AUTO-ENCODING VARIATIONAL NEURAL MACHINE TRANSLATION

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ABSTRACT

We present a deep generative model of bilingual sentence pairs. The model generates source and target sentences jointly from a shared latent representation and is parameterised by neural networks. Efficient training is done by amortised variational inference and reparameterised gradients. Additionally, we discuss the statistical implications of joint modelling and propose an efficient approximation to maximum a posteriori decoding for fast test-time predictions. We demonstrate the effectiveness of our model in three machine translation scenarios: in-domain training, mixed-domain training, and learning from a mix of gold-standard and synthetic data. Our experiments show consistently that our joint formulation outperforms conditional modelling in all such scenarios.

1 INTRODUCTION

Neural machine translation (NMT) systems (Kalchbrenner & Blunsom, 2013; Sutskever et al., 2014; Cho et al., 2014b) require vast amounts of labelled data, i.e. bilingual sentence pairs, to be trained effectively. Often times, the data we use to train these systems are a byproduct of mixing different sources of data. For example, labelled data are sometimes obtained by putting together corpora from different domains (Sennrich et al., 2017). Even for a single domain, parallel data sometimes result from the combination of documents independently translated from different languages by different people or agencies, possibly following different guidelines. When resources are scarce, it is not uncommon to mix in some synthetic data, e.g. bilingual data artificially obtained by having a model translate target monolingual data to the source language (Sennrich et al., 2016a). Translation direction, original language, and quality of translation are some of the many factors that we typically choose not to control for (due to lack of information or simply for convenience). All those arguably contribute to making our labelled data a mixture of samples from various data distributions.

Regular NMT systems do not explicitly account for latent factors of variation, instead, given a source sentence, NMT models a single conditional distribution over target sentences as a fully supervised problem. In this work, we introduce a deep generative model that generates source and target sentences jointly from a shared latent representation. The model has the potential to use the latent representation to capture global aspects of the observations, such as some of the latent factors of variation just discussed. The result is a model that accommodates members of a larger class of marginal distributions. Due to the presence of latent variables, this model requires posterior inference, in particular, we employ the framework of amortised variational inference (Kingma & Welling, 2014; Rezende et al., 2014). Additionally, we propose an efficient approximation to maximum a posteriori (MAP) decoding for fast test-time predictions.

Contributions In §3 we introduce a deep generative auto-encoder for neural machine translation and discuss theoretical advantages of joint modelling over conditional modelling. We also derive an efficient approximation to MAP decoding that requires a single forward pass through the network for prediction. Finally, we show in §4 that our proposed model improves translation performance in

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1 Also note that this list is by no means exhaustive. For example, Rabinovich et al. (2017) show influence of factors such as personal traits and demographics in translation. Another clear case is presented by Johnson et al. (2017), who combine parallel resources for multiple languages to train a single encoder-decoder architecture.
at least three practical scenarios: i) in-domain training on little data, where test data are expected to follow the training data distribution closely; ii) mixed-domain training, where we attempt adaptation to two domains at once; and iii) learning from large noisy synthetic data.

**Notation** We use capital Roman letters for random variables, e.g. $Z$, and their lowercase variants for assignments, e.g. $z$. Our observations $x = \langle x_1, \ldots, x_m \rangle$ and $y = \langle y_1, \ldots, y_n \rangle$ are outcomes of random sequences whose lengths we denote by $|x|$ and $|y|$, respectively. We use the shorthand $x_{<i}$ to denote a prefix sequence, which is empty if $i \leq 1$. For probability mass functions we will use uppercase $P(\cdot)$, and for probability density functions we will use lowercase $p(\cdot)$. Dependency on deterministic parameters $\theta$ is explicitly denoted by $p(\cdot|\theta)$ or the shorthand $p_\theta(\cdot)$. We reserve boldface symbols (e.g. $h$, $W$) for deterministic vectors and matrices. Finally, we use $\odot$ to denote elementwise multiplication.

## 2 Neural Machine Translation

In neural machine translation, the likelihood of a target sentence $y$ given a source sentence $x$

$$P(y|x, \theta) = \prod_{j=1}^{\lfloor |y| / |z| \rfloor} P(y_j|x, y_{<j}, \theta)$$  \hspace{1cm} (1a)

$$= \prod_{j=1}^{\lfloor |y| / |z| \rfloor} \text{Cat}(y_j|f_\theta(x, y_{<j}))$$  \hspace{1cm} (1b)

factorises without Markov assumptions (Sutskever et al., 2014; Bahdanau et al., 2015; Cho et al., 2014a). We have a fixed parameterised function, i.e. a neural network architecture, compute the categorical parameters for varying inputs, namely, source sentence and target prefix.

Given a dataset $D$ of i.i.d. observations, the parameters of the model, in this case the parameters $\theta$ of $f$, are point-estimated to attain a local maximum of the log-likelihood function

$$\mathcal{L}(\theta|D) = \sum_{(x,y) \in D} \sum_{j=1}^{\lfloor |y| / |z| \rfloor} \log P(y_j|x, y_{<j}, \theta)$$  \hspace{1cm} (2)

via stochastic gradient-based optimisation (Robbins & Monro, 1951; Bottou & Cun, 2004).

In this work, $f_\theta$ is a fairly standard recurrent encoder-decoder architecture (Bahdanau et al., 2015; Luong et al., 2015), but other designs (Gehring et al., 2017; Vaswani et al., 2017) are equally applicable.

**Predictions** For a trained model, predictions are performed by searching for the target sentence $y$ that maximises the conditional $P(y|x)$, or equivalently its logarithm, with a greedy algorithm

$$\arg \max_y \log P(y|x, \theta) \approx \text{greedy } \log P(y|x, \theta)$$  \hspace{1cm} (3)

such as beam-search (Sutskever et al., 2014), possibly aided by a manually tuned length penalty or reward to compensate for lack of an explicit length model. This decision rule is often referred to as MAP decoding (Smith, 2011).

## 3 Auto-Encoding Variational NMT

To account for a latent space where global features of observations can be captured, we introduce a random sentence embedding $Z$ and model the joint distribution over observations as a marginal of $p(z, x, y|\theta) = p(z)P(x, y|z, \theta)$. That is, $(x, y) \in D$ is assumed to be sampled from the marginal distribution

$$P(x, y|\theta) = \int p(z)P(x, y|z, \theta)dz$$  \hspace{1cm} (4)
We impose a standard Gaussian prior on the latent space, i.e. \( Z \sim \mathcal{N}(0, I) \), and given a sentence embedding \( z \in \mathbb{R}^d \), the joint likelihood factorises as

\[
P(x, y|z; \theta) = \prod_{i=1}^{|x|} P(x_i|z, x_{<i}, \theta) \prod_{j=1}^{|y|} P(y_j|z, x, y_{<j}, \theta)
\]

\[
= \prod_{i=1}^{|x|} \text{Cat}(x_i|\alpha \theta (z, x_{<i})) \prod_{j=1}^{|y|} \text{Cat}(y_j|\beta \theta (z, x, y_{<j}))
\]

where the source is generated first conditioned on \( z \), and then the target is generated conditioned on the source and \( z \). Note that the source sentence is generated without Markov assumptions by drawing one word at a time from a categorical distribution parameterised by a recurrent neural network. The target sentence is generated similarly by drawing target words in context from a categorical distribution parameterised by a sequence-to-sequence architecture. This essentially combines a neural language model (Mikolov et al., 2010) and a neural translation model (§2), each extended to condition on an additional stochastic input, namely, \( z \).

**Statistical considerations** Modelling the conditional directly, as in standard NMT, corresponds to the statistical assumption that the *distribution* over source sentences can provide no information about the conditional distribution over target sentences given a source. In other words, conditional NMT assumes independence of \( \beta \) determining \( P(y|x, \beta) \) and \( \alpha \) determining \( P(x|\alpha) \). Scenarios where this assumption is unlikely to hold are not too uncommon: consider a situation where \( x \) is noisy (e.g. synthetic or crowdsourced), then poor quality \( x \) should be assigned low probability \( P(x|\alpha) \) which in turn should inform the conditional. Implications of this assumption extend to parameter estimation: the parameter updates for the conditional are not sensitive to how exotic \( x \) is.

Let us be a bit more explicit about how we parameterise our model by identifying 3 sets of parameters \( \theta = \{ \theta_{\text{emb-x}}, \theta_{\text{LM}}, \theta_{\text{TM}} \} \), where \( \theta_{\text{emb-x}} \) parameterises an embedding layer for the source language. The embedding layer is shared between the two model components

\[
P(x, y|z; \theta) = P(x|z, \theta_{\text{emb-x}}, \theta_{\text{LM}}) P(y|x, z, \theta_{\text{emb-x}}, \theta_{\text{TM}})
\]

and it is then clear by inspection that \( \alpha \cap \beta = \{ z, \theta_{\text{emb-x}} \} \). In words, we break the independence assumption in two ways, namely, by having the two distributions share parameters and by having them depend on a shared latent sentence representation \( z \). Note that while the embedding layer is deterministic and local to all sentence pairs in the training data, the latent representation is stochastic and local to each sentence pair.

**Parameter estimation** The marginal in Equation (4) is clearly intractable, thus precluding maximum likelihood estimation. Instead, we resort to variational inference (Jordan et al., 1999; Blei et al., 2017) and introduce a variational approximation \( q(z|x, y, \lambda) \) to the intractable posterior \( p(z|x, y, \theta) \). We let the approximate posterior be Gaussian with diagonal covariance

\[
Z|\lambda, x, y \sim \mathcal{N}(\mu(x, y), \text{diag}(\sigma(x, y)))
\]

\[
\mu = \mu_\lambda(x, y)
\]

\[
\sigma = \sigma_\lambda(x, y)
\]

and predict its parameters (i.e. \( \mu \in \mathbb{R}^d, \sigma \in \mathbb{R}_+^d \)) with neural networks whose parameters we denote by \( \lambda \). This makes the model an instance of a variational auto-encoder (Kingma & Welling, 2014).

We can then jointly estimate the parameters of both models (generative \( \theta \) and inference \( \lambda \)) by maximising the ELBO (Jordan et al., 1999), a lowerbound on the marginal log-likelihood,

\[
\log P(x, y|\theta) \geq \mathbb{E}_{q(z|x, y, \lambda)} \left[ \log P(x, y|Z = \mu + \sigma \circ s, \theta) \right] - KL(\mathcal{N}(z|\mu, \text{diag}(\sigma \circ s))|\mathcal{N}(z|0, I))
\]

where we have expressed the expectation with respect to a fixed distribution—a reparameterisation available to location-scale families such as the Gaussian distribution (Kingma & Welling, 2014; Rezende et al., 2014). Due to this reparameterisation, we can compute a Monte Carlo estimate of the gradient of the first term via back-propagation (Rumelhart et al., 1986; Schulman et al., 2015). As we have a Gaussian prior and a Gaussian approximate posterior we can compute the KL divergence in closed form (Kingma & Welling, 2014, see Appendix B).
Predictions. In this case, MAP decoding requires searching through the marginal distribution (9a), where the equality holds because $x$ is constant. In addition to approximating the $\arg \max$ with a greedy algorithm, a number of other approximations are necessary to make sure prediction times are not orders of magnitude worse than that of a conditional model. First, rather than searching through the true marginal, we search through the lowerbound (9b). Second, we replace the approximate posterior by an auxiliary distribution $r(z|x)$ which conditions on the source alone (9c). This circumvents the combinatorial explosion due to conditioning on the target and allows us to drop all terms that depend on $x$ alone (9d). Finally, instead of approximating the expectation via MC sampling, we search through the conditional in (9e), where we condition on the expected latent representation.

\[
\arg \max_y \log P(y|x) = \arg \max_y \log P(y, x) = \arg \max_y \log P(y, x) - \text{KL}(q(z|x, y) || p(z)) \quad (9a)
\]

\[
\approx \arg \max_y \mathbb{E}_{q(z|x, y)}[\log P(y, x|Z)] - \text{KL}(q(z|x, y) || p(z)) \quad (9b)
\]

\[
\approx \arg \max_y \mathbb{E}_{z|x}[\log P(y|Z, x) + \log P(x|Z)] - \text{KL}(r(z|x) || p(z)) \quad (9c)
\]

\[
= \arg \max_y \mathbb{E}_{z|x}[\log P(y|Z, x)] \quad (9d)
\]

\[
\approx \arg \max_y \log P(y|\mathbb{E}_{r(z|x)}[Z], x) \quad (9e)
\]

Together, these approximations enable prediction with a single call to an $\arg \max$ solver. For this we employ a standard greedy search algorithm which leads to prediction times that are very close to that of the conditional model (on GPUs, the added computations have a negligible cost). Obviously we employ a standard greedy search algorithm which leads to prediction times that are very close to this is a decoding heuristic which offers no guarantees. Nevertheless, the derivation clearly suggests how to obtain an auxiliary distribution $r(z|x)$, namely, it should approximate $q(z|x, y)$ closely.

To learn a good auxiliary distribution $r_\phi(z|x)$, we parameterise it by a neural network architecture and investigate different options to estimate its parameters $\phi$. As a first option, we restrict the approximate posterior to conditioning on $x$ alone, i.e. we approach posterior inference with $q_\lambda(z|x)$ rather than $q_\lambda(z|x, y)$, and thus, we can use $r_\phi = q_\lambda$ for prediction. This has the benefit of being very simple and requiring no additional resources, but it does limit the context available for posterior inference. As a second option we make $r_\phi(z|x) = \mathcal{N}(z|\mu_\phi(x), \sigma_\phi(x)^2)$ and estimate parameters $\phi$ to make $r_\phi(z|x)$ close to the approximate posterior $q_\lambda(z|x, y)$ as measured by a divergence $D(r_\phi, q_\lambda)$. For as long as $D(r_\phi, q_\lambda) \in \mathbb{R}_{>0}$ for every choice of $\phi$ and $\lambda$, we can estimate $\phi$ jointly with $\theta$ and $\lambda$ by maximising a modified ELBO

\[
\log P(x, y|\theta) \geq \text{ELBO}(\theta, \lambda|x, y) - D(r_\phi, q_\lambda) \quad (10)
\]

where the resulting bound is loosened by the gap between $r_\phi$ and $q_\lambda$. In experiments we investigate a few options for $D(r_\phi, q_\lambda)$ such as $\text{KL}(r_\phi || q_\lambda)$, $\text{KL}(q_\lambda || r_\phi)$, as well as $\text{JS}(r_\phi || q_\lambda) = 0.5 \text{KL}(r_\phi || q_\lambda) + 0.5 \text{KL}(q_\lambda || r_\phi)$. Note that these divergences can be computed in closed form for Gaussians.

Note that $r_\phi$ is used only for prediction as a decoding heuristic and as such need not be stochastic. We can, for example, design $r_\phi(x)$ to be a point estimate of the posterior mean and optimise

\[
\log P(x, y|\theta) \geq \text{ELBO}(\theta, \lambda|x, y) - \|r_\phi(x) - \mathbb{E}_{q_\lambda(z|x, y)}[Z]\|^2_2 \quad (11)
\]

which remains a lowerbound on log-likelihood. Though note that training a distribution, rather than a point estimate, has the advantage that the model can be used at test time both to approximate 1-best prediction and for sampling.

4 Experiments

We investigate two translation tasks, namely, WMT’s translation of news (Bojar et al., 2016) and IWSLT’s translation of transcripts of TED talks (Cettolo et al., 2014), and concentrate on translations for German (De) and English (En) in either direction. In this section we aim to investigate our models in scenarios where we expect observations to be representative of various data distributions. As a sanity check, we start with a scenario where training conditions can be considered in-domain
We then mix datasets from these two remarkably different translation tasks and investigate whether translation performance can be improved across tasks with a single model. Finally, we investigate the case where we learn from synthetic data in addition to gold-standard data. For this investigation we derive synthetic data from observations that are close to the domain of the test set in an attempt to avoid further confounders.

Data  For bilingual data we use News Commentary (NC) v12 (Bojar et al., 2017) and IWSLT 2014 (Cettolo et al., 2014), where we assume NC to be representative of the test domain of the WMT News task. The datasets consist of 255,591 training sentences and 153,326 training sentences respectively. In experiments with synthetic data, we subsample $10^9$ sentences from the News Crawl 2016 articles (Bojar et al., 2017) for either German or English depending on the target language. For the WMT task, we concatenate newstest2014 and newstest2015 for validation/development (5,172 sentence pairs) and report test results on newstest2016 (2,999 sentence pairs). For IWSLT, we use the split proposed by Ranzato et al. (2016) who separated 6,969 training instances for validation/development and reported test results on a concatenation of dev2010, dev2012 and tst2010-2012 (6,750 sentence pairs).

Pre-processing  We tokenized and truecased all data using standard scripts from the Moses toolkit (Koehn et al., 2007), and removed sentences longer than 50 tokens. For computational efficiency and to avoid problems with closed vocabularies, we segment the data using BPE (Sennrich et al., 2016b) with 32,000 merge operations independently for each language. For training the truecaser and the BPEs we used a concatenation of all the available bilingual and monolingual data for German and all bilingual data for English.

Systems  We develop all of our models on top of Tensorflow NMT (Luong et al., 2017). Our baseline system is a standard implementation of CONDITIONAL NMT (Bahdanau et al., 2015). To illustrate the importance of latent variable modelling, we also include in the comparison a simpler attempt at JOINT modelling where we do not induce a shared latent space. Instead, the model is trained in a fully-supervised manner to maximise what is essentially a combination of two nearly independent objectives,

$$
\mathcal{L}(\theta|D) = \sum_{(x,y) \in D} \sum_{i=1}^{(|x|)} \log P(x_i|x_{<i}, \theta_{emb-s}, \theta_{LM}) + \sum_{j=1}^{(|y|)} \log P(y_j|x, y_{<j}, \theta_{emb-s}, \theta_{TM}),
$$

namely, a language model and a conditional translation model. Note that the two components of the model share very little, i.e. an embedding layer for the source language. Finally, we aim at investigating the effectiveness of our auto-encoding variational NMT (AEVNMT). Appendix A contains a detailed description of the architectures that parameterise our systems.

Hyperparameters  All recurrent cells in this work are 256-dimensional GRU units (Cho et al., 2014b). We use Adam (Kingma & Ba, 2015) for optimisation with learning rate $3 \times 10^{-4}$. We train on batches of 64 sentence pairs for at least 10 updates and then perform convergence checks every 500 batches, where we stop after 20 checks without any improvement—which we measure in terms of BLEU (Papineni et al., 2002). For in-domain training we set $T = 140,000$, and for mixed-domain training, as well as training with synthetic data, we set $T = 280,000$. For decoding we use a beam width of 10 and a length penalty of 1.0.

We investigate the use of dropout (Srivastava et al., 2014) in recurrent layers, we tested the conditional baseline with rates from 10% to 60% in increments of 10%. We did so independently for each dataset and translation direction and found that, for best validation performance, WMT requires 40% for EN-DE and 50% for DE-EN, and that IWSLT requires 50% for either translation direction. To spare resources, we use these rates also for training the simple JOINT model.

Avoiding collapsing to prior  Many have noticed that VAEs whose observation models are parameterised by strong generators, such as recurrent neural networks, learn to ignore the latent representation (Bowman et al., 2016; Higgins et al., 2017; Sønderby et al., 2016; Alemi et al., 2018).

Note that this does not preclude the potential for appreciable variability in observations as various other latent factors of variation still likely play a role (see §1).

\footnote{AEVNMT and baselines available from \url{github.com/Roxot/AEVNMT}.}
In such cases, the approximate posterior “collapses” to the prior, and where one has a fixed prior, such as our standard Gaussian, this means that the posterior becomes independent of the data, which is obviously not desirable. Bowman et al. (2016) proposed two techniques to counter this effect, namely, “KL annealing”, and target word dropout. KL annealing consists in incorporating the KL term of Equation (8) into the objective gradually, thus allowing the posterior to move away from the prior more freely at early stages of training. After a number of annealing steps, the KL term is incorporated in full and training continues with the actual ELBO. In our search we considered annealing for 20,000 to 80,000 training steps. Word dropout consists in randomly masking words in observed target prefixes at a given rate. The idea is to harm the potential of the decoder to capitalise on correlations internal to the structure of the observation. With a weaker encoder, the model tends to rely more on the latent representation. We considered rates from 20% to 40% in increments of 10%. Table 1 shows the configurations that achieve best validation results on EN-DE. To spare resources, we reuse these hyperparameters for DE-EN experiments.4

|                   | NC   | IWSLT |
|-------------------|------|-------|
| Dropout           | 30%  | 30%   |
| Word dropout rate | 10%  | 20%   |
| KL annealing steps| 80,000| 80,000|

Table 1: Strategies to promote better use of the latent representation along with the validation KL achieved at the end of training.

**ELBO variants** We investigate the effect of conditioning on target observations for training against a simpler variant that conditions on the source alone. Recall that conditioning on the target for training requires learning an approximation \( r_\phi \) that conditions on the source alone in order to circumvent combinatorial explosion for predictions with beam-search. Table 2 shows EN-DE validation results for training on NC, where ELBO\( _x \) corresponds to the case where we omit the target sentence for training. Results suggest that conditioning on \( x \) is sufficient and thus we opt to continue with this simpler version.5

| Objective                        | NC   |
|----------------------------------|------|
| \( \text{ELBO}_{x,y} - KL(r_\phi(z|x)||q_\lambda(z|x,y)) \) | 14.7 |
| \( \text{ELBO}_{x,y} - KL(q_\lambda(z|x,y)||r_\phi(z|x)) \) | 14.8 |
| \( \text{ELBO}_{x,y} - JS(r_\phi(z|x)||q_\lambda(z|x,y)) \) | 14.9 |
| \( \text{ELBO}_{x,y} - ||r_\phi(x) - E_{q_\lambda(z|x,y)}[Z]||^2_2 \) | 14.8 |
| \( \text{ELBO}_x \)               | 14.9 |

Table 2: EN-DE validation results. ELBO\( _x \) means we condition on the source alone for posterior inference, i.e. the variational approximation \( q(z|x^n) \) is used for training and for predictions. In all other cases, we condition on both observations for training, i.e. \( q(z|x^n, y^n) \), and train either a distribution \( r(z|x^n) \) or a point estimate \( r(x^n) \) for predictions.

### 4.1 Results

In this section we report test results in terms of BLEU (Papineni et al., 2002) and BEER (Stanojević & Sima’an, 2014), but in Appendix C we additionally report METEOR.

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4We did not perform a full grid search for hyperparameter values. Instead, we first searched for good values of each hyperparameter independently, and then defined a small grid, with the two best options for each hyperparameter, which we searched through.

5Note that with \( r_\phi \) we have additional parameters to estimate (e.g. a bidirectional encoder and a couple of dense layers), thus it may be the case that these variants require prolonged training.
(Denkowski & Lavie, 2011) and TER (Snover et al., 2006). In Appendix B we report validation results, in this case in terms of BLEU alone as that is what we used for model selection.

We start with the case where we can reasonably assume training data to be in-domain with respect to test data. Table 3 shows in-domain training performance for IWSLT. First, we remark that our conditional baseline matches an external baseline trained on the same data (Bahdanau et al., 2016). The results suggest a clear benefit from joint modelling and in particular from doing so with a shared latent space. Table 4 shows performance for NC, where BLEU shows a similar trend, namely, joint modelling with a shared latent space (AEVNMT) outperforms both conditional modelling and the simple joint model. BEER tells a different story, however.

| IWSLT14     | EN-DE       | DE-EN       |
|-------------|-------------|-------------|
|             | BLEU ↑ BEER ↑ | BLEU ↑ BEER ↑ |
| Conditional | 23.4 59.1   | 28.7 60.6   |
| Joint       | 23.6 59.2   | 28.7 60.6   |
| AEVNMT      | 23.9 59.4   | 29.3 61.0   |

Table 3: Test results for in-domain training on IWSLT.

| WMT16       | EN-DE       | DE-EN       |
|-------------|-------------|-------------|
|             | BLEU ↑ BEER ↑ | BLEU ↑ BEER ↑ |
| Conditional | 17.7 53.5   | 20.5 54.3   |
| Joint       | 18.0 53.8   | 20.5 54.2   |
| AEVNMT      | 18.4 53.7   | 20.8 54.1   |

Table 4: Test results for in-domain training on NC.

We now consider the scenario where we know for a fact that observations come from two different data distributions, which we realise by training our models on a concatenation of IWSLT and NC data. Our setup is similar to that of “adapting to all domains at once”, that is, we perform model selection once on the concatenation of both development sets and evaluate the same model on each domain separately. Results are shown in Table 5 for EN-DE and in Table 6 for DE-EN. Here we omit JOINT as it was never better than AEVNMT. Once more in all but one comparison our AEVNMT outperforms the conditional baseline, and now also in terms of BEER.

WMT test sets are typically evaluated with models trained on much more bilingual data than our NC models. To improve our models we capitalise on the abundance of monolingual data and train on a concatenation of NC gold-standard data and synthetic bilingual data derived from monolingual News Crawl via the back-translation heuristic (Sennrich et al., 2016a). Table 7 shows results for both baselines and AEVNMT. First, note that synthetic data greatly improves the conditional baseline, in particular translating into English. Finally, once again AEVNMT consistently outperforms conditional modelling and joint modelling without latent variables.

5 RELATED WORK

Joint modelling Concurrently to our work, Shah & Barber (2018) propose a joint generative model whose probabilistic formulation is essentially identical to ours. Besides some small differences in architecture, our work differs in two regards: motivation and strategy for predictions. Their goal is to put together bilingual corpora for various language pairs, as parameter sharing has been shown to somewhat balance availability of resources (Johnson et al., 2017). Their strategy for prediction is based on a form of stochastic hill-climbing, where they sample an initial $z$.
from the standard Gaussian prior and decode via beam search in order to obtain a draft translation $\tilde{y} = \text{greedy}_y P(y|z, x)$. From there, this translation is iteratively refined by encoding the pair $(x, \tilde{y})$, re-sampling $z$ this time from $q(z|x, \tilde{y})$, and re-decoding with beam search. Note that unlike our approach, this requires multiple calls to the inference network and to beam search. Moreover, the inference model, which is trained on gold-standard observations, is used on noisy target sentences for prediction.

Cotterell & Kreutzer (2018) interpret back-translation as a single iteration of a wake-sleep algorithm (Hinton et al., 1995) for a joint generative model of bitext $P(x, y|\theta) = P(y|x, \theta)P_\star(x)$. In their formulation, there is no parameterised distribution over source sentences, instead they sample directly from the data distribution $P_\star(x)$ and learn two conditionals NMT models, namely, a generative $P(y|x, \theta)$ and an auxiliary model $Q(x|y, \phi)$ that operates in target-to-source direction. Parameter estimation uses a separate objective for each conditional. In this particular instance, joint modelling happens without induction of a shared latent space.

In an attempt to make use of monolingual data for both source and target languages, Zhang et al. (2018) propose a joint model of bitext trained in a way as to incorporate the back-translation heuristic as a trainable component. Their formulation is similar to that of Cotterell & Kreutzer (2018), but in justifying their objectives they do not make the connection to the wake-sleep algorithm as explicit. Again, joint modelling is achieved without explicitly modelling a shared latent space and without directly modelling a distribution over source sentences.

Multi-task learning An alternative to joint learning is to turn to multi-task learning and explore parameter sharing across models trained on different, though related, data with different objectives. For example, Cheng et al. (2016) incorporate both source and target monolingual data by multi-tasking with a non-differentiable auto-encoding objective. They jointly train a source-to-target and

| Training          | Model        | WMT16 | IWSLT14 |
|-------------------|--------------|-------|---------|
| EN-DE             |              |       |         |
| Training Model    | BLEU ↑       | BEER ↑| BLEU ↑  | BEER ↑ |
| In-Domain         | CONDITIONAL  | 17.7  | 53.5    | 23.4   | 59.1   |
| AEVNMT            | 18.4         | 53.7  | 23.9    | 59.4   |
| Mixed-Domain      | CONDITIONAL  | 17.3  | 54.2    | 24.1   | 59.7   |
| AEVNMT            | 18.6         | 55.1  | 24.2    | 59.8   |

Table 5: EN-DE test results for mixed-domain training. In-domain results copied from Tables 3 and 4 for comparison.

| Training          | Model        | WMT16 | IWSLT14 |
|-------------------|--------------|-------|---------|
| DE-EN             |              |       |         |
| Training Model    | BLEU ↑       | BEER ↑| BLEU ↑  | BEER ↑ |
| In-Domain         | CONDITIONAL  | 20.5  | 54.3    | 28.7   | 60.6   |
| AEVNMT            | 20.8         | 54.1  | 29.3    | 61.0   |
| Mixed-Domain      | CONDITIONAL  | 22.2  | 55.7    | 30.6   | 61.8   |
| AEVNMT            | 22.7         | 56.2  | 30.5    | 61.9   |

Table 6: DE-EN test results for mixed-domain training. In-domain results copied from Tables 3 and 4 for comparison.

| Training          | Model        | WMT16 |         | IWSLT14 |         |
|-------------------|--------------|-------|---------|---------|---------|
| EN-DE             |              |       |         |         |         |
| + synthetic data  | CONDITIONAL  | 17.7  | 53.5    | 20.5    | 54.3    |
|                   | 22.3         | 57.4  | 27.0    | 59.0    |
| JOINT + synthetic data | CONDITIONAL | 22.3  | 57.5    | 27.2    | 59.1    |
|                   | 22.6         | 57.6  | 27.9    | 59.3    |

Table 7: Test results for training on NC plus synthetic data (back-translated News Crawl).
target-to-source system that act as encoder and decoder respectively. Zhang & Zong (2016) combine a source language model objective with a source-to-target conditional NMT objective and shared the source encoder in a multi-task learning fashion. Note that in both cases there is no shared latent space.

**Variational NMT**  
Zhang et al. (2016) proposed the first VAE model for NMT. They augment the conditional with a Gaussian distributed sentence embedding \( P(y, z|x, \theta) \) and model the observations as draws from the marginal \( P(y|x, \theta) = \int p(z|x, \theta) P(y|x, z, \theta) dz \). This makes their formulation a conditional deep generative model (Sohn et al., 2015), where, rather than a fixed standard Gaussian, the latent model is itself parameterised and depends on the data. Schulz et al. (2018) extend the model of Zhang et al. (2016) with a Markov chain of latent variables, one per timestep, allowing the model to capture greater variability as well as more complex conditionals.

**Domain adaptation**  
In our experiments we explore applications related to domain adaptation because we feel that is a natural use of a latent variable model such as ours. However, one should be aware that there is a vast literature on domain adaptation for statistical machine translation (Cuong & Sima’an, 2017), as well as for NMT (Chu & Wang, 2018). A full characterisation of this exciting field is beyond the scope of this paper.

## 6 Discussion and Future Work

We have presented a joint generative model of translation data that generates both observations conditioned on a shared latent Gaussian representation. Our formulation leads to questions such as why joint learning? and why latent variable modelling? to which we give a statistical answer and empirical evidence of superior performance. We have started to investigate what information the latent representation encodes. To diagnose that we have been exploring the idea of training simple linear probes (Alain & Bengio, 2017). With simple linear models we have managed to predict from \( Z \sim q(z|x, y) \) domain indicators (WMT vs IWSLT) and gold-standard vs synthetic data at performance above 90% accuracy on development set. However, a similar performance is achieved from the deterministic average state of the bidirectional encoder of the conditional baseline. We have also been able to predict from \( Z \sim q(z|x, y) \) the level of noise in back-translated data, measured on the dev set at the sentence level by an automatic metric such as METEOR, with performance above what can be done with random features. Though again, the performance is not much better than what can be done with a conditional baseline. Still, it is worth highlighting that these aspects are rather coarse, and it is possible that the performance gains we report in §4 are due to far more nuanced variations in the data. At this point, however, we do not have a good qualitative assessment of this conjecture. In future work, we shall investigate datasets annotated with demographics and personal traits in an attempt to assess how far we can go in capturing fine grained variation. Though note that if such factors of variation vary widely in distribution, it may be naïve to expect we can model them well with a simple Gaussian prior. If that turns out to be the case, we will investigate mixing Gaussian components (Miao et al., 2016; Srivastava & Sutton, 2017) and/or employing a hierarchical prior (Goyal et al., 2017).

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A ARCHITECTURES

Here we describe parameterisation of the different models presented in §3. Rather than completely specifying standard blocks, we use the notation block(inputs; parameters), where we give an indication of the relevant parameter set. This makes it easier to visually track which model a component belongs to.

A.1 SOURCE LANGUAGE MODEL

The source language model consists of a sequence of categorical draws for \(i = 1, \ldots, |x|\)

\[
X_i \mid z, x_{<i} \sim \text{Cat}(g_\theta(z, x_{<i})))
\] (13)

parameterised by a single-layer recurrent neural network using GRU units.

\[
f_i = \text{emb}(x_i; \theta_{\text{emb-x}})
\] (14a)

\[
h_0 = \tanh(\text{affine}(z; \theta_{\text{init-lm}}))
\] (14b)

\[
h_i = \text{GRU}(h_{i-1}, f_{i-1}; \theta_{\text{gru-lm}})
\] (14c)

\[
g_\theta(z, x_{<i}) = \text{softmax}(\text{affine}(h_i; \theta_{\text{out-x}}))
\] (14d)

We initialise the GRU cell with a transformation (14b) of the stochastic encoding \(z\). For the simple joint model baseline we initialise the GRU with a vector of zeros as there is no stochastic encoding we can condition on in that case.

A.2 TRANSLATION MODEL

The translation model consists of a sequence of categorical draws for \(j = 1, \ldots, |y|\)

\[
Y_j \mid z, x, y_{<j} \sim \text{Cat}(f_\theta(z, x, y_{<j}))
\] (15)

parameterised by an architecture that roughly follows Bahdanau et al. (2015). The encoder is a bidirectional GRU encoder (16a) that shares source embeddings with the language model (14a) and is initialised with its own projection of the latent representation put through a tanh activation. The decoder, also initialised with its own projection of the latent representation (16c), is a single-layer recurrent neural network with GRU units (16e). At any timestep the decoder is a function of the previous state, previous output word embedding, and a context vector. This context vector (16d) is a weighted average of the bidirectional source encodings, of which the weights are computed by a Bahdanau-style attention mechanism. The output of the GRU decoder is projected to the target vocabulary size and mapped to the simplex using a softmax activation (16f) to obtain the categorical parameters \(f_\theta(z, x, y_{<j})\).

\[
s_j = \text{BiGRU}(f_j, \tanh(\text{affine}(z; \theta_{\text{init-enc}})); \theta_{\text{bigru-x}})
\] (16a)

\[
e_j = \text{emb}(y_j; \theta_{\text{emb-y}})
\] (16b)

\[
t_0 = \tanh(\text{affine}(z; \theta_{\text{init-dec}}))
\] (16c)

\[
c_j = \text{attention}(s_j, t_{j-1}; \theta_{\text{bahd}})
\] (16d)

\[
t_j = \text{GRU}(t_{j-1}, [e_j, c_{j-1}]; \theta_{\text{gru-dec}})
\] (16e)

\[
f_\theta(z, x, y_{<j}) = \text{softmax}(\text{affine}([t_j, e_j]; \theta_{\text{out-y}}))
\] (16f)

In baseline models, recurrent cells are initialised with a vector of zeros as there is no stochastic encoding we can condition on.

A.3 INFERENCE NETWORK

The inference model \(q(z|x, y, \lambda)\) is a diagonal Gaussian

\[
Z \mid x, y \sim \mathcal{N}(\mathbf{u}, \text{diag}(\mathbf{s} \odot \mathbf{s}))
\] (17)

whose parameters are computed by an inference network. We use two bidirectional GRU encoders to encode the source and target sentences separately. To spare memory, we reuse embeddings from the generative model (18a-18b), but we prevent updates to those parameters based on gradients of the
inference network, which we indicate with the function $\text{detach}$. To obtain fixed-size representations for the sentences, GRU encodings are averaged (18c-18d).

$$f^m_1 = \text{detach}(\text{emb}(x^m_1; \theta_{\text{emb}-x})) \quad (18a)$$
$$e^m_1 = \text{detach}(\text{emb}(y^m_1; \theta_{\text{emb}-y})) \quad (18b)$$
$$h_x = \text{avg} \ (\text{BiGRU} (f^m_1; \lambda_{\text{gru-x}})) \quad (18c)$$
$$h_y = \text{avg} \ (\text{BiGRU} (e^m_1; \lambda_{\text{gru-y}})) \quad (18d)$$
$$h_{xy} = \text{concat} (h_x, h_y) \quad (18e)$$
$$u = \text{affine}(\text{ReLU}(\text{affine}(h_{xy}; \lambda_{\text{u-hid}})); \lambda_{\text{u-out}}) \quad (18f)$$
$$s = \text{softplus}(\text{affine}(\text{ReLU}(\text{affine}(h_{xy}; \lambda_{s-hid})); \lambda_{s-out})) \quad (18g)$$

We use a concatenation $h_{xy}$ of the average source and target encodings (18e) as inputs to compute the parameters of the Gaussian approximate posterior, namely, $d$-dimensional location and scale vectors. Both transformations use ReLU hidden activations (Nair & Hinton, 2010), but locations live in $\mathbb{R}^d$ and therefore call for linear output activations (18f), whereas scales live in $\mathbb{R}^d > 0$ and call for strictly positive outputs (18g), we follow Kucukelbir et al. (2017) and use softplus. The complete set of parameters used for inference is thus $\lambda = \{\lambda_{\text{gru-x}}, \lambda_{\text{gru-y}}, \lambda_{\text{u-hid}}, \lambda_{\text{u-out}}, \lambda_{s-hid}, \lambda_{s-out}\}$.

### A.4 Prediction Network

The prediction network parameterises our prediction model $r(z|x, \phi)$, a variant of the inference model that conditions on the source sentence alone. In §4 we explore several variants of the ELBO using different parameterisations of $r_\phi$. In the simplest case we do not condition on the target sentence during training, thus we can use the same network both for training and prediction. The network is similar to the one described in A.3, except that there is a single bidirectional GRU and we use the average source encoding (18c) as input to the predictors for $u$ and $s$ (19a-19b).

$$u = \text{affine}(\text{ReLU}(\text{affine}(h_x; \phi_{\text{u-hid}})); \phi_{\text{u-out}}) \quad (19a)$$
$$s = \text{softplus}(\text{affine}(\text{ReLU}(\text{affine}(h_x; \phi_{s-hid})); \phi_{s-out})) \quad (19b)$$

In all other cases we use $q(z|x, y, \lambda)$ parameterised as discussed in A.3 for training, and design a separate network to parameterise $r_\phi$ for prediction. Much like the inference model, the prediction model is a diagonal Gaussian

$$Z|x \sim \mathcal{N}(\hat{u}, \text{diag}(\hat{s} \odot \hat{s})) \quad (20)$$

also parameterised by $d$-dimensional location and scale vectors, however in predicting $\hat{u}$ and $\hat{s}$ (21b-21c) it can only access an encoding of the source (21a).

$$h_x = \text{avg} \ (\text{BiGRU} (f^m_1; \phi_{\text{gru-x}})) \quad (21a)$$
$$\hat{u} = \text{affine}(\text{ReLU}(\text{affine}(h_x; \phi_{\text{u-hid}})); \phi_{\text{u-out}}) \quad (21b)$$
$$\hat{s} = \text{softplus}(\text{affine}(\text{ReLU}(\text{affine}(h_x; \phi_{s-hid})); \phi_{s-out})) \quad (21c)$$

The complete set of parameters is then $\phi = \{\phi_{\text{gru-x}}, \phi_{\text{u-hid}}, \phi_{\text{u-out}}, \phi_{s-hid}, \phi_{s-out}\}$. For the deterministic variant, we use $\hat{u}$ (21b) alone to approximate $u$ (18f), i.e. the posterior mean of $Z$. 


B Validation results

|                 | WMT16 | IWSLT14 |
|----------------|-------|---------|
|                | EN-DE | DE-EN   | EN-DE | DE-EN |
| CONDITIONAL    | 14.4  | 17.0    | 25.0  | 30.9  |
| JOINT          | 14.8  | 17.1    | 25.2  | 31.0  |
| AEVNMT         | 14.9  | 17.7    | 25.6  | 31.5  |

Table 8: Validation results reported in BLEU for in-domain training on NC and IWSLT.

|                 | WMT & IWSLT | EN-DE | DE-EN |
|----------------|-------------|-------|-------|
| CONDITIONAL    | 20.5        | 25.9  |       |
| AEVNMT         | 20.7        | 26.0  |       |

Table 9: Validation results reported in BLEU for mixed-domain training. The validation set used is a concatenation of the development sets from WMT and IWSLT.

|                 | WMT16 |         |
|----------------|-------|---------|
|                | EN-DE | DE-EN   |
| CONDITIONAL    | 14.4  | 17.0    |
| + synthetic    | 17.5  | 22.0    |
| JOINT + SYNTHETIC | 17.3   | 21.8    |
| AEVNMT + SYNTHETIC | **17.7** | **22.2** |

Table 10: Validation results reported in BLEU for training on NC plus synthetic data.

C Additional Metrics
|                  | EN-DE                  | DE-EN                  |
|------------------|------------------------|------------------------|
|                  | BLEU ↑ | METEOR ↑ | TER ↓ | BEER ↑ | BLEU ↑ | METEOR ↑ | TER ↓ | BEER ↑ |
| **IWSLT14**      |        |          |       |        |        |          |       |        |
| **CONDITIONAL**  | 23.4   | 43.4     | 56.2  | 59.1   | 28.7   | 31.3     | 52.0  | 60.6   |
| **JOINT**        | 23.6   | 43.7     | 56.1  | 59.2   | 28.7   | 31.2     | 51.8  | 60.6   |
| **AEVNMT**       | **23.9** | **43.9** | **55.8** | **59.4** | **29.3** | **31.5** | **49.9** | **61.0** |
| **WMT16**        |        |          |       |        |        |          |       |        |
| **CONDITIONAL**  | 17.7   | 36.2     | 65.4  | 53.5   | 20.5   | **26.6** | 61.4  | 54.3   |
| **JOINT**        | 18.0   | 36.6     | 64.2  | 53.8   | 20.5   | **26.6** | 62.1  | 54.2   |
| **AEVNMT**       | **18.4** | **36.8** | **63.7** | **53.7** | **20.8** | **26.5** | **60.9** | **54.1** |

Table 11: Test results for in-domain training on IWSLT.

|                  | EN-DE                  | DE-EN                  |
|------------------|------------------------|------------------------|
|                  | BLEU ↑ | METEOR ↑ | TER ↓ | BEER ↑ | BLEU ↑ | METEOR ↑ | TER ↓ | BEER ↑ |
| **WMT16**        |        |          |       |        |        |          |       |        |
| **CONDITIONAL**  | 17.7   | 36.2     | 65.4  | 53.5   | 20.5   | 26.6     | 61.4  | 54.3   |
| + synthetic data | 22.3   | 41.2     | 58.9  | 57.4   | 27.0   | 31.1     | 53.5  | 59.0   |
| **JOINT**        | 22.3   | 41.3     | 58.2  | 57.5   | 27.2   | 30.9     | 51.8  | 59.1   |
| + synthetic data | **22.6** | **41.5** | **57.8** | **57.6** | **27.9** | **31.2** | **51.5** | **59.3** |

Table 12: Test results for in-domain training on NC.

|                  | EN-DE                  | DE-EN                  |
|------------------|------------------------|------------------------|
|                  | BLEU ↑ | METEOR ↑ | TER ↓ | BEER ↑ | BLEU ↑ | METEOR ↑ | TER ↓ | BEER ↑ |
| **WMT16**        |        |          |       |        |        |          |       |        |
| **CONDITIONAL**  | 17.7   | 36.2     | 65.4  | 53.5   | 20.5   | 26.6     | 61.4  | 54.3   |
| + synthetic data | 22.3   | 41.2     | 58.9  | 57.4   | 27.0   | 31.1     | 53.5  | 59.0   |
| **JOINT**        | 22.3   | 41.3     | 58.2  | 57.5   | 27.2   | 30.9     | 51.8  | 59.1   |
| + synthetic data | **22.6** | **41.5** | **57.8** | **57.6** | **27.9** | **31.2** | **51.5** | **59.3** |

Table 13: Test results for training on NC plus synthetic data (back-translated News).
| EN-DE | WMT16 | IWSLT14 |
|-------|-------|---------|
|       | BLEU↑ | METEOR↑ | TER↓ | BEER↑ | BLEU↑ | METEOR↑ | TER↓ | BEER↑ |
| In-Domain | CONDITIONAL | 17.7 | 36.2 | 65.4 | 53.5 | 23.4 | 43.4 | 56.2 | 59.1 |
|         | AEVNM | 18.4 | 36.8 | 63.7 | 53.7 | 23.9 | 43.9 | 55.8 | 59.4 |
| Mixed-Domain | CONDITIONAL | 17.3 | 35.8 | 62.8 | 54.2 | 24.1 | 43.8 | 54.9 | 59.7 |
|          | AEVNM | 18.6 | 37.3 | 60.6 | 55.1 | 24.2 | 43.9 | 54.3 | 59.8 |

Table 14: EN-DE test results for mixed-domain training

| DE-EN | WMT16 | IWSLT14 |
|-------|-------|---------|
|       | BLEU↑ | METEOR↑ | TER↓ | BEER↑ | BLEU↑ | METEOR↑ | TER↓ | BEER↑ |
| In-Domain | CONDITIONAL | 20.5 | 26.6 | 61.4 | 54.3 | 28.7 | 31.3 | 52.0 | 60.6 |
|         | AEVNM | 20.8 | 26.5 | 60.9 | 54.1 | 29.3 | 31.5 | 49.9 | 61.0 |
| Mixed-Domain | CONDITIONAL | 22.2 | 27.7 | 58.8 | 55.7 | 30.6 | 32.4 | 49.2 | 61.8 |
|           | AEVNM | 22.7 | 28.0 | 57.3 | 56.2 | 30.5 | 32.4 | 48.2 | 61.9 |

Table 15: DE-EN test results for mixed-domain training.