want to go there. Where was it?

ist nicht zu gut

Patrolling the Mojave almost makes you wish for a nuclear winter.

Eine neue Buchhandlung wurde eröffnet. Ich habe vor, dort für eine

What book is this? I want to go there. Where was it?

Lesung zu gehen. What book is this? I want to go there. Where was it?

Our lives begin to end the day we become silent about things that matter.

What news? Patrolling the Mojave almost makes you wish for a nuclear winter.

Forest Gump hat einen erstaunlichen Soundtrack. Habe seit seiner Kindheit zugehört und sie in neuem Licht gesehen, wenn ich erwachsen bin.

This film is older. I love it too. Movie?

Ich bin ziemlich gelangweilt in diesen Tagen. Brauchen Sie eine neue

r/stoppedworking Be the change you want to see! Becoming?

Berufung.

Der neue verkabelte Artikel ist ziemlich aufschlussreich über

Unternehmenspolitik So business as usual? This film is older. I love it too. Movie?

Ich habe das Problem mit unzusammen gelöst. Das war ein Fehler!

Not a problem! You're not my supervisor! Thank you for your service!

Hast du das neueste Album gehört? Es ist einfach genial, weggeblasen!!!

r/fakealbumcovers Another! Yes I did :) Great project, congratulations! Thanks! Me too!

Haben Sie den neuen Film gesehen? Es war wirklich lustig! Wunsch, dass wir es zusammen gesehen haben.

Thank you! I’m glad you enjoyed it. It was amazing! It was awesome!

Say hi to your newsletter.

Your ideas are intriguing to me and I wish to subscribe to your newsletter. Please, read and follow the instructions at the top of the page. Thanks!

Thank you for your positive feedback! :) Thank you, I will. I will :) Glorious! Recorded! Love it! Thank you! Thank you so very much.

Wabbit season! r/nhlstreams Six seasons and a movie!

He sure is! Love him! So much winning!

What is this? I want to go there. Where was it?

Video is up on this sub! You can edit since I gave new info.

Infowars.com

Thank you! I definitely will! Pics please! Thanks! Me too!

What evidence? What was his reaction?

You're going down a path I can't follow! Thank you! Translated Freedom!

What was his reaction?

Wabbit season! r/nhlstreams Six seasons and a movie!

He sure is! Love him! So much winning!

What time zone are you in? Gotta go fast!

6pm is up on this sub! You can edit since I gave new info.

Infowars.com

Thank you! I definitely will! Pics please! Thanks! Me too!

What is this? I want to go there. Where was it?

Patrolling the Mojave almost makes you wish for a nuclear winter.

We become silent about things that matter. What news?

The quality here is definitely poorer that German to English, perhaps since EN and JA are not as closely related.

However we still get the general close match of intents of the message and responses illustrates the cross lingual ability of of the model.

Figure 11: Some samples of German messages and predicted with English replies using the CGM-M Model. While the quality is not as good as when the input message is in German, the general close match of intents of the message and responses illustrates the cross lingual ability of of the model.

Figure 12: Some samples of Japanese messages and predicted with English replies using the CGM-M Model. The quality here is definitely poorer that German to English, perhaps since EN and JA are not as closely related.

However we still get the general close match of intents of the message and responses.