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# Multitask Spectral Learning of Weighted Automata (Supplementary Material)

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Guillaume Rabusseau<sup>\*</sup>  
McGill University

Borja Balle<sup>†</sup>  
Amazon Research Cambridge

Joelle Pineau<sup>‡</sup>  
McGill University

## 1 Proofs

### 1.1 Proof of Theorem 3

**Theorem.** Let  $\vec{f} : \Sigma^* \rightarrow \mathbb{R}^d$  and let  $\mathcal{H}$  be the corresponding Hankel tensor. Then  $\text{rank}(f) = \text{rank}(\mathcal{H}_{(1)})$ .

*Proof.* We first show that  $\text{rank}(\vec{f}) \geq \text{rank}(\mathcal{H}_{(1)})$ . Let  $A = (\alpha, \{\mathbf{A}^\sigma\}_{\sigma \in \Sigma}, \Omega)$  be a vv-WFA with  $n$  states computing  $\vec{f}$  and let  $\mathbf{P} \in \mathbb{R}^{\Sigma^* \times n}$  and  $\mathcal{S} \in \mathbb{R}^{n \times d \times \Sigma^*}$  be defined by

$$\mathbf{P}_{u,:} = \alpha^\top \mathbf{A}^u \text{ and } \mathcal{S}_{:,v} = \mathbf{A}^v \Omega.$$

It is easy to check that  $\mathcal{H} = \mathcal{S} \times_1 \mathbf{P}$  which implies  $\mathcal{H}_{(1)} = \mathbf{P} \mathcal{S}_{(1)}$  and thus  $\text{rank}(\mathcal{H}_{(1)}) \leq n$ .

For the converse, we first define the notion of *residual functions* of  $\vec{f}$ : for any  $x \in \Sigma^*$  the residual  $\bar{x} : \Sigma^* \rightarrow \mathbb{R}^d$  is the function defined by  $\bar{x}(u) = \vec{f}(xu)$  for any  $u \in \Sigma^*$ . Let  $V = \{\bar{x} : x \in \Sigma^*\} \subset (\mathbb{R}^d)^{\Sigma^*}$  be the space of residual functions of  $f$ . Suppose that  $\text{rank}(\mathcal{H}_{(1)}) = n$ . Since each residual  $\bar{x}$  can be identified with the row vector  $(\mathcal{H}_{(1)})_{x,:}$ , the dimension of  $V$  is equal to  $n$ . Thus there exist  $n$  words  $e_1, \dots, e_n \in \Sigma^*$  such that  $(\bar{e}_1, \dots, \bar{e}_n)$  is a basis of  $V$ . Expressing  $\bar{\lambda}$  and  $\bar{e}_i \bar{\sigma}$  for each  $i \in [n]$ ,  $\sigma \in \Sigma$  in this basis, we know that there exist  $\alpha \in \mathbb{R}^n$  and  $\mathbf{A}^\sigma \in \mathbb{R}^{n \times n}$  for each  $\sigma$  such that

$$\bar{\lambda} = \sum_i \alpha_i \bar{e}_i \text{ and } \bar{e}_i \bar{\sigma} = \sum_j \mathbf{A}_{i,j}^\sigma \bar{e}_j.$$

We now show by induction on  $|x|$  that  $\bar{e}_i \bar{x} = \sum_j \mathbf{A}_{i,j}^x \bar{e}_j$  for any non-empty string  $x \in \Sigma^*$ . The case  $x = \sigma \in \Sigma$  is immediate by definition of  $\mathbf{A}^\sigma$ . Let  $x, y$  be two non-empty words, for any  $u \in \Sigma^*$  and any  $i \in [n]$  we get

$$\begin{aligned} \bar{e}_i \bar{xy}(u) &= \vec{f}(e_i xy u) = \bar{e}_i \bar{x}(yu) \\ &= \sum_j \mathbf{A}_{i,j}^x \bar{e}_j(yu) = \sum_j \mathbf{A}_{i,j}^x \vec{f}(e_j y u) = \sum_j \mathbf{A}_{i,j}^x \bar{e}_j \bar{y}(u) \\ &= \sum_j \mathbf{A}_{i,j}^x \sum_k \mathbf{A}_{j,k}^y \bar{e}_k(u) = \sum_k \mathbf{A}_{i,k}^{xy} \bar{e}_k(u) \end{aligned}$$

using the induction hypothesis twice. To conclude the proof, let  $\Omega \in \mathbb{R}^{n \times d}$  be the matrix with rows  $\bar{e}_i(\lambda)$  for  $i \in [n]$ . For any  $x \in \Sigma^*$  we have

$$\begin{aligned} \vec{f}(x) &= \bar{\lambda}(x) = \sum_i \alpha_i \bar{e}_i(x) = \sum_i \alpha_i \bar{e}_i \bar{x}(\lambda) \\ &= \sum_i \alpha_i \sum_j \mathbf{A}_{i,j}^x \bar{e}_j(\lambda) = \alpha^\top \mathbf{A}^x \Omega, \end{aligned}$$

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<sup>\*</sup> guillaume.rabusseau@mail.mcgill.ca

<sup>†</sup> pigem@amazon.co.uk

<sup>‡</sup> jpineau@cs.mcgill.ca

showing that the vv-WFA  $(\alpha, \{\mathbf{A}^\sigma\}_{\sigma \in \Sigma}, \Omega)$  computes  $\vec{f}$  and consequently that  $\text{rank}(\vec{f}) \leq n = \text{rank}(\mathcal{H}_{(1)})$ .  $\square$

## 1.2 Proof of Corollary 4

**Corollary.** Let  $\vec{f} : \Sigma^* \rightarrow \mathbb{R}^d$  be a recognizable function with rank  $n$ , let  $\mathcal{H} \in \mathbb{R}^{\Sigma^* \times d \times \Sigma^*}$  be its Hankel tensor, and for each  $\sigma \in \Sigma$  let  $\mathcal{H}^\sigma \in \mathbb{R}^{\Sigma^* \times d \times \Sigma^*}$  be defined by  $\mathcal{H}_{u,::,v}^\sigma = f(u\sigma v)$  for all  $u, v \in \Sigma^*$ .

Then, for any  $\mathbf{P} \in \mathbb{R}^{\Sigma^* \times n}$  and  $\mathcal{S} \in \mathbb{R}^{n \times d \times \Sigma^*}$  such that  $\mathcal{H} = \mathcal{S} \times_1 \mathbf{P}$ , the vv-WFA  $A = (\alpha, \{\mathbf{A}^\sigma\}_{\sigma \in \Sigma}, \Omega)$  defined by  $\alpha^\top = \mathbf{P}_{\lambda,::}$ ,  $\Omega = \mathcal{S}_{::,\lambda}$ , and  $\mathbf{A}^\sigma = \mathbf{P}^\dagger \mathcal{H}_{(1)}^\sigma (\mathcal{S}_{(1)})^\dagger$  is a minimal vv-WFA computing  $\vec{f}$ .

*Proof.* Let  $\hat{A} = (\hat{\alpha}^\top, \{\hat{\mathbf{A}}^\sigma\}_{\sigma \in \Sigma}, \hat{\Omega})$  be a minimal vv-WFA computing  $\vec{f}$  and let  $\hat{\mathbf{P}} \in \mathbb{R}^{\Sigma^* \times n}$  and  $\hat{\mathcal{S}} \in \mathbb{R}^{n \times d \times \Sigma^*}$  be defined by

$$\hat{\mathbf{P}}_{u,::} = \alpha^\top \hat{\mathbf{A}}^u \text{ and } \hat{\mathcal{S}}_{::,v} = \hat{\mathbf{A}}^v \Omega, \quad u, v \in \Sigma^*,$$

hence  $\mathcal{H} = \hat{\mathcal{S}} \times_1 \hat{\mathbf{P}}$  and, equivalently,  $\mathcal{H}_{(1)} = \hat{\mathbf{P}} \hat{\mathcal{S}}_{(1)}$ . We will show that  $\alpha^\top = \hat{\alpha}^\top \mathbf{M}^{-1}$ ,  $\Omega = \mathbf{M} \hat{\Omega}$  and  $\mathbf{A}^\sigma = \mathbf{M} \hat{\mathbf{A}}^\sigma \mathbf{M}^{-1}$  for each  $\sigma \in \Sigma$  where  $\mathbf{M} = \mathbf{P}^\dagger \hat{\mathbf{P}}$ , which will imply  $\vec{f}_A = \vec{f}_{\hat{A}} = \vec{f}$ .

To simplify the notations, let  $\mathbf{H} = \mathcal{H}_{(1)}$ ,  $\mathbf{S} = \mathcal{S}_{(1)}$ ,  $\hat{\mathbf{S}} = \hat{\mathcal{S}}_{(1)}$ , and  $\mathbf{H}^\sigma = (\mathcal{H}^\sigma)_{(1)}$  for each  $\sigma \in \Sigma$ . First observe that since  $\mathbf{P}^\dagger \hat{\mathbf{P}} \hat{\mathbf{S}} \hat{\mathbf{S}}^\dagger = \mathbf{P}^\dagger \mathbf{H} \mathbf{S}^\dagger = \mathbf{I}$ , the matrix  $\mathbf{M}$  is invertible with  $\mathbf{M}^{-1} = \hat{\mathbf{S}} \hat{\mathbf{S}}^\dagger$ . Using the identities  $\mathbf{H}^\sigma = \hat{\mathbf{P}} \hat{\mathbf{A}}^\sigma \hat{\mathbf{S}}$ ,  $\mathbf{H}_{\lambda,::} = \hat{\alpha}^\top \hat{\mathbf{S}}$ ,  $\mathbf{P}^\dagger \mathcal{H}_{::,\lambda} = \mathcal{S}_{::,\lambda}$ , and  $\mathcal{H}_{::,\lambda} = \hat{\mathbf{P}} \hat{\Omega}$ , we then get

$$\begin{aligned} \mathbf{A}^\sigma &= \mathbf{P}^\dagger \mathbf{H}^\sigma \mathbf{S}^\dagger = \mathbf{P}^\dagger \hat{\mathbf{P}} \hat{\mathbf{A}}^\sigma \hat{\mathbf{S}} \hat{\mathbf{S}}^\dagger = \mathbf{M} \hat{\mathbf{A}}^\sigma \mathbf{M}^{-1}, \\ \alpha^\top &= \mathbf{P}_{\lambda,::} = \mathbf{H}_{\lambda,::} \mathbf{S}^\dagger = \hat{\alpha}^\top \hat{\mathbf{S}} \hat{\mathbf{S}}^\dagger = \hat{\alpha}^\top \mathbf{M}^{-1}, \text{ and} \\ \Omega &= \mathcal{S}_{::,\lambda} = \mathbf{P}^\dagger \mathcal{H}_{::,\lambda} = \mathbf{P}^\dagger \hat{\mathbf{P}} \hat{\Omega} = \mathbf{M} \hat{\Omega}. \end{aligned} \quad \square$$

## 1.3 Proof of Proposition 1

**Proposition.** Let  $\vec{f} : \Sigma^* \rightarrow \mathbb{R}^d$  be a function computed by a vv-WFA  $A = (\alpha, \{\mathbf{A}^\sigma\}_{\sigma \in \Sigma}, \Omega)$  with  $n$  states and let  $\mathcal{P}, \mathcal{S} \subseteq \Sigma^*$  be a complete basis for  $\vec{f}$ . For any  $i \in [d]$ , let  $f_i : \Sigma^* \rightarrow \mathbb{R}$  be defined by  $f_i(x) = \vec{f}(x)_i$  for all  $x \in \Sigma^*$  and let  $n_i$  denote the rank of  $f_i$ .

Let  $\mathbf{P} \in \mathbb{R}^{\mathcal{P} \times n}$  be defined by  $\mathbf{P}_{x,::} = \alpha^\top \mathbf{A}^x$  for all  $x \in \mathcal{P}$  and, for  $i \in [d]$ , let  $\mathbf{H}_i = \mathbf{U}_i \mathbf{D}_i \mathbf{V}_i^\top$  be the thin SVD of  $\mathbf{H}_i$  (i.e.  $\mathbf{D}_i \in \mathbb{R}^{n_i \times n_i}$ ) where  $\mathbf{H}_i \in \mathbb{R}^{\mathcal{P} \times \mathcal{S}}$  is the hankel matrix of  $f_i$ .

Then, for any  $i \in [d]$ , the WFA  $A_i = \langle \alpha_i, \{\mathbf{A}_i^\sigma\}_{\sigma \in \Sigma}, \omega_i \rangle$  defined by

$$\alpha_i^\top = \alpha^\top \mathbf{P}^\dagger \mathbf{U}_i, \quad \omega_i = \mathbf{U}_i^\top \mathbf{P} \Omega_{:,i} \text{ and } \mathbf{A}_i^\sigma = \mathbf{U}_i^\top \mathbf{P} \mathbf{A}^\sigma \mathbf{P}^\dagger \mathbf{U}_i \text{ for each } \sigma \in \Sigma,$$

is a minimal WFA computing  $f_i$ .

*Proof.* For each  $i \in [d]$ , let  $\mathbf{S}_i \in \mathbb{R}^{n \times \mathcal{S}}$  be defined by  $(\mathbf{S}_i)_{:,x} = \mathbf{A}^x \Omega_{:,i}$  and consider the  $|\mathcal{P}| \times d|\mathcal{S}|$  block matrices  $\mathbf{H} = [\mathbf{H}_1, \dots, \mathbf{H}_d]$ ,  $\mathbf{H}^\sigma = [\mathbf{H}_1^\sigma, \dots, \mathbf{H}_d^\sigma]$  for each  $\sigma \in \Sigma$ , and  $\mathbf{S} = [\mathbf{S}_1, \dots, \mathbf{S}_d]$ .

We show the result for  $i = 1$ . First, it follows from applying Corollary 2 to the factorization  $\mathbf{H}_1 = \mathbf{U}_1 (\mathbf{D}_1 \mathbf{V}_1^\top)$  that the WFA  $\hat{A} = \langle \hat{\alpha}, \{\hat{\mathbf{A}}^\sigma\}_{\sigma \in \Sigma}, \hat{\omega} \rangle$  defined by

$$\hat{\alpha}^\top = (\mathbf{U}_1)_{\lambda,::}, \quad \hat{\omega} = (\mathbf{D} \mathbf{V}_1^\top)_{:, \lambda} \text{ and } \hat{\mathbf{A}}^\sigma = \mathbf{U}_1^\top \mathbf{H}_1^\sigma \mathbf{V}_1 \mathbf{D}_1^{-1} \text{ for each } \sigma \in \Sigma$$

is a minimal WFA computing  $f_1$ . We will show that the WFA  $A_1$  is exactly  $\hat{A}$ .

Let  $\sigma \in \Sigma$ . We start by showing that  $\mathbf{A}_1^\sigma = \hat{\mathbf{A}}^\sigma$ . It is easy to check that  $\mathbf{H} = \mathbf{P} \mathbf{S}$  and  $\mathbf{H}^\sigma = \mathbf{P} \mathbf{A}^\sigma \mathbf{S}$ . Furthermore, since  $\mathbf{H}^\sigma = \mathbf{H}^\sigma \mathbf{S}^\dagger \mathbf{S}$  we have  $\mathbf{H}_1^\sigma = \mathbf{H}^\sigma \mathbf{S}^\dagger \mathbf{S}_1$ , which implies  $\mathbf{A}^\sigma \mathbf{S}_1 = \mathbf{P}^\dagger \mathbf{H}^\sigma \mathbf{S}^\dagger \mathbf{S}_1 =$

$\mathbf{P}^\dagger \mathbf{H}_1^\sigma$ . It then follows that

$$\begin{aligned}\mathbf{A}_1^\sigma &= \mathbf{U}_1^\top \mathbf{P} \mathbf{A}^\sigma \mathbf{P}^\dagger \mathbf{U}_1 \\ &= \mathbf{U}_1^\top \mathbf{P} \mathbf{A}^\sigma \mathbf{P}^\dagger \mathbf{U}_1 (\mathbf{D}_1 \mathbf{V}_1^\top \mathbf{V}_1 \mathbf{D}_1^{-1}) \\ &= \mathbf{U}_1^\top \mathbf{P} \mathbf{A}^\sigma \mathbf{P}^\dagger \mathbf{H}_1 \mathbf{V}_1 \mathbf{D}_1^{-1} \\ &= \mathbf{U}_1^\top \mathbf{P} \mathbf{A}^\sigma \mathbf{S}_1 \mathbf{V}_1 \mathbf{D}_1^{-1} \\ &= \mathbf{U}_1^\top \mathbf{P} \mathbf{P}^\dagger \mathbf{H}_1^\sigma \mathbf{V}_1 \mathbf{D}_1^{-1} \\ &= \mathbf{U}_1^\top \mathbf{H}_1^\sigma \mathbf{V}_1 \mathbf{D}_1^{-1} = \hat{\mathbf{A}}^\sigma\end{aligned}$$

where we also used the fact that  $\mathbf{P} \mathbf{P}^\dagger \mathbf{H}_1^\sigma = \mathbf{H}_1^\sigma$  and  $\mathbf{P}^\dagger \mathbf{H}_1 = \mathbf{S}_1$ . Now since the column space of  $\mathbf{U}_1$  is contained in the column space of  $\mathbf{P}$ , we have  $\mathbf{U}_1^\top \mathbf{P} \mathbf{P}^\dagger = \mathbf{U}_1^\top$  (and similarly  $\mathbf{P} \mathbf{P}^\dagger \mathbf{U}_1 = \mathbf{U}_1$ ). Using the this fact and observing that  $\boldsymbol{\alpha}^\top = \mathbf{H}_{\lambda,:} \mathbf{S}^\dagger$  and  $\boldsymbol{\Omega} = \mathbf{P}^\dagger (\mathcal{H}_{:, :, \lambda})$  we get

$$\boldsymbol{\alpha}_1^\top = \boldsymbol{\alpha}^\top \mathbf{P}^\dagger \mathbf{U}_1 = \mathbf{H}_{\lambda,:} \mathbf{S}^\dagger \mathbf{P}^\dagger \mathbf{U}_1 = \mathbf{P}_{\lambda,:} \mathbf{P}^\dagger \mathbf{U}_1 = (\mathbf{U}_1)_{\lambda,:} = \hat{\boldsymbol{\alpha}}^\top$$

and

$$\boldsymbol{\omega}_1 = \mathbf{U}_1^\top \mathbf{P} \boldsymbol{\Omega}_{:,1} = \mathbf{U}_1^\top \mathbf{P} \mathbf{P}^\dagger (\mathcal{H}_{:,1,\lambda}) = \mathbf{U}_1^\top (\mathbf{H}_1)_{:, \lambda} = \hat{\boldsymbol{\omega}}$$

which concludes the proof.  $\square$

#### 1.4 Proof of Theorem 5

**Theorem.** Let  $\mathbf{M} \in \mathbb{R}^{d_1 \times d_2}$  be of rank  $R$  and let  $\hat{\mathbf{M}} = \mathbf{M} + \mathbf{E}$  where  $\mathbf{E}$  is a random noise term such that  $\frac{\text{vec}(\mathbf{E})}{\|\mathbf{E}\|_F}$  follows a uniform distribution on the unit sphere in  $\mathbb{R}^{d_1 d_2}$ . Let  $\boldsymbol{\Pi}_U, \boldsymbol{\Pi}_{\hat{U}} \in \mathbb{R}^{d_1 \times d_1}$  be the matrices of the orthogonal projections onto the space spanned by the top  $R$  left singular vectors of  $\mathbf{M}$  and  $\hat{\mathbf{M}}$  respectively.

Let  $\delta > 0$ , let  $\alpha = \mathfrak{s}_R(\mathbf{M})$  be the smallest non-zero singular value of  $\mathbf{M}$  and suppose that  $\|\mathbf{E}\|_F \leq \alpha/2$ . Then, with probability at least  $1 - \delta$ ,

$$\|\boldsymbol{\Pi}_U - \boldsymbol{\Pi}_{\hat{U}}\|_F \leq 4 \left( \sqrt{\frac{(d_1 - R)R + 2 \log(1/\delta)}{d_1 d_2}} \frac{\|\mathbf{E}\|_F}{\alpha} + \frac{\|\mathbf{E}\|_F^2}{\alpha^2} \right).$$

Let  $\boldsymbol{\Pi}_{U_\perp} = \mathbf{I} - \boldsymbol{\Pi}_U$  and  $\boldsymbol{\Pi}_{V_\perp} = \mathbf{I} - \boldsymbol{\Pi}_V$ . Then, under the assumption  $\|\mathbf{E}\|_F \leq \alpha/2$ , it follows from Theorem 1 in [?] that

$$\|\boldsymbol{\Pi}_U - \boldsymbol{\Pi}_{\hat{U}}\|_F \leq \frac{2\sqrt{2}}{\alpha} \left( \|\boldsymbol{\Pi}_{U_\perp} \mathbf{E} \boldsymbol{\Pi}_V\|_F + \frac{\|\boldsymbol{\Pi}_{U_\perp} \mathbf{E} \boldsymbol{\Pi}_{V_\perp}\|_F \cdot \|\boldsymbol{\Pi}_U \mathbf{E} \boldsymbol{\Pi}_{V_\perp}\|_F}{\alpha} \right).$$

The second term of the sum can be bounded using the fact that both  $\|\boldsymbol{\Pi}_{U_\perp} \mathbf{E} \boldsymbol{\Pi}_{V_\perp}\|_F$  and  $\|\boldsymbol{\Pi}_U \mathbf{E} \boldsymbol{\Pi}_{V_\perp}\|_F$  are bounded by  $\|\mathbf{E}\|_F$ . Indeed we have e.g.

$$\|\boldsymbol{\Pi}_{U_\perp} \mathbf{E} \boldsymbol{\Pi}_{V_\perp}\|_F = \|(\boldsymbol{\Pi}_{V_\perp} \otimes \boldsymbol{\Pi}_{U_\perp}) \text{vec}(\mathbf{E})\|_F \leq \|\text{vec}(\mathbf{E})\|_F = \|\mathbf{E}\|_F$$

since  $\boldsymbol{\Pi}_{V_\perp} \otimes \boldsymbol{\Pi}_{U_\perp}$  is the matrix of an orthogonal projection. To bound the first term, we use the following lemma showing that the norm of a  $d$ -dimensional random vector  $\mathbf{v}$  projected onto a fixed subspace of dimension  $k$  will be concentrated around  $\sqrt{k/d} \|\mathbf{v}\|$ .

**Lemma 1.** Let  $\boldsymbol{\Pi} \in \mathbb{R}^{d \times d}$  be a rank  $k$  projection matrix and let  $\mathbf{v} \in \mathbb{R}^d$  be a random variable such that  $\frac{\mathbf{v}}{\|\mathbf{v}\|}$  follows a uniform distribution on the unit sphere in  $\mathbb{R}^d$ . Then, for any  $\delta > 0$ ,

$$\mathbb{P} \left[ \|\boldsymbol{\Pi} \mathbf{v}\|_2^2 > 2 \frac{k + 2 \log(1/\delta)}{d} \|\mathbf{v}\|_2^2 \right] \leq \delta.$$

*Proof.* This directly comes from the following classical result (see e.g. Lemma 2.4 in [?]): if  $\mathbf{x}$  is a random unit vector drawn uniformly from the unit sphere we have for any  $\beta > 1$

$$\mathbb{P} \left[ \|\boldsymbol{\Pi} \mathbf{x}\|_2^2 \leq \beta \frac{k}{d} \right] \leq \exp \left\{ \frac{k}{2} (1 - \beta + \log \beta) \right\}.$$

Using the inequality  $\log \beta \leq \beta/2$ , the right term can be upper bounded by  $\exp(k/2(1 - \beta/2))$ , and by setting this upper bound equal to  $\delta$  we get  $\beta = 2(1 + 2 \log(1/\delta)/k)$  which leads to the result.  $\square$

Applying this lemma to  $\|\Pi_{U^\perp} \mathbf{E} \Pi_V\|_F = \|(\Pi_V \otimes \Pi_{U^\perp}) \text{vec}(\mathbf{E})\|_2$  by observing that  $\Pi_V \otimes \Pi_{U^\perp}$  is a  $d_1 d_2 \times d_1 d_2$  projection matrix of rank  $R(d_1 - R)$ , we get that  $\|\Pi_{U^\perp} \mathbf{E} \Pi_V\|_F \leq \sqrt{2 \frac{(d_1 - R)R + 2 \log(1/\delta)}{d_1 d_2}} \|\mathbf{E}\|_F$  with probability at least  $1 - \delta$  which concludes the proof.

## 2 Additional Experiments on Synthetic Data

In Figure 1, we present additional experimental results on the synthetic datasets: we added the case of totally unrelated tasks ( $d_S = 0, d_T = 10$ ) and we included the performances of MT-SL-noproj in all plots. These additional results show that the projection step of MT-SL is crucial when the tasks are loosely related or totally unrelated, and that the results for the case of totally unrelated tasks are similar to the ones obtained when the tasks are only loosely related ( $d_S = 10, d_T = 10$ ).

## 3 Detailed Results for Experiments on Real Data

The perplexity and WER on the test sets for all languages are reported in Table 1 when MT-SL is used with all other languages as related tasks, and in Table 2 when only the 4 closest languages are used. The list of the closest languages used for each task can be found in Table 3.

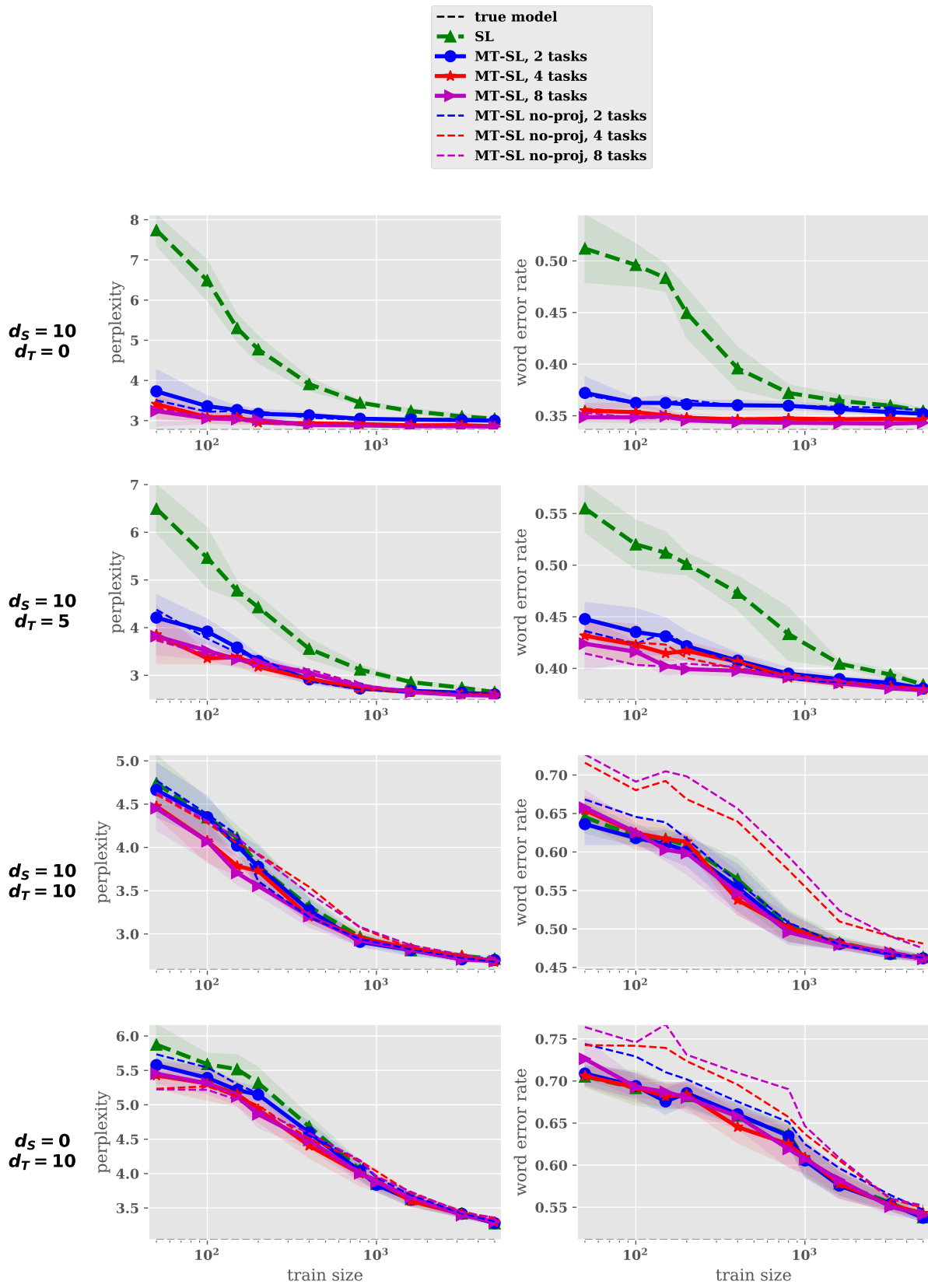


Figure 1: Additional experimental results on the synthetic datasets.

Table 1: Detailed experimental results on the UNIDEP dataset when all other languages are used as related tasks.

Language	Training size	Perplexity				Word Error Rate			
		SL	SL bagging	MT-SL	MT-SL no proj.	SL	SL bagging	MT-SL	MT-SL no proj.
Ancient Greek	100	4.053	4.997	4.030	4.266	82.445	<b>76.293</b>	82.445	79.883
	500	4.194	5.000	4.195	4.233	81.572	76.211	<b>74.438</b>	78.768
	1000	4.203	4.995	4.192	4.246	77.696	76.185	<b>75.020</b>	77.601
	all	4.582	4.925	4.564	4.676	75.596	75.875	75.804	79.972
Arabic	100	2.316	2.347	2.258	2.291	77.306	77.264	77.161	82.452
	500	2.298	2.347	2.298	2.298	68.804	77.285	68.804	73.954
	1000	2.315	2.347	2.311	2.311	68.066	77.288	68.066	74.109
	all	2.306	2.336	2.338	2.338	66.595	77.578	66.595	73.668
Basque	100	5.932	9.370	5.932	6.842	75.956	77.305	<b>73.515</b>	75.796
	500	6.057	9.368	<b>5.950</b>	7.009	76.300	77.240	<b>70.351</b>	75.223
	1000	6.261	9.364	6.261	7.369	77.129	77.290	<b>68.666</b>	74.329
	all	6.760	9.276	6.760	7.640	75.803	76.602	<b>68.192</b>	75.754
Bulgarian	100	5.103	6.659	<b>4.722</b>	5.613	74.647	<b>67.490</b>	73.525	73.525
	500	5.475	6.649	5.475	5.669	68.576	67.644	<b>65.312</b>	73.329
	1000	5.649	6.617	5.649	5.888	66.059	67.875	<b>64.279</b>	76.350
	all	6.162	6.485	6.162	6.380	66.018	70.736	<b>62.196</b>	73.389
Croatian	100	5.510	4.946	4.870	4.870	75.468	76.694	75.653	79.445
	500	5.336	<b>4.946</b>	5.167	5.167	77.503	76.717	77.757	79.098
	1000	5.454	<b>4.947</b>	5.257	5.257	77.526	76.532	77.757	<b>75.329</b>
	all	5.285	<b>4.938</b>	5.260	5.260	77.919	76.624	76.000	77.942
Czech	100	4.292	5.319	4.292	4.357	77.897	<b>75.868</b>	77.262	77.760
	500	4.482	5.316	4.444	4.501	77.257	75.899	<b>71.326</b>	75.608
	1000	4.530	5.310	4.530	4.533	75.254	75.887	74.471	74.623
	all	5.091	5.141	5.091	5.125	73.849	73.382	<b>71.325</b>	75.827
Danish	100	4.977	5.016	<b>4.838</b>	5.011	78.891	<b>75.137</b>	79.133	80.986
	500	5.033	5.054	5.034	5.034	71.737	75.185	71.737	81.228
	1000	5.189	5.062	5.016	5.016	71.737	75.314	71.737	79.842
	all	5.363	<b>4.999</b>	5.176	5.176	70.674	74.460	70.674	78.714
Dutch	100	6.456	6.592	<b>5.603</b>	6.302	77.525	75.649	75.113	78.094
	500	7.679	6.556	7.694	<b>6.402</b>	75.498	75.314	75.498	79.434
	1000	7.517	<b>6.563</b>	7.327	7.438	73.874	75.264	73.874	79.434
	all	8.025	<b>6.524</b>	8.201	8.201	72.785	74.711	72.785	76.101
English	100	5.203	6.862	<b>4.874</b>	5.086	73.853	74.397	73.853	77.573
	500	<b>5.620</b>	6.820	5.774	5.722	71.729	74.508	71.777	79.741
	1000	5.781	6.805	5.748	5.748	72.716	74.559	<b>69.672</b>	72.925
	all	6.464	6.572	6.464	6.595	67.626	74.143	67.626	74.213
Estonian	100	5.301	9.339	<b>4.534</b>	5.219	50.506	71.389	50.506	57.866
	500	6.108	8.776	5.625	<b>5.341</b>	<b>49.586</b>	72.493	50.874	68.169
	1000	6.605	8.557	<b>6.254</b>	7.443	50.138	68.721	50.138	57.222
	all	6.653	8.522	<b>5.706</b>	7.221	50.046	68.629	50.414	58.786
Finnish	100	5.598	9.418	<b>5.153</b>	5.153	68.774	70.140	68.774	72.302
	500	5.964	9.370	<b>5.712</b>	5.970	67.586	70.062	66.701	74.047
	1000	6.231	9.290	<b>5.844</b>	6.008	66.366	70.012	65.724	74.778
	all	7.709	8.580	<b>7.420</b>	7.642	63.811	70.893	62.848	66.612
French	100	3.744	3.843	<b>3.273</b>	3.493	69.245	<b>66.115</b>	68.658	70.831
	500	3.611	3.855	3.611	3.720	63.669	66.143	63.600	71.911
	1000	3.735	3.843	3.657	3.657	59.787	66.170	60.662	74.194
	all	3.823	3.830	3.823	3.875	59.732	65.377	59.732	69.615
German	100	5.756	5.825	<b>5.234</b>	5.234	78.498	<b>74.769</b>	78.458	80.864
	500	5.960	5.812	<b>5.580</b>	5.580	76.283	<b>74.891</b>	76.283	78.684
	1000	5.722	5.814	5.722	5.424	75.436	74.949	74.868	78.150
	all	6.056	<b>5.704</b>	6.056	5.920	<b>72.554</b>	74.683	73.790	79.467
Gothic	100	6.124	8.726	6.183	6.196	81.109	76.555	76.165	79.461
	500	6.694	8.708	<b>6.565</b>	7.091	76.484	76.502	<b>72.869</b>	75.740
	1000	6.934	8.701	<b>6.676</b>	6.904	75.244	76.537	<b>72.391</b>	76.874
	all	7.777	8.704	<b>7.178</b>	7.613	74.074	76.927	<b>72.479</b>	75.137
Greek	100	4.178	3.868	3.769	3.769	67.287	69.386	67.287	74.632
	500	4.071	3.868	3.949	3.949	66.323	69.403	66.323	74.886
	1000	4.190	<b>3.868</b>	3.985	3.985	66.847	69.369	66.847	74.801
	all	4.110	<b>3.866</b>	3.997	3.997	66.695	69.352	67.203	72.686
Hebrew	100	3.899	3.914	<b>3.790</b>	3.790	72.796	73.129	72.796	82.966
	500	3.928	3.912	3.828	3.828	76.625	<b>73.114</b>	76.625	76.316
	1000	3.904	3.908	3.859	3.859	73.724	73.145	73.724	78.131
	all	4.022	3.910	3.945	3.945	73.359	73.137	73.359	79.027

Language	Training size	Perplexity				Word Error Rate			
		SL	SL bagging	MT-SL	MT-SL no proj.	SL	SL bagging	MT-SL	MT-SL no proj.
Hindi	100	4.167	5.019	4.099	4.099	61.818	77.203	61.818	75.473
	500	4.015	5.018	4.015	4.150	60.958	77.197	60.958	76.208
	1000	4.235	5.016	4.235	4.557	62.850	77.197	62.850	73.142
	all	4.340	4.952	4.319	4.411	59.818	77.162	59.818	70.731
Hungarian	100	5.762	5.048	<b>4.845</b>	4.845	69.368	76.319	69.368	76.668
	500	5.727	<b>5.047</b>	5.184	5.184	68.949	76.319	68.599	80.091
	1000	5.801	<b>5.051</b>	5.215	5.215	68.809	76.249	68.914	79.776
	all	5.592	5.056	5.147	5.147	69.263	76.249	69.193	79.462
Indonesian	100	4.687	4.663	<b>4.139</b>	4.351	74.581	77.871	74.581	79.890
	500	4.630	4.658	<b>4.296</b>	4.296	71.411	77.880	71.411	78.204
	1000	4.601	4.663	<b>4.494</b>	4.494	70.901	77.807	70.901	78.520
	all	4.734	4.658	4.614	4.614	71.160	77.896	71.160	77.734
Irish	100	3.587	<b>3.446</b>	3.591	3.591	67.086	73.835	67.086	79.451
	500	3.548	3.453	3.463	3.463	66.230	73.835	66.230	73.659
	1000	3.594	<b>3.453</b>	3.559	3.559	66.885	73.886	66.885	76.077
	all	3.594	<b>3.453</b>	3.559	3.559	66.885	73.886	66.885	76.077
Italian	100	3.343	3.769	3.249	3.254	64.584	70.483	<b>63.036</b>	70.090
	500	3.450	3.765	<b>3.276</b>	3.276	58.054	69.688	58.054	63.867
	1000	3.466	3.761	<b>3.355</b>	3.355	57.880	69.094	57.880	62.757
	all	3.620	3.580	3.506	3.506	57.574	63.307	57.574	63.972
Japanese	100	2.981	3.586	2.888	3.162	64.651	82.419	64.651	74.700
	500	3.148	3.566	3.124	3.175	60.545	82.773	60.545	69.113
	1000	3.197	3.564	3.197	3.199	61.664	82.618	61.664	69.308
	all	3.196	3.538	3.221	3.255	61.837	82.946	<b>59.632</b>	73.626
Latin	100	4.707	6.825	4.707	5.137	79.580	<b>74.320</b>	75.690	79.660
	500	5.143	6.815	5.143	5.462	76.556	<b>74.317</b>	75.753	79.837
	1000	5.299	6.805	5.299	5.625	75.919	74.345	74.974	81.735
	all	6.241	6.711	6.239	6.428	75.179	74.300	<b>72.662</b>	78.787
Norwegian	100	5.089	6.190	<b>4.911</b>	4.911	74.544	74.435	<b>72.514</b>	76.952
	500	5.164	6.152	<b>4.983</b>	5.117	71.926	74.297	<b>70.353</b>	73.650
	1000	5.235	6.141	5.147	5.318	69.887	74.194	69.199	75.864
	all	5.733	6.009	<b>5.632</b>	5.882	69.487	72.937	<b>66.716</b>	75.626
Old Church Slavonic	100	5.959	11.445	5.886	6.203	74.092	77.813	<b>72.284</b>	74.588
	500	7.172	11.465	<b>6.733</b>	7.096	70.441	77.778	69.697	73.932
	1000	7.765	11.420	<b>7.307</b>	7.901	68.297	77.760	67.978	73.826
	all	8.889	11.086	<b>8.465</b>	8.949	68.067	75.970	<b>66.968</b>	69.981
Persian	100	3.231	3.489	<b>3.012</b>	3.209	67.501	72.542	61.352	61.352
	500	3.256	3.501	3.244	3.345	59.253	72.560	59.253	76.483
	1000	3.274	3.495	3.318	3.332	58.429	72.500	<b>56.822</b>	74.437
	all	3.339	3.473	3.339	3.423	58.164	72.554	<b>55.354</b>	65.353
Polish	100	4.686	8.871	4.745	5.276	65.963	69.578	65.078	70.210
	500	5.288	8.858	<b>5.108</b>	5.579	68.643	69.565	<b>62.588</b>	69.565
	1000	5.466	8.832	<b>5.333</b>	5.978	68.984	69.451	<b>63.208</b>	72.434
	all	6.404	8.295	<b>6.184</b>	6.865	63.802	68.466	63.802	69.363
Portuguese	100	3.761	4.359	3.679	3.891	74.216	<b>67.880</b>	72.819	79.643
	500	3.988	4.402	3.989	3.989	69.862	67.864	67.815	71.990
	1000	<b>4.059</b>	4.382	4.210	4.210	68.952	68.058	68.952	68.725
	all	4.288	4.308	4.342	4.342	68.757	67.490	<b>65.491</b>	69.829
Romanian	100	7.269	5.799	<b>4.923</b>	4.923	71.105	71.997	71.311	78.655
	500	7.269	<b>5.792</b>	6.288	6.288	<b>69.526</b>	71.997	70.899	79.753
	1000	7.269	<b>5.792</b>	6.288	6.288	<b>69.526</b>	71.997	70.899	79.753
	all	7.269	<b>5.792</b>	6.288	6.288	<b>69.526</b>	71.997	70.899	79.753
Slovenian	100	5.156	5.383	<b>4.540</b>	4.788	81.297	<b>71.790</b>	74.692	77.903
	500	5.429	5.385	<b>4.993</b>	4.993	71.231	71.790	71.231	80.213
	1000	5.387	5.384	<b>5.083</b>	5.083	71.588	71.783	<b>68.754</b>	77.257
	all	5.605	5.347	5.406	5.406	70.875	71.635	<b>64.943</b>	77.244
Spanish	100	3.109	3.125	2.983	<b>2.969</b>	67.607	<b>66.355</b>	67.607	76.468
	500	3.114	3.121	3.069	3.069	67.898	<b>66.440</b>	67.898	73.794
	1000	3.166	3.120	3.070	3.070	64.750	66.452	64.750	68.798
	all	3.265	3.107	3.176	3.176	64.702	66.136	64.702	71.727
Swedish	100	5.184	5.480	<b>4.761</b>	4.768	72.166	73.602	72.166	76.144
	500	5.379	5.482	<b>5.108</b>	5.108	70.268	73.634	70.268	77.311
	1000	5.482	5.481	<b>5.202</b>	5.202	68.971	73.662	68.971	75.125
	all	5.737	5.461	5.489	5.489	68.878	72.819	68.878	78.565
Tamil	100	8.289	6.884	<b>5.859</b>	5.859	66.999	76.102	66.098	74.395
	500	8.305	6.884	<b>6.149</b>	6.149	66.524	76.055	67.330	80.512
	1000	8.305	6.884	<b>6.149</b>	6.149	66.524	76.055	67.330	80.512
	all	8.305	6.884	<b>6.149</b>	6.149	66.524	76.055	67.330	80.512

Table 2: Detailed experimental results on the UNIDEP dataset when the 4 closest languages are used as related tasks. The closest languages used for each target task are reported in Table 3.

Language	Training size	Perplexity				Word Error Rate			
		SL	SL bagging	MT-SL	MT-SL no proj.	SL	SL bagging	MT-SL	MT-SL no proj.
Ancient Greek	100	4.053	4.960	3.998	4.288	82.445	<b>77.187</b>	81.998	81.998
	500	4.194	4.952	4.128	4.211	81.572	77.493	78.207	80.225
	1000	4.203	5.014	4.212	4.375	77.696	77.268	79.554	79.554
	all	4.582	4.651	4.612	4.640	75.596	76.220	76.850	76.850
Arabic	100	2.316	2.367	2.245	2.289	77.306	<b>76.098</b>	77.161	81.334
	500	2.298	2.365	2.285	2.285	68.804	75.839	68.804	77.468
	1000	2.315	2.362	2.287	2.287	68.066	75.970	68.066	80.260
	all	2.306	2.334	2.300	2.300	66.595	75.794	66.595	75.418
Basque	100	5.932	9.375	5.984	6.544	75.956	77.129	<b>70.290</b>	75.333
	500	6.057	9.307	5.961	7.264	76.300	76.892	<b>65.820</b>	73.121
	1000	6.261	9.271	6.170	7.281	77.129	76.747	<b>68.582</b>	72.586
	all	6.760	8.815	6.760	7.868	75.803	75.280	<b>69.064</b>	73.813
Bulgarian	100	5.103	6.853	<b>5.001</b>	5.596	74.647	<b>67.056</b>	70.861	73.288
	500	5.475	6.800	5.475	5.801	68.576	67.027	66.065	69.021
	1000	5.649	6.785	<b>5.436</b>	5.696	66.059	66.855	<b>63.816</b>	70.386
	all	6.162	6.403	6.162	6.269	66.018	66.303	<b>64.024</b>	67.596
Croatian	100	5.510	4.918	<b>4.475</b>	4.475	75.468	<b>70.636</b>	75.653	80.301
	500	5.336	4.927	<b>4.608</b>	4.608	77.503	<b>70.636</b>	75.561	75.561
	1000	5.454	4.896	4.841	4.841	77.526	<b>70.636</b>	76.069	76.069
	all	5.285	<b>4.897</b>	5.163	5.163	77.919	<b>70.613</b>	77.387	77.387
Czech	100	4.292	5.383	4.232	4.232	77.897	<b>75.731</b>	77.342	77.891
	500	4.482	5.373	4.482	4.518	77.257	75.155	<b>72.426</b>	74.847
	1000	4.530	5.370	4.531	4.548	75.254	75.451	74.346	75.049
	all	5.091	5.087	5.091	5.106	73.849	70.747	71.693	74.949
Danish	100	4.977	4.943	<b>4.662</b>	4.894	78.891	<b>74.299</b>	77.892	77.892
	500	5.033	<b>4.929</b>	5.045	4.963	71.737	74.041	72.430	78.005
	1000	5.189	4.952	<b>4.828</b>	4.828	71.737	73.816	71.737	77.409
	all	5.363	<b>4.864</b>	5.203	5.022	70.674	73.751	<b>69.562</b>	73.284
Dutch	100	6.456	6.777	<b>5.956</b>	5.956	77.525	77.307	76.470	80.807
	500	7.679	<b>6.847</b>	7.232	7.156	75.498	76.888	75.498	78.262
	1000	7.517	<b>6.774</b>	7.107	7.107	73.874	76.218	73.874	78.664
	all	8.025	<b>6.509</b>	8.062	8.062	72.785	73.020	72.098	77.608
English	100	5.203	7.387	5.115	5.444	73.853	<b>70.478</b>	73.956	73.956
	500	5.620	7.391	5.684	5.574	71.729	70.408	70.158	71.483
	1000	5.781	7.337	<b>5.631</b>	5.817	72.716	70.559	69.720	70.180
	all	6.464	6.456	6.681	6.438	67.626	70.754	67.262	71.284
Estonian	100	5.301	7.457	5.140	<b>4.447</b>	50.506	55.934	50.506	56.210
	500	6.108	7.864	<b>5.250</b>	5.250	49.586	53.450	49.770	57.038
	1000	6.605	7.433	<b>6.011</b>	6.374	50.138	52.346	50.138	57.590
	all	6.653	7.287	7.322	<b>6.504</b>	50.046	52.070	50.046	56.210
Finnish	100	5.598	9.683	<b>4.777</b>	4.777	68.774	73.697	68.595	71.606
	500	5.964	9.780	5.731	<b>5.699</b>	67.586	71.407	67.397	69.773
	1000	6.231	9.714	<b>5.920</b>	6.257	66.366	71.125	65.870	67.807
	all	7.709	8.494	<b>7.516</b>	7.672	63.811	66.091	63.558	64.885
French	100	3.744	3.825	3.643	<b>3.540</b>	69.245	<b>62.247</b>	65.787	68.548
	500	3.611	3.821	3.611	3.586	63.669	62.165	61.577	68.617
	1000	3.735	3.911	<b>3.596</b>	3.596	<b>59.787</b>	62.083	61.331	62.739
	all	3.823	3.736	3.800	3.800	<b>59.732</b>	62.097	60.894	64.858
German	100	5.756	5.829	<b>5.392</b>	5.392	78.498	<b>73.685</b>	78.458	80.968
	500	5.960	5.826	5.515	<b>5.496</b>	76.283	<b>73.047</b>	77.176	74.543
	1000	5.722	5.834	<b>5.478</b>	5.540	75.436	73.105	73.958	76.921
	all	6.056	<b>5.651</b>	6.056	6.117	72.554	72.728	72.264	76.979
Gothic	100	6.124	8.230	<b>5.966</b>	5.966	81.109	76.573	76.590	80.082
	500	6.694	8.261	<b>6.539</b>	6.539	76.484	76.077	<b>73.348</b>	76.023
	1000	6.934	8.334	6.876	6.876	75.244	76.147	<b>72.018</b>	75.031
	all	7.777	8.069	<b>7.187</b>	7.551	74.074	75.563	<b>72.391</b>	74.216
Greek	100	4.178	3.971	<b>3.679</b>	3.679	67.287	74.750	67.287	75.038
	500	4.071	3.975	3.961	3.961	66.323	74.344	66.323	75.207
	1000	4.190	3.959	3.997	3.997	66.847	73.549	66.847	72.821
	all	4.110	3.953	3.964	3.964	66.695	73.837	67.203	73.803
Hebrew	100	3.899	3.873	<b>3.736</b>	3.736	72.796	74.897	72.796	75.127
	500	3.928	3.873	3.802	3.802	76.625	<b>74.889</b>	76.625	78.702
	1000	3.904	3.873	3.910	3.910	73.724	74.881	73.724	77.957
	all	4.022	3.870	3.907	3.907	73.359	74.929	73.359	77.172



Language	Training size	Perplexity				Word Error Rate			
		SL	SL bagging	MT-SL	MT-SL no proj.	SL	SL bagging	MT-SL	MT-SL no proj.
Hindi	100	4.167	4.727	4.165	4.164	61.818	70.421	60.942	68.074
	500	4.015	4.713	4.003	4.144	60.958	70.108	60.271	65.886
	1000	4.235	4.709	4.202	4.202	62.850	70.297	<b>61.001</b>	66.746
	all	4.340	4.511	4.344	4.344	59.818	64.019	59.341	62.004
Hungarian	100	5.762	5.190	<b>4.837</b>	4.837	69.368	78.484	69.368	78.764
	500	5.727	5.121	5.136	5.136	68.949	78.589	67.971	78.449
	1000	5.801	5.215	5.118	5.118	<b>68.809</b>	79.008	70.031	76.808
	all	5.592	5.119	5.089	5.089	69.263	79.218	69.752	76.808
Indonesian	100	4.687	4.694	<b>4.248</b>	4.248	74.581	77.790	74.581	76.372
	500	4.630	4.672	<b>4.339</b>	4.339	71.411	78.382	71.411	77.985
	1000	4.601	4.675	4.522	4.522	70.901	78.439	70.901	76.745
	all	4.734	4.626	4.572	4.572	71.160	78.520	71.160	75.902
Irish	100	3.587	3.490	3.431	3.326	67.086	72.400	67.086	73.105
	500	3.548	3.457	3.417	3.417	66.230	72.425	66.230	74.969
	1000	3.594	3.455	3.425	3.425	66.885	72.098	66.885	72.450
	all	3.594	3.455	3.425	3.425	66.885	72.098	66.885	72.450
Italian	100	3.343	3.719	3.359	3.359	64.584	62.215	<b>58.719</b>	72.625
	500	3.450	3.717	<b>3.336</b>	3.336	58.054	62.320	58.054	66.594
	1000	3.466	3.678	3.457	3.457	57.880	61.822	56.962	65.274
	all	3.620	3.542	3.575	3.575	57.574	59.156	57.276	61.183
Japanese	100	2.981	3.492	3.003	3.030	64.651	67.524	64.651	69.963
	500	3.148	3.479	3.094	3.135	60.545	67.971	60.545	64.841
	1000	3.197	3.479	3.114	3.168	61.664	67.021	61.151	61.066
	all	3.196	3.274	3.243	3.243	61.837	66.008	61.837	63.632
Latin	100	4.707	6.542	4.713	4.972	79.580	78.638	<b>75.902</b>	81.986
	500	5.143	6.541	5.143	5.646	76.556	78.468	75.878	79.462
	1000	5.299	6.544	5.269	5.805	75.919	76.517	75.085	78.937
	all	6.241	6.407	6.235	6.526	75.179	77.213	<b>73.198</b>	79.170
Norwegian	100	5.089	6.234	<b>4.929</b>	4.929	74.544	71.695	72.483	72.483
	500	5.164	6.167	5.166	5.166	71.926	71.848	<b>69.965</b>	72.655
	1000	5.235	6.157	5.186	5.281	69.887	71.341	<b>68.836</b>	70.900
	all	5.733	5.800	5.743	5.739	69.487	70.738	<b>68.132</b>	70.550
Old Church Slavonic	100	5.959	10.250	5.894	5.899	74.092	71.735	72.656	75.917
	500	7.172	10.273	7.071	<b>6.934</b>	70.441	71.806	<b>69.360</b>	71.699
	1000	7.765	10.284	7.418	<b>7.374</b>	68.297	72.072	68.138	71.629
	all	8.889	9.712	8.662	<b>8.523</b>	68.067	71.505	68.262	70.370
Persian	100	3.231	3.536	3.158	3.161	67.501	74.311	<b>63.272</b>	70.124
	500	3.256	3.533	3.238	3.286	59.253	74.221	59.199	70.545
	1000	<b>3.274</b>	3.533	3.377	3.377	58.429	73.679	<b>57.328</b>	70.419
	all	3.339	3.523	3.335	3.418	58.164	72.843	<b>56.100</b>	67.585
Polish	100	4.686	10.034	<b>4.387</b>	5.003	65.963	<b>63.220</b>	65.963	68.984
	500	5.288	9.415	<b>5.106</b>	5.352	68.643	<b>62.639</b>	65.950	68.579
	1000	5.466	9.563	<b>5.256</b>	5.666	68.984	<b>62.551</b>	64.800	70.071
	all	6.404	8.088	<b>6.048</b>	6.537	63.802	<b>60.389</b>	63.802	69.742
Portuguese	100	3.761	4.448	<b>3.631</b>	3.827	74.216	<b>63.704</b>	73.696	74.427
	500	3.988	4.387	3.940	4.104	69.862	<b>63.477</b>	67.116	73.534
	1000	4.059	4.393	4.016	4.094	68.952	<b>63.656</b>	67.295	67.295
	all	4.288	4.382	<b>4.113</b>	4.195	68.757	<b>63.672</b>	65.053	67.912
Romanian	100	7.269	5.970	<b>5.401</b>	5.401	71.105	73.095	71.311	74.674
	500	7.269	5.961	5.936	5.936	<b>69.526</b>	74.262	70.899	80.851
	1000	7.269	5.961	5.936	5.936	<b>69.526</b>	74.262	70.899	80.851
	all	7.269	5.961	5.936	5.936	<b>69.526</b>	74.262	70.899	80.851
Slovenian	100	5.156	5.277	<b>4.600</b>	4.600	81.297	69.696	69.932	78.153
	500	5.429	5.267	<b>5.026</b>	5.026	71.231	<b>69.945</b>	71.231	76.920
	1000	5.387	5.289	<b>5.055</b>	5.055	71.588	69.629	69.804	72.713
	all	5.605	5.222	5.300	5.300	70.875	67.939	66.949	73.850
Spanish	100	3.109	3.079	3.015	3.015	67.607	<b>64.045</b>	67.607	68.688
	500	3.114	3.082	3.034	3.034	67.898	<b>62.380</b>	67.898	69.199
	1000	3.166	3.079	3.083	3.083	64.750	63.583	64.446	63.899
	all	3.265	3.062	3.140	3.140	64.702	<b>61.213</b>	62.514	62.514
Swedish	100	5.184	5.773	<b>5.009</b>	5.009	72.166	<b>68.119</b>	72.166	77.417
	500	5.379	5.708	<b>5.225</b>	5.225	70.268	<b>68.360</b>	70.268	76.056
	1000	5.482	5.773	<b>5.277</b>	5.277	68.971	68.286	<b>67.230</b>	75.218
	all	5.737	5.669	<b>5.558</b>	5.558	68.878	67.425	66.619	74.935
Tamil	100	8.289	6.988	<b>6.334</b>	6.334	66.999	76.339	66.098	78.284
	500	8.305	6.719	<b>6.205</b>	6.205	66.524	76.766	67.330	72.072
	1000	8.305	6.719	<b>6.205</b>	6.205	66.524	76.766	67.330	72.072
	all	8.305	6.719	<b>6.205</b>	6.205	66.524	76.766	67.330	72.072

Target task	4 closest tasks w.r.t. subspace distance (closest first)			
Ancient Greek	Old Church Slavonic	Latin	Gothic	Hungarian
Arabic	Czech	Polish	Persian	Slovenian
Basque	Finnish	Polish	Czech	Indonesian
Bulgarian	Czech	Norwegian	Finnish	Slovenian
Croatian	Estonian	Slovenian	Czech	Finnish
Czech	Finnish	Norwegian	Bulgarian	Danish
Danish	Norwegian	Swedish	English	Czech
Dutch	German	Norwegian	Danish	English
English	Norwegian	Danish	Italian	Swedish
Estonian	Finnish	Swedish	Norwegian	Polish
Finnish	Estonian	Czech	Swedish	Norwegian
French	Italian	Spanish	German	English
German	Dutch	Swedish	English	French
Gothic	Old Church Slavonic	Latin	Ancient Greek	Finnish
Greek	Swedish	Spanish	Czech	German
Hebrew	Portuguese	Norwegian	Czech	Danish
Hindi	Japanese	Croatian	Tamil	Persian
Hungarian	Danish	Ancient Greek	German	Portuguese
Indonesian	Finnish	Czech	Bulgarian	Norwegian
Irish	Polish	Czech	Greek	Arabic
Italian	English	French	Spanish	Dutch
Japanese	Hindi	Persian	Arabic	Tamil
Latin	Old Church Slavonic	Ancient Greek	Gothic	Finnish
Norwegian	Danish	English	Swedish	Czech
Old Church Slavonic	Latin	Gothic	Ancient Greek	Finnish
Persian	Japanese	Czech	Swedish	Finnish
Polish	Slovenian	Czech	Finnish	Estonian
Portuguese	Hebrew	Norwegian	Italian	Danish
Romanian	Finnish	Estonian	Norwegian	Czech
Slovenian	Polish	Czech	Danish	Swedish
Spanish	French	Italian	Portuguese	Greek
Swedish	Danish	Norwegian	Finnish	Estonian
Tamil	Finnish	Indonesian	Basque	Croatian

Table 3: Related tasks used in the UNIDEP experiment. The 4 closest tasks were selected using subspace distance (i.e. Frobenius norm of the difference between the orthogonal projection matrices) between the space spanned by the top 50 left singular vectors of their Hankel matrices. The common basis of prefixes/suffixes ( $\mathcal{P}, \mathcal{S}$ ) for these Hankel matrices was obtained by taking the union of the 100 most frequent prefixes/suffixes for each task.