Parameter Space Factorization for Zero-Shot Learning across Tasks and Languages

Edoardo M. Ponti1, Ivan Vulić1, Ryan Cotterell2, Marinela Parovic1, Roi Reichart3, Anna Korhonen1

1Language Technology Lab, TAL, University of Cambridge
2Computer Laboratory, University of Cambridge
3Faculty of Industrial Engineering and Management, Technion, IIT

1{ep490, iv250, mp939, rdc42, alk23}@cam.ac.uk
3roiri@ie.technion.ac.il

Abstract

Most combinations of NLP tasks and language varieties lack in-domain examples for supervised training because of the paucity of annotated data. How can neural models make sample-efficient generalizations from task–language combinations with available data to low-resource ones? In this work, we propose a Bayesian generative model for the space of neural parameters. We assume that this space can be factorized into latent variables for each language and each task. We infer the posteriors over such latent variables based on data from seen task–language combinations through variational inference. This enables zero-shot classification on unseen combinations at prediction time. For instance, given training data for named entity recognition (NER) in Vietnamese and for part-of-speech (POS) tagging in Wolof, our model can perform accurate predictions for NER in Wolof. In particular, we experiment with a typologically diverse sample of 33 languages from 4 continents and 11 families, and show that our model yields comparable or better results than state-of-the-art, zero-shot cross-lingual transfer methods; it increases performance by 4.49 points for POS tagging and 7.73 points for NER on average compared to the strongest baseline.

1 Introduction

Transfer learning is a toolbox to extract knowledge from a source domain and perform sample-efficient generalizations in a target domain (Yogatama et al., 2019; Talmor and Berant, 2019). In practice, this approach holds promise to mitigate the data scarcity issue which is inherent to a large spectrum of NLP applications (Täckström et al., 2012; Agić et al., 2016; Ammar et al., 2016; Ponti et al., 2018; Ziser and Reichart, 2018, inter alia). Zero-shot transfer across tasks within the same language, on the other hand, verges on the impossible, because no information is provided for the target classes or scalars (in the case of regression). Hence, cross-task transfer has mostly focused on the few-shot or joint learning settings (Ruder et al., 2019).

In this work, we show how the neural parameters for a particular unseen task–language combination can be approximated by zero-shot transferring knowledge both from related tasks and from related languages, i.e., from seen combinations. For instance, the availability of a model for part-of-speech (POS) tagging in Wolof and for named-entity recognition (NER) model in Vietnamese supplies plenty of information which should be effectively harnessed to estimate the parameters of a Wolof NER model.

As our main contribution, we introduce a generative model of a neural parameter space, which is factorized into latent variables1 for each language and each task. All possible task–language combinations give rise to a task × language × parameter tensor. While some entries could be populated through supervised learning, completing the empty portion of such a tensor is less straightforward than standard matrix completion methods for collaborative filtering (Mnih and Salakhutdinov, 2008; Dziugaite and Roy, 2015), as the parameters are never observed. Rather, in our approach the interaction of the latent variables determine the parameters, which in turn determine the data likelihood.

1By latent variable we mean every variable that has to be inferred from observed (directly measurable) variables. To avoid confusion, we use the terms seen and unseen when referring to different task–language combinations.
We adopt a Bayesian perspective towards inference on the proposed generative model. The posterior distribution over latent variables is approximated through stochastic variational inference (VI), based on the mean-field assumption (Hoffman et al., 2013). We choose multivariate Gaussians as a variational family for the latent variables. Given the enormous number of parameters, however, a full co-variance matrix cannot be stored in memory. Hence, we explore a factor co-variance structure that is expressive while remaining tractable.

We evaluate the model on two related sequence tagging tasks: POS and NER, relying on a typologically representative sample of 33 languages from 4 continents and 11 families. The results clearly indicate that the proposed neural parameter space factorization method surpasses standard baselines based on cross-lingual transfer 1) from the source language with the most abundant in-domain data (usually English). The average gains over the strongest baseline are 4.49 points for POS tagging and 7.73 points for NER. The code is available at: github.com/cambridgelstl/parameter-factorization.

2 A Bayesian Generative Model of Parameter Space

The annotation efforts in NLP have achieved impressive feats, such as the Universal Dependencies (UD) project (Nivre et al., 2019) which now covers over 70 languages. Yet, these account for only a meagre subset of the world’s 8,506 languages according to Glottolog (Hammarström et al., 2016). At the same time, the ACL Wiki lists 24 separate language-related tasks. The lack of costly and labor intensive labelled data for many languages in such tasks hinders the development of computational models for the majority of the world’s languages (Snyder and Barzilay, 2010; Ponti et al., 2019a).

In this work, we propose a Bayesian generative model of multi-task, multi-lingual NLP. We train one Bayesian neural network for several tasks and languages jointly. The core modeling assumption is that the parameter space of the neural network is structured, that is, that certain parameters correspond to certain tasks and others correspond to certain languages. This structure allows us to generalize to unseen task–language pairs. The model, which is reminiscent of matrix factorization for collaborative filtering (Mnih and Salakhutdinov, 2008; Dziugaite and Roy, 2015), is presented in Figure 1.

Formally, we consider a set of \( n \) tasks \( T = \{t_1, \ldots, t_n\} \) and a set of \( m \) languages \( L = \{l_1, \ldots, l_m\} \). The variational family of each task variable and language variable is a multivariate Gaussian with mean \( \mu \in \mathbb{R}^{h} \) and diagonal covariance \( \sigma^2 I \in \mathbb{R}^{h \times h} \), where \( h \) is the dimensionality of the Gaussian. Consequently, \( t_i \sim \mathcal{N}(\mu_i, \sigma^2 I) \) and \( l_j \sim \mathcal{N}(\mu_l, \sigma^2 I) \), respectively.

The space of parameters for all tasks and languages forms a tensor \( \Theta \in \mathbb{R}^{n \times m \times d} \), where \( d \) is the number of parameters of the largest model.\(^3\) We denote with \( \theta_{ij} \in \mathbb{R}^d \) the parameters of the model for the \( i \)th language and the \( j \)th task. These parameters are also considered to be sampled from a multivariate Gaussian, whose mean \( \mu \in \mathbb{R}^{d} \) and diagonal co-variance \( \sigma^2 I \in \mathbb{R}^{d \times d} \) are functions of the corresponding task and language latent variables, i.e. \( f_\psi(t_i, l_j) \) and \( f_\phi(t_i, l_j) \), respectively. Hence \( \theta_{ij} \sim \mathcal{N}(f_\psi(\cdot), f_\phi(\cdot)) \).

The likelihood of the classes \( y_k \) for the \( k \)th sentence \( x_k \) is equivalent to \( p(\cdot | x_k, \theta_{kl}) \). In general, we will only possess the data for a subset \( S \) of the Cartesian product of all tasks and languages \( T \times L = S \cup U \), and not for the unseen pairs \( U \). However, as we estimate all task–language parameter vectors \( \theta_{ij} \) jointly, our model allows us to

\(^3\)aclweb.org/aclwiki/State_of_the_art

\(^4\)Different tasks might involve different class numbers, and as a consequence the number of parameters oscillates. The extra dimensions not needed for a task can be considered as padded with zeros.
perform inference over the parameters for combinations in $\mathcal{L}$ as well. Intuitively, if data for NER in Basque and POS in Kazakh is provided, our model assigns posterior distributions over 2 language variables (Basque and Kazakh) and 2 task variables (NER and POS) based on such data. Afterwards, they can be recombined to make predictions for NER in Kazakh and POS in Basque. A summary of generative story of how we hypothesize the data ‘came into being’ is offered in Algorithm 1.

**Algorithm 1** Generative model of the data.

\[
\begin{align*}
\text{for } t_i & \in T \quad t_i \sim \mathcal{N}(\mu_i, \Sigma_i) \\
\text{for } l_j & \in L \quad l_j \sim \mathcal{N}(\mu_j, \Sigma_j) \\
\text{for } t_i & \in T \quad \text{for } l_j \in L \\
\mu_{t_j} & = f_\psi(t_i, l_j) \\
\Sigma_{t_j} & = f_\phi(t_i, l_j) \\
\theta_{t_j} & \sim \mathcal{N}(\mu_{t_j}, \Sigma_{t_j}) \\
\text{for } x_k & \in X_{t_j} \\
y_k & \sim p(\cdot | x_k, \theta_{t_j})
\end{align*}
\]

### 3 Inference and Prediction

In order to perform inference on the generative model outlined in Section 2, we take a Bayesian perspective. This enables smooth estimates of the posteriors for typically under-specified models such as neural networks (Garipov et al., 2018). In particular, we resort to stochastic Variational Inference based on batch-level optimization (Hoffman et al., 2013). In Section 3.1 we derive the Evidence Lower Bound (ELBO) for VI on the generative model of Figure 1. Then, in Section 3.2, we detail how we implement such a model through a neural network. Finally, in Section 3.3, we explore several co-variance structures for the Gaussian distributions of the latent variables, including a diagonal matrix and a low-rank factor matrix.

#### 3.1 ELBO Derivation

In order to perform inference through the hierarchical Bayesian model described in Algorithm 1, we need to estimate the joint posterior over the latent variable sets $\Theta$, $t$, and $l$. The posterior given the observed data $x$ is shown in Equation (1), which factorizes according to the independence assumption $Y \perp\!\!\!\!\perp (T,L) \mid \Theta$ ingrained in the graphical model of Figure 1:

\[
p(\theta, t, l \mid x) = \frac{p(x \mid \theta)p(\theta \mid t, l)p(t)p(l)}{p(x)}. \quad (1)
\]

Unfortunately, term $p(x)$ in the denominator of Equation (1) is intractable. Therefore, by integrating out the latent variables, we derive the lower bound for the log-probability of $x$ in Equation (2). A way to interpret the ELBO is that we should minimize the variational gap, which is the KL-divergence between the true joint posterior and the approximate joint posterior. To see this we define the following:

\[
q_\lambda = \mathcal{N}(\mu_{t}, \sigma^2_{t} I) \quad q_\nu = \mathcal{N}(\mu_{l}, \sigma^2_{l} I) \quad q_\xi = \mathcal{N}(f_\psi(t, l), f_\phi(t, l))
\]

Note that Equation (2) contains a log-likelihood term that needs to be approximated through gradient descent, and 3 KL-divergence terms that have analytical solutions, provided that the true distribution is a multivariate Gaussian $p(\cdot) \sim \mathcal{N}(0, I)$:

\[
KL(q \parallel p) = \frac{1}{2} \sum_{i=1}^{d} \left( \mu_{i}^2 + \sigma_{i}^2 \right) - d - \sum_{i=1}^{d} \ln \sigma_{i}^2
\]

#### 3.2 Neural Model

Given the recent success of approaches for zero-shot cross-lingual transfer such as multilingual BERT (i.e., M-BERT; Pires et al., 2019), MultiFIT (Eisenschlos et al., 2019) and XLM (Lample and Conneau, 2019), we adopt a similar neural network architecture with a a classifier stacked on top of an encoder. In particular, the encoder consists of a multi-layer Transformer (Vaswani et al., 2017) whose parameters are initialized with a model pretrained for masked language modeling and next sentence prediction on multiple languages. In this work, we treat such encoder as a black-box function $x_{BERT} \in \mathbb{R}^{e} = \text{BERT}(x)$ to encode tokens into multi-lingual contextualized representations.\footnote{The full details of its implementation can be found in Devlin et al. (2019).}

On the other hand, the classifier is an affine layer. In other words, the probability over classes $y$ is computed as $y = \text{softmax}(W x_{BERT} + b)$. Crucially, parameter factorization takes place on the space of parameters for task–language-specific classifiers $\theta_{ij} = \{W_{ij}, b_{ij}\}$ only, whereas the parameters of the encoder $\theta_{BERT}$ are shared across all task-language combinations and fine-tuned through...
\[
\log p(x) = \log \left( \int \int \int p(x, \theta, t, l) \, d\theta \, dt \, dl \right) \\
= \log \left( \int \int \int p(x \mid \theta) \, p(\theta \mid t, l) \, p(t) \, p(l) \, d\theta \, dt \, dl \right) \\
= \log \left( \int \int \int \frac{q_\lambda(t) q_\nu(l)|q_\xi(\theta)}{q_\lambda(t) q_\nu(l)|q_\xi(\theta)} \, p(x \mid \theta) \, p(\theta \mid t, l) \, p(t) \, p(l) \, d\theta \, dt \, dl \right) \\
= \log \left( \mathbb{E}_{t \sim q_\lambda} \mathbb{E}_{l \sim q_\nu} \mathbb{E}_{\theta \sim q_\xi} \frac{1}{q_\lambda(t) q_\nu(l)|q_\xi(\theta)} \, p(x \mid \theta) \, p(\theta \mid t, l) \, p(t) \, p(l) \right) \\
\geq \mathbb{E}_{t \sim q_\lambda} \mathbb{E}_{l \sim q_\nu} \mathbb{E}_{\theta \sim q_\xi} \left[ \log \frac{p(x \mid \theta) \, p(\theta \mid t, l) \, p(t) \, p(l)}{q_\lambda(t) q_\nu(l)|q_\xi(\theta)} \right] \\
= \mathbb{E}_{\theta \sim q_\xi} \left[ \log p(x \mid \theta) + \log \frac{p(\theta \mid t, l)}{q_\xi(\theta)} + \log \frac{p(t)}{q_\lambda(t)} + \log \frac{p(l)}{q_\nu(l)} \right] \\
= \mathbb{E}_{\theta \sim q_\xi} \left[ \log p(x \mid \theta) - KL(q_\lambda(t) || p(t)) - KL(q_\nu(l) || p(l)) - KL(q_\xi(\theta) || p(\theta \mid t, l)) \right] \\
\text{(closed form solution)} 
\]

maximum-likelihood optimization during training. Throughout this paper, by parameters we refer to those of the classifier, unless otherwise indicated.

In each training iteration, we randomly sample a task \( t_i \in T \) and language \( l_j \in L \) among seen combinations, and randomly select a batch of examples from the dataset of such combination. Based on the generative model of Figure 1, the variational family of each task and language is a multivariate Gaussian. In order to allow the gradient to flow through, we generate samples for the latent variables through the re-parametrization trick (Blundell et al., 2015): \( t_i = \mu_{t_i} + \sigma_{t_i} \odot \epsilon \) and \( l_j = \mu_{l_j} + \sigma_{l_j} \odot \epsilon \), where \( \epsilon \sim N(0, I) \) and \( \odot \) means element-wise multiplication. The co-variance matrix must be non-negative. Hence, we obtain the diagonal standard deviation \( \sigma \) as \( \ln(1 + \exp(\rho)) \). We place a prior \( N(0, S_t) \) on each task and a prior \( N(0, S_l) \) on each language, where \( S_t \) and \( S_l \) are hyper-parameters.

The mean \( \mu_{\psi_{ij}} \) and (diagonal) log-variance \( \rho_{\theta_{ij}} \) for the parameters \( \theta_{ij} \) for \( t_i \) and \( l_j \) are generated through a pair of deep feed-forward neural networks \( f_\psi : \mathbb{R}^h \rightarrow \mathbb{R}^d \) and \( f_\phi : \mathbb{R}^h \rightarrow \mathbb{R}^d \) parametrized by \( \psi \) and \( \phi \), respectively, similarly to Kingma and Welling (2014). The networks \( f_\psi \) and \( f_\phi \) take as input features based on the task and language samples, namely \( \{ t \oplus l - l \oplus t \oplus l \} \), where \( \oplus \) stands for concatenation. As mentioned before, the \( \theta_{ij} \) is a concatenation of a weight \( W_{ij} \in \mathbb{R}^{e \times c_i} \) and a bias \( b_{ij} \in \mathbb{R}^{c_i} \). Hence the number of parameters \( d = e \times c_i + c_i \) depends on the dimensionality of the contextualized token embeddings \( e \) and the number of task-specific classes \( c_i \). We place a Gaussian prior on the parameters \( N(0, S_{\theta, i}) \). \( S_{\theta} \), as well as the number of hidden layers and the hidden size of \( f_\psi \) and \( f_\phi \), are hyper-parameters. We tie the parameters \( \psi \) and \( \phi \) for all layers save the last for faster training.

Finally, the parameters \( \theta_{ij} \) are sampled from \( N(\mu_{\theta_{ij}}, \ln(1 + \exp(\rho_{\theta_{ij}}))) \), again through the re-parametrization trick. These are used as parameters for the affine classifier layer to generate a distribution over classes \( y \) for every token \( x_{\text{BERT}} \). During training, we optimize the following parameters of the network: \( \{ \mu_{t_i}, \rho_{t_i}, \mu_{l_j}, \rho_{l_j}, \psi, \phi \} \). We perform zero-shot predictions on examples from unseen task–language pairs by plugging in the mean of the latent variable estimates.\(^6\)

### 3.3 Low-rank Co-variance

The co-variance matrix of latent variables is often taken to be diagonal in Variational approximations (Kingma and Welling, 2014; Blundell et al., 2015),\(^5\) as an alternative for prediction, we experimented with model averaging over 100 samples from the posteriors, but this approach obtained lower performances on the dev sets.
in order to make computations in the model feasible. In fact, a full-rank co-variance matrix $\Sigma$ would: i) be too massive to store in memory; and ii) require $O(h^2)$ time to sample from the distribution it defines, where $h$ is the dimensionality of the Gaussian. In contrast, a diagonal co-variance matrix makes computation feasible with a complexity of $O(h)$; this, however, comes at the cost of not letting parameters influence each other, and thus failing to capture their complex interactions.

To avoid these sub-optimal solutions, we turn to a factored co-variance matrix, in the spirit of Miller et al. (2017) and Ong et al. (2018). Such a factored structure offers a balanced solution, being parsimonious in the memory and time complexity while having non-zero non-diagonal entries. In particular, we factorize our co-variance matrices $\Sigma_{t_i}$ and $\Sigma_{t_j}$ as:

$$\Sigma = \sigma^2 I + BB^T$$

(3)

which is the dot product of a matrix $B \in \mathbb{R}^{h \times k}$ of rank $k$ with itself plus the diagonal entries $\sigma^2$. The complexity of sampling from a multivariate normal distribution with such a co-variance matrix is $O(kh)$, which is tractable for suitably low $k$ as it does not require to calculate the full matrix explicitly. In particular, through the re-parametrization trick, a sample takes the form:

$$\mu + \sigma \odot \epsilon + B\zeta^T$$

(4)

where $\epsilon \in \mathbb{R}^h$, $\zeta \in \mathbb{R}^k$, and both are sampled from $\mathcal{N}(0, I)$. Moreover, the KL divergence computation of the ELBO approximation in Equation (2) can be estimated analytically without explicitly calculating the low-rank co-variance matrix, provided that $p(\cdot) \sim \mathcal{N}(0, I)$, for the prior $p(\cdot)$:

$$\mathbb{KL}(q || p) = \frac{1}{2} \sum_{i=1}^{h} (\mu_i^2 + \sigma_i^2 + \sum_{j=1}^{k} B_{ij}^2) - h - \ln \det(\Sigma)$$

(5)

The last term can be estimated without computing the full matrix explicitly thanks to the generalization of the matrix determinant lemma,\(^7\) which, applied to the factored co-variance structure, yields:

$$\ln \det(\Sigma) = \ln \left[ \det(I_k + BB^T) \right] + \sum_{i=1}^{h} \ln(\sigma_i^2)$$

(6)

where $I_k \in \mathbb{R}^k$.

4 Experimental Setup

Data. We select NER and POS tagging as our experimental tasks because their datasets encompass an ample and diverse sample of languages. In particular, we opt for WikiANN (Pan et al., 2017) for the NER task and Universal Dependencies 2.4 (UD, Nivre et al., 2019) for POS tagging. Our sample of languages results from the intersection of those available in WikiANN and UD. However, this sample is heavily biased towards the Indo-European family (Gerz et al., 2018). Instead, the selection should be: i) typologically diverse, to ensure that our model generalizes well; ii) focused on low-resource languages to recreate a realistic setting. Hence, we further filter the languages in order to make the sample more balanced. In particular, we exclude all resource-rich Indo-European languages.

Our final sample comprises 33 languages from 4 continents (17 from Asia, 11 from Europe, 4 from Africa, and 1 from South America) and from 11 families (6 Uralic, 5 Afroasiatic, 5 Indo-European, 3 Niger-Congo, 3 Turkic, 2 Austroasiatic, 2 Austro-Asiatic, 2 Dravidian, 1 Kra-Dai, 1 Tupian, 1 Sino-Tibetan), as well as 2 isolates. The full list of language iso 639-2 codes is reported in Figure 2.

In order to simulate a zero-shot setting, we hold out half of all possible task–language combinations in 2 distinct runs and regard them as unseen, while treating the others as seen combinations. The partition is performed in such a way that a held-out combination has data available for the same task in a different language, and for the same language in a different task.\(^8\)

We randomly split the WikiANN datasets into training, development, and test portions with a proportion of 80-10-10. We use the provided splits for Universal Dependencies; if the training set for a language is missing, we treat the test set as such when the language is held out, and as a training set when it is among the seen combinations.\(^9\)

Hyper-parameters. The multilingual M-BERT encoder is initialized with parameters pre-trained on

---

\(^7\)We use the controlled partitioning for the following reason. If a language lacks tensor entries both for NER and for POS, the proposed factorization method cannot estimates for its posterior. We leave model extensions that can handle such cases for future work.

\(^8\)Note that, in the second case, no evaluation takes place on such language.
masked language modeling and next sentence prediction on 104 languages (Devlin et al., 2019). We opt for the cased BERT-BASE architecture, which consists of 12 layers with 12 attention heads and a hidden size of 768. As a consequence, this is also the dimension $e$ of the each encoded WordPiece unit. The dimension $h$ of the multivariate Gaussian for task and language latent variables is set to 100. Deep feed-forward networks $f_\psi$ and $f_\phi$ have 6 layers with a hidden size of 400 for the first layer, 768 for the internal layers.

The expectations in Equation (2) are approximated through Monte Carlo estimation with 3 samples per batch during training. The KL terms are weighted with $\frac{1}{12N_B}$ uniformly across training, where $|B|$ is the number of mini-batches. All the $\mu$ parameters are initialized with a random sample from $\mathcal{N}(0, 0.1)$, whereas $\rho$ and $\mathbf{B}$ with $\mathcal{U}(0, 0.5)$, similarly to Stolee and Patterson (2019). We place a prior of $\mathcal{N}(0, 1)$ over $t$, $l$, and $\theta$. The factor covariance matrix has a rank $k = 10$ to fit in memory.

The maximum sequence length for inputs is limited to 250. The batch size is set to 8, and the best setting for the Adam optimizer (Kingma and Ba, 2015) was found to be an initial learning rate of $5 \cdot 10^{-6}$ and an $\epsilon = 10^{-8}$ based on grid search. In order to avoid over-fitting, we perform early stopping with a patience of 10 and a validation frequency of 2.5K steps.

**Baselines.** In this work, we propose a Bayesian generative model over a structured parameter space for neural models. In particular, we explore an approximate inference scheme with diagonal covariance, hereby defined Parameter Factorization, and another with Factor Covariance. As baselines, we consider two widespread approaches for cross-lingual transfer. Both of them are implemented sharing the BERT encoder across all languages while dedicating a private affine classifier to each task–language combination.

Transfer from the Nearest Source (NS) language selects the most compatible source to a target language in terms of similarity. In particular, the selection can be based on family membership (Zeman and Resnik, 2008; Cotterell and Heigold, 2017; Kann et al., 2017), typological features (Deri and Knight, 2016), KL-divergence between part-of-speech trigrams (Rosa and Zabokrtsky, 2015; Agić, 2017), tree edit distance of delexicalized dependency parses (Ponti et al., 2018), or a combination of the above (Lin et al., 2019). In our work, for prediction on each held-out language, we use the classifier associated with the observed language with the highest cosine similarity in terms of typological features. These features are sourced from URIEL (Littell et al., 2017) and contain information about family, area, syntax, and phonology.

The second baseline is transfer from the Largest Source (LS) language, i.e. the language with most training examples, which is usually English. This approach has been adopted by several recent works on cross-lingual transfer (Conneau et al., 2018; Artetxe et al., 2019, *inter alia*). In our implementation, we always select the English classifier for prediction. In order to make this baseline comparable to our model, we adjust the number of English NER training examples to the sum of the examples available for all seen languages $S$.

It must be noted that, for both baselines, the number of parameters of each task–language-specific classifier is lower than of our proposed model. However, increasing the depth of such network is detrimental if the BERT encoder parameters are kept trainable, which we also verified in our experiments (Peters et al., 2019).

## 5 Results and Discussion

### 5.1 Zero-shot Transfer

Firstly, we present the results for zero-shot prediction of the generative model of the parameter space and the two approximate inference schemes (with diagonal co-variance PF and factor co-variance +FC). Table 1 summarizes the results on the two tasks of POS tagging and NER averaged across all languages. Our model outperforms both baselines with a large margin on both tasks. In particular, our model gains +4.49 in accuracy (+6.93%) for POS tagging and +7.73 in F1 score (+9.80%) for NER in average compared to transfer from the nearest source (NS), the strongest baseline.

More details about the individual results on each task–language combination are depicted in Figure 2, which includes the mean and variance of

---

10Available at [github.com/google-research/bert/blob/master/multilingual.md](https://github.com/google-research/bert/blob/master/multilingual.md)

11A WordPiece is a sub-word unit obtained through BPE (Wu et al., 2016).

12We found this weighting strategy to work better than annealing as proposed by Blundell et al. (2015).

---
Figure 2: Results for NER (top) and POS tagging (bottom): Transfer from Nearest Source and from Largest Source compared to Matrix Factorization with diagonal co-variance and low-rank factored co-variance.
Table 1: Results per task averaged across all languages.

| Task | NS         | LS         | PF         | +FC        |
|------|------------|------------|------------|------------|
| POS  | 42.84 ± 1.23 | 60.51 ± 0.43 | **65.00 ± 0.12** | 64.71 ± 0.18 |
| NER  | 74.16 ± 0.56 | 78.97 ± 0.56 | 86.26 ± 0.17 | **86.70 ± 0.10** |

the results over 3 separate runs. Overall, we obtain improvements in 31/33 languages for NER and on 36/45 treebanks for POS tagging, which further supports the benefits of transferring both from tasks and languages. Selecting the best and worst performances of FC compared to NS, the strongest baseline, we report +30.08 in F1 score (+51%) for Kurmanji and -5.72 (-10.37%) for Amharic on NER; +29.91 in accuracy (+119.71%) for Uyghur and -1.72 (-12.07%) for Guaraní on POS tagging.

Considering the baselines, the relative performance of LS versus NS is an interesting finding per se. LS largely outperforms NS on both POS tagging and NER. This shows that having more data is more informative than taking into account similarity based on linguistic properties. This finding contradicts the hypothesis formulated by (Rosa and Zabokrtsky, 2015; Cotterell and Heigold, 2017; Lin et al., 2019, inter alia) that related languages tend to be the most reliable source. We conjecture that this is due to the pre-trained multi-lingual BERT encoder, which effectively bridges the gap between unrelated languages.

Secondly, comparing the two approximate inference schemes, FC obtains a small but statistically significant improvement over PF in NER, whereas they achieve the same performance on POS tagging. This means that the posterior is modeled well enough by a spherical Gaussian, such that a richer co-variance structure is not needed.

Finally, we note that even for the best model (FC) there is a wide variation in the scores for the same task across languages. POS tagging accuracy ranges from 12.56 ± 4.07 in Guarani to 86.71 ± 0.67 in Galician, and NER F1 scores range from 49.44±0.69 in Amharic to 96.20±0.11 in Upper Sorbian. Part of this variation is explained by the fact that the multilingual BERT encoder is not pre-trained in a subset of these languages (which includes Amharic, Guarani, Uyghur, and Assyrian Neo-Aramaic). Another cause of variance is more straightforward: the scores are expected to be lower in languages for which we have less training examples in the seen task–language combinations (e.g., Yoruba, Wolof, Armenian).

5.2 Visualization of the Learned Posteriors

The approximate posteriors of the latent variables can be visualized in order to study the learned representations for languages. Previous works (Johnson et al., 2017; Östling and Tiedemann, 2017; Malaviya et al., 2017; Bjerva and Augenstein, 2018) induced point estimates of language representations from artificial tokens concatenated to every input sentence, or from the aggregated values of the hidden state of a neural encoder. The information contained in such representations depends on the task (Bjerva and Augenstein, 2018), but mainly reflects the structural properties of each language.

In our work, due to the estimation procedure, languages are represented by full distributions rather than point estimates. By inspecting the learned representations, language similarities appear to follow higher-level properties of languages, rather than structural properties. This is most likely due to the fact that parameter factorization takes place after the multi-lingual BERT encoding, which blends the structural differences across languages. A fair comparison with previous works without such encoder is left for future investigation.
As an example, consider two pairs of languages from two distinct families: Yoruba and Wolof are Niger-Congo from the Atlantic-Congo branch, Tamil and Telugu are Dravidian. We take 1,000 samples from the approximate posterior over the latent variables for each of these languages. In particular, we focus on the variational scheme with a low-rank covariance structure Gaussian. Subsequently, we reduce the dimensionality of each sample to 4 through PCA,\textsuperscript{14} and we plot the density along each resulting dimension in Figure 3. As it is evident, density areas of each dimension do not necessarily overlap between members of the same family. Hence, the learned representations do not depend on genealogical properties. We leave it to future work to probe which information they contain instead.

5.3 Entropy of the Predictions

A notable problem of point estimate methods is their tendency to assign most of the probability mass to a single class even in scenarios with high uncertainty. Zero-shot transfer is one of such scenarios, because it involves drastic distribution shifts in the data (Rabanser et al., 2019). A key advantage of Bayesian inference, instead, is marginalization over parameters, which yields smoother predictions (Kendall and Gal, 2017; Wilson, 2019).

We run an analysis on predictions based on (approximate) Bayesian model averaging. First, we randomly sample 800 examples from each test set of a task–language combination. For each example, we predict a distribution over classes $Y$ through model averaging based on 10 samples from the posteriors. We then measure the prediction entropy of each example, i.e.

$$H(p) = - \sum_{y \in [Y]} p(Y = y) \ln p(Y = y),$$

whose plot is shown in Figure 4.

Entropy is a measure of uncertainty. Intuitively, the uniform categorical distribution (maximum uncertainty) has the highest entropy, whereas if the whole probability mass falls into a single class (maximum confidence), then the entropy $H = 0$.\textsuperscript{15}

As it emerges from Figure 4, predictions in certain languages tend to have higher entropy on average, such as in Amharic, Guaraní, Uyghur, or Assyrian Neo-Aramaic. This aligns well with the performances, because it involves drastic distribution shifts in the data (Rabanser et al., 2019). A key advantage of Bayesian inference, instead, is marginalization over parameters, which yields smoother predictions (Kendall and Gal, 2017; Wilson, 2019).

We run an analysis on predictions based on (approximate) Bayesian model averaging. First, we randomly sample 800 examples from each test set of a task–language combination. For each example, we predict a distribution over classes $Y$ through model averaging based on 10 samples from the posteriors. We then measure the prediction entropy of each example, i.e. $H(p) = - \sum_{y \in [Y]} p(Y = y) \ln p(Y = y)$, whose plot is shown in Figure 4.

Entropy is a measure of uncertainty. Intuitively, the uniform categorical distribution (maximum uncertainty) has the highest entropy, whereas if the whole probability mass falls into a single class (maximum confidence), then the entropy $H = 0$.\textsuperscript{15}

As it emerges from Figure 4, predictions in certain languages tend to have higher entropy on average, such as in Amharic, Guaraní, Uyghur, or Assyrian Neo-Aramaic. This aligns well with the performances, because it involves drastic distribution shifts in the data (Rabanser et al., 2019). A key advantage of Bayesian inference, instead, is marginalization over parameters, which yields smoother predictions (Kendall and Gal, 2017; Wilson, 2019).

As an example, consider two pairs of languages from two distinct families: Yoruba and Wolof are Niger-Congo from the Atlantic-Congo branch, Tamil and Telugu are Dravidian. We take 1,000 samples from the approximate posterior over the latent variables for each of these languages. In particular, we focus on the variational scheme with a low-rank covariance structure Gaussian. Subsequently, we reduce the dimensionality of each sample to 4 through PCA,\textsuperscript{14} and we plot the density along each resulting dimension in Figure 3. As it is evident, density areas of each dimension do not necessarily overlap between members of the same family. Hence, the learned representations do not depend on genealogical properties. We leave it to future work to probe which information they contain instead.

\textsuperscript{14}Note that the dimensionality reduced samples are also Gaussian, since PCA is a linear method.

\textsuperscript{15}The maximum entropy is $\approx 2.2$ for 9 classes as in NER and $\approx 2.83$ for 17 classes as in POS tagging.
mance metrics in Figure 2. In practice, languages with low performances tend to display high entropy in the predictive distribution, as expected.

6 Related Work

Data Matrix Factorization. Although we are the first to propose a factorization of the parameter space for unseen combinations of tasks and languages, the factorization of data for collaborative filtering and social recommendation is an established research area. In particular, the missing values in sparse data structures such as user-movie review matrices can be filled via probabilistic matrix factorization (PMF) through a linear combination of user and movie matrices (Mnih and Salakhutdinov, 2008; Ma et al., 2008; Shan and Banerjee, 2010, inter alia) or through neural networks (Dziugaite and Roy, 2015). Inference for PMF can be carried out through MAP inference (Dziugaite and Roy, 2015), Markov Chain Monte Carlo (MCMC; Salakhutdinov and Mnih, 2008) or stochastic VI (Stolee and Patterson, 2019). Contrary to the prior work, we perform factorization on a latent variable (task-language parameters) rather than an observed one (data), which requires a different model.

Contextual Parameter Generation. Our model is reminiscent of the idea that parameters can be conditioned on language representations, as proposed by Platanios et al. (2018). However, since this approach is limited to a single task and a joint learning setting, it is not suitable for cross-task transfer and zero-shot predictions.

Neural Bayesian Methods are especially suited for cross-lingual transfer learning, but so far they have found only limited application in this research area. Firstly, they incorporate priors over parameters: Ponti et al. (2019) constructed a prior imbued with universal linguistic knowledge for zero- and few-shot character-level language modeling. Secondly, they avoid the risk of over-fitting and take into account parameter uncertainty through model averaging. For instance, Shareghi et al. (2019) and Doitch et al. (2019) use a perturbation model to sample high-quality and diverse solutions for structured prediction in cross-lingual parsing.

7 Conclusion and Future Work

The main contribution of our work is a Bayesian generative model of the space of neural parameters which can be factorized according to the combination of languages and tasks. We performed inference through stochastic Variational Inference and evaluated our model on zero-shot prediction for unseen task-language combinations in two tasks: named entity recognition (NER) and part-of-speech (POS) tagging, across a typologically diverse set of 33 languages. Based on these results, we conclude that leveraging the information from tasks and languages simultaneously is superior to model transfer from English (relying on more abundant in-task data in the source language) or from the most typologically similar language (relying on prior information on language similarity). On average, we report improvements of 4.49 in POS tagging accuracy and 7.73 in NER F1 score over the strongest baseline. As a consequence, our approach holds promise to alleviating data paucity issues for a wide spectrum of languages and tasks.

In the future, we will port a similar approach to multilingual tasks beyond sequence labelling tasks, such as Natural Language Inference (Conneau et al., 2018) and Question Answering (Artetxe et al., 2019; Lewis et al., 2019). Moreover, one exciting research path is extending the framework of parameter space factorization to take into account also multiple modalities (e.g., speech, text, vision).

Acknowledgements

This work is supported by the ERC Consolidator Grant LEXICAL (no 648909). RR was partially funded by ISF personal grants No. 1625/18.

References

Željko Agić. 2017. Cross-lingual parser selection for low-resource languages. In Proceedings of the NoDaLiDa 2017 Workshop on Universal Dependencies (UDW 2017), pages 1–10.

Željko Agić, Anders Johannsen, Barbara Plank, Héctor Martinez Alonso, Natalie Schluter, and Anders Søgaard. 2016. Multilingual projection for parsing truly low-resource languages. Transactions of the ACL, 4:301–312.

Waleed Ammar, George Mulcaire, Miguel Balles-teros, Chris Dyer, and Noah A. Smith. 2016. Many languages, one parser. Transactions of the ACL, 4:431–444.

Mikel Artetxe, Sebastian Ruder, and Dani Yogatama. 2019. On the cross-lingual transfer-
ability of monolingual representations. arXiv preprint arXiv:1910.11856.

Mikel Artetxe and Holger Schwenk. 2019. Massively multilingual sentence embeddings for zero-shot cross-lingual transfer and beyond. Transactions of the Association for Computational Linguistics, 7:597–610.

Johannes Bjerva and Isabelle Augenstein. 2018. From phonology to syntax: Unsupervised linguistic typology at different levels with language embeddings. In Proceedings of NAACL-HLT, pages 907–916.

Johannes Bjerva, Robert Östling, Maria Han Veiga, Jörg Tiedemann, and Isabelle Augenstein. 2019. What do language representations really represent? Computational Linguistics, 45(2):381–389.

Charles Blundell, Julien Cornebise, Koray Kavukcuoglu, and Daan Wierstra. 2015. Weight uncertainty in neural networks. In Proceedings of ICML, pages 1613–1622.

Alexis Conneau, Guillaume Lample, Ruty Rinott, Adina Williams, Samuel R Bowman, Holger Schwenk, and Veselin Stoyanov. 2018. XNLI: Evaluating cross-lingual sentence representations. In Proceedings of EMNLP, pages 2475–2485.

Ryan Cotterell and Georg Heigold. 2017. Cross-lingual character-level neural morphological tagging. In Proceedings of EMNLP, pages 748–759.

Aliya Deri and Kevin Knight. 2016. Grapheme-to-phone models for (almost) any language. In Proceedings of ACL, pages 399–408.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of NAACL-HLT, pages 4171–4186.

Amichay Doitch, Ram Yazdi, Tamir Hazan, and Roi Reichart. 2019. Perturbation based learning for structured nlp tasks with application to dependency parsing. Transactions of the Association for Computational Linguistics, 7:643–659.

Gintare Karolina Dziugaite and Daniel M. Roy. 2015. Neural network matrix factorization. arXiv preprint arXiv:1511.06443.

Julian Eisenschlos, Sebastian Ruder, Piotr Czapla, Marcin Kardas, Sylvain Gugger, and Jeremy Howard. 2019. MultiFiT: Efficient multi-lingual language model fine-tuning. In Proceedings of EMNLP, pages 5706–5711.

Timur Garipov, Pavel Izmailov, Dmitrii Podoprikhin, Dmitry P. Vetrov, and Andrew G. Wilson. 2018. Loss surfaces, mode connectivity, and fast ensembling of DNNs. In Proceedings of NeurIPS, pages 8789–8798.

Daniela Gerz, Ivan Vulić, Edoardo Maria Ponti, Roi Reichart, and Anna Korhonen. 2018. On the relation between linguistic typology and (limitations of) multilingual language modeling. In Proceedings of EMNLP, pages 316–327.

Harald Hammarström, Robert Forkel, Martin Haspelmath, and Sebastian Bank, editors. 2016. Glottolog 2.7. Max Planck Institute for the Science of Human History, Jena.

Matthew D. Hoffman, David M. Blei, Chong Wang, and John Paisley. 2013. Stochastic variational inference. The Journal of Machine Learning Research, 14(1):1303–1347.

Melvin Johnson, Mike Schuster, Quoc V Le, Maxim Krikun, Yonghui Wu, Zhifeng Chen, Nikhil Thorat, Fernanda Viégas, Martin Wattenberg, Greg Corrado, et al. 2017. Google’s multilingual neural machine translation system: Enabling zero-shot translation. Transactions of the Association for Computational Linguistics, 5:339–351.

Katharina Kann, Ryan Cotterell, and Hinrich Schütze. 2017. One-shot neural cross-lingual transfer for paradigm completion. In Proceedings of ACL, pages 1993–2003.

Alex Kendall and Yarin Gal. 2017. What uncertainties do we need in Bayesian deep learning for computer vision? In Proceedings of NeurIPS, pages 5574–5584.

Diederik P. Kingma and Jimmy L. Ba. 2015. Adam: A method for stochastic optimization. In Proceedings of ICLR.
Diederik P. Kingma and Max Welling. 2014. Auto-encoding variational Bayes. In Proceedings of ICLR.

Guillaume Lample and Alexis Conneau. 2019. Cross-lingual language model pretraining. Proceedings of NeurIPS, pages 7057–7067.

Patrick S. H. Lewis, Barlas Oguz, Ruty Rinott, Sebastian Riedel, and Holger Schwenk. 2019. MLQA: Evaluating cross-lingual extractive question answering. CoRR, abs/1910.07475.

Yu-Hsiang Lin, Chian-Yu Chen, Jean Lee, Zirui Li, Yuyan Zhang, Mengzhou Xia, Shruti Rijhwani, Junxian He, Zhisong Zhang, Xuezhe Ma, Antonios Anastasopoulos, Patrick Littell, and Graham Neubig. 2019. Choosing transfer languages for cross-lingual learning. In Proceedings of ACL, pages 3125–3135.

Patrick Littell, David R Mortensen, Ke Lin, Katherine Kairis, Carlisle Turner, and Lori Levin. 2017. URIEL and lang2vec: Representing languages as typological, geographical, and phylogenetic vectors. In Proceedings of EACL, pages 8–14.

Hao Ma, Haixuan Yang, Michael R. Lyu, and Irwin King. 2008. SoRec: Social recommendation using probabilistic matrix factorization. In Proceedings of CIKM, pages 931–940.

Chaitanya Malaviya, Graham Neubig, and Patrick Littell. 2017. Learning language representations for typology prediction. In Proceedings of EMNLP, pages 2529–2535.

Andrew C. Miller, Nicholas J. Foti, and Ryan P. Adams. 2017. Variational boosting: Iteratively refining posterior approximations. In Proceedings of ICML, pages 3732–3747.

Andriy Mnih and Ruslan Salakhutdinov. 2008. Probabilistic matrix factorization. In Proceedings of NeurIPS, pages 1257–1264.

Joakim Nivre, Mitchell Abrams, Željko Agić, Lars Ahrenberg, Gabriélle Aleksandrovčičute, Lene Antonsen, Katya Aplonova, Maria Jesus Aranzabe, Gashaw Arutie, Masayuki Asahara, et al. 2019. Universal dependencies 2.4. LINDAT/CLARIN digital library at the Institute of Formal and Applied Linguistics (ÚFAL), Faculty of Mathematics and Physics, Charles University.

Victor M-H Ong, David J Nott, and Michael S Smith. 2018. Gaussian variational approximation with a factor covariance structure. Journal of Computational and Graphical Statistics, 27(3):465–478.

Robert Östling and Jörg Tiedemann. 2017. Continuous multilinguality with language vectors. In Proceedings of the EACL, pages 644–649.

Xiaoman Pan, Boliang Zhang, Jonathan May, Joel Nothman, Kevin Knight, and Heng Ji. 2017. Cross-lingual name tagging and linking for 282 languages. In Proceedings of ACL, volume 1, pages 1946–1958.

Matthew E. Peters, Sebastian Ruder, and Noah A. Smith. 2019. To tune or not to tune? Adapting pretrained representations to diverse tasks. In Proceedings of the 4th Workshop on Representation Learning for NLP (RepL4NLP-2019), pages 7–14.

Telmo Pires, Eva Schlinger, and Dan Garrette. 2019. How multilingual is multilingual BERT? In Proceedings of ACL, pages 4996–5001.

Emmanouil Antonios Platanios, Mrinmaya Sachan, Graham Neubig, and Tom Mitchell. 2018. Contextual parameter generation for universal neural machine translation. In Proceedings of EMNLP, pages 425–435.

Edoardo Maria Ponti, Helen O’Horan, Yevgeni Berzak, Ivan Vulić, Roi Reichart, Thierry Poibeau, Ekaterina Shutova, and Anna Korhonen. 2019a. Modeling language variation and universals: A survey on typological linguistics for natural language processing. Computational Linguistics, 45(3):559–601.

Edoardo Maria Ponti, Roi Reichart, Anna Korhonen, and Ivan Vulić. 2018. Isomorphic transfer of syntactic structures in cross-lingual NLP. In Proceedings of ACL, pages 1531–1542.

Edoardo Maria Ponti, Ivan Vulić, Ryan Cotterell, Roi Reichart, and Anna Korhonen. 2019b. Towards zero-shot language modeling. In Proceedings of EMNLP, pages 2900–2910.

Stephan Rabanser, Stephan Günemann, and Zachary Lipton. 2019. Failing loudly: An empirical study of methods for detecting dataset shift. In Proceedings of NeurIPS, pages 1394–1406.
Shruti Rijhwani, Jiateng Xie, Graham Neubig, and Jaime G. Carbonell. 2019. Zero-shot neural transfer for cross-lingual entity linking. In Proceedings of AAAI, pages 6924–6931.

Rudolf Rosa and Zdenek Zabokrtsky. 2015. KL-cpos3 - A language similarity measure for delexicalized parser transfer. In Proceedings of ACL, pages 243–249.

Sebastian Ruder, Matthew E. Peters, Swabha Swayamdipta, and Thomas Wolf. 2019. Transfer learning in natural language processing. In Proceedings of NAACL-HLT: Tutorials, pages 15–18.

Ruslan Salakhutdinov and Andriy Mnih. 2008. Bayesian probabilistic matrix factorization using Markov chain Monte Carlo. In Proceedings of ICML, pages 880–887.

Hanhuai Shan and Arindam Banerjee. 2010. Generalized probabilistic matrix factorizations for collaborative filtering. In Proceedings of ICDM, pages 1025–1030.

Ehsan Shareghi, Yingzhen Li, Yi Zhu, Roi Reichart, and Anna Korhonen. 2019. Bayesian learning for neural dependency parsing. In Proceedings of NAACL-HLT, pages 3509–3519.

Benjamin Snyder and Regina Barzilay. 2010. Climbing the tower of Babel: Unsupervised multilingual learning. In Proceedings of ICML, pages 29–36.

Jake Stolee and Neill Patterson. 2019. Matrix factorization with neural networks and stochastic variational inference. Technical report, University of Toronto.

Oscar Täckström, Ryan McDonald, and Jakob Uszkoreit. 2012. Cross-lingual word clusters for direct transfer of linguistic structure. In Proceedings of NAACL-HLT, pages 477–487.

Alon Talmor and Jonathan Berant. 2019. MultiQA: An empirical investigation of generalization and transfer in reading comprehension. In Proceedings of ACL, pages 4911–4921.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In Proceedings of NeurIPS, pages 5998–6008.

Andrew Gordon Wilson. 2019. The case for Bayesian deep learning. NYU Courant Technical Report.

Yonghui Wu, Mike Schuster, Zhifeng Chen, Quoc V Le, Mohammad Norouzi, Wolfgang Macherey, Maxim Krikun, Yuan Cao, Qin Gao, Klaus Macherey, et al. 2016. Google’s neural machine translation system: Bridging the gap between human and machine translation. arXiv preprint arXiv:1609.08144.

Dani Yogatama, Cyprien de Masson d’Autume, Jerome Connor, Tomas Kocisky, Mike Chrzanowski, Lingpeng Kong, Angeliki Lazaridou, Wang Ling, Lei Yu, Chris Dyer, et al. 2019. Learning and evaluating general linguistic intelligence. arXiv preprint arXiv:1901.11373.

Daniel Zeman and Philip Resnik. 2008. Cross-language parser adaptation between related languages. In Proceedings of IJCNLP, pages 35–42.

Yftah Ziser and Roi Reichart. 2018. Deep pivot-based modeling for cross-language cross-domain transfer with minimal guidance. In Proceedings of EMNLP, pages 238–249.