Topic-Guided Variational Autoencoders for Text Generation

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Overview

Framework for Variational Inference

- MLE: $\hat{\theta}_{ML} = \underset{\theta}{\operatorname{argmax}}\ p(x;\theta)$
  - Intractable when latent variables z with prior $p(z;\theta)$ are introduced
  - Marginal likelihood: $p(x;\theta) = \int p(x,z;\theta)dz = \int p(x|z;\theta)p(z;\theta)dz$
  - Posterior: $p(z|x;\theta) = \frac{p(x|z;\theta)p(z;\theta)}{p(x;\theta)}$ also intractable
- Assumptions
  - $p(z;\theta) \sim \mathcal{N}(0, I)$
  - $p(x|z;\theta) \sim \mathcal{N}(f(z), cI)$
- This implies posterior $p(z|x;\theta)$ also follow a Gaussian distribution
  - The mean and variance depends on the function f which can be complex

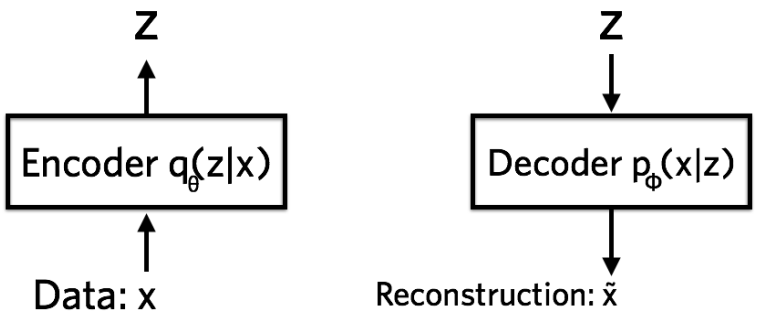
VI Formulation

- Variational Inference (VI) is a technique to approximate complex distributions
- Approximate $p(z|x;\theta)$ by $q(z|x;\phi) \sim \mathcal{N}(g(x), h(x))$
- Find best approximation by minimizing the Kullback-Leibler divergence between the $q(z|x;\phi)$ and the target $p(z|x;\theta)$

$$
\begin{aligned}
\phi^* &= \operatorname*{argmin}_{\phi} \mathrm{KL}(q(z|x;\phi)||p(z|x;\theta)) \\
&= \operatorname*{argmin}_{\phi} \mathbb{E}_{q(z|x;\phi)} \log q(z|x;\phi) - \mathbb{E}_{q(z|x;\phi)} \log \frac{p(x|z;\theta)p(z;\theta)}{p(x;\theta)} \\
&= \operatorname*{argmin}_{\phi} \mathbb{E}_q \log q_\phi(z|x) - \mathbb{E}_q p_\theta(x|z) - \mathbb{E}_q p_\theta(z) + \mathbb{E}_q p_\theta(x) \\
&= \operatorname*{argmax}_{\phi} \mathbb{E}_q p_\theta(x|z) - \mathrm{KL}(q_\phi(z|x)||p_\theta(z)) \\
&= \operatorname*{argmax}_{\phi} \mathbb{E}_q(-\frac{\|x - f(z)\|^2}{2c}) - \mathrm{KL}(q_\phi(z|x)||p_\theta(z))
\end{aligned}
$$

Variational Autoencoder (VAE)

- VAE is a autoencoder that employs re-parameterization of variational lower bound and optimized using standard gradient methods



- Define $p_\theta(x|z)$ to be the decoder network parameterized by θ, and $q_\phi(z|x)$ be the encoder network parameterized by ϕ
- VAE encode an input as a distribution over the latent space instead of a single point
- Regularity of the latent space allows the generative process to be possible through two main properties
  - Continuity
  - Completeness
- Want to regularise both the covariance matrix and the mean of the distributions returned by the encoder (Standard Gaussian)

Evidence Lower Bound (ELBO)

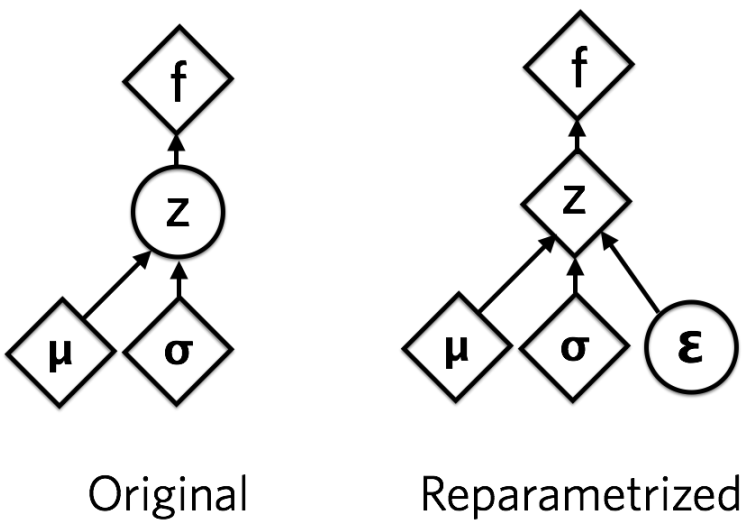
- Integrating over evidence $p(x) = \int p(x|z)p(z)dz$ requires exponential time to compute
- Since from Jensen's inequality we know that when f is concave, $f(E[X]) \geq E[f(X)]$, then we have

$$
\begin{aligned}
\log p(x) &= \log \int_z p(x, z) \\
&= \log \int_z p(x, z) \frac{q_\phi(z|x)}{q_\phi(z|x)} \\
&= \log(\mathbb{E}_{q_\phi} \left[\frac{p(x, z)}{q_\phi(z|x)} \right]) \\
&\geq \mathbb{E}_{q_\phi} \left[\log(\mathrm{p(x,\ z)}) \right] - \mathbb{E}_{q_\phi} \left[\log(q_\phi(z|x)) \right]
\end{aligned}
$$

- Let $ELBO = \mathbb{E}_{q_\phi} \left[\log(q_\phi(z|x)) \right] - \mathbb{E}_{q_\phi} \left[\log(\mathrm{p(x,\ z)}) \right]$, then maximizing $ELBO$ is equivalent to minimizing $\mathrm{KL}(q(z|x; \phi)||p(z|x; \theta))$

Re-parametrization Trick

- Implementing VAE requires taking the derivatives with respect to the parameters of a stochastic variable z drawn from distribution $q_\phi(z|x)$
- Want the samples to deterministically depend on the parameters of the distribution in order to perform back-propagation
- For the normal distribution $q_\phi(z|x)$, we can sample z such that
  - $z = \mu + \sigma \odot \epsilon$, where $\epsilon \sim \mathcal{N}(0, I)$



- Allows backpropagation with respect to θ through the objective (the ELBO) which is a function of samples of the latent variables z

Overview

Motivation

- VAE is of particular interest when one desires not only text generation, but also the capacity to infer meaningful latent codes from text
- Semantically meaningful latent codes can provide high-level guidance while generating sentences
  - E.g. the vocabulary could potentially be narrowed down if the input latent code corresponds to a certain topic

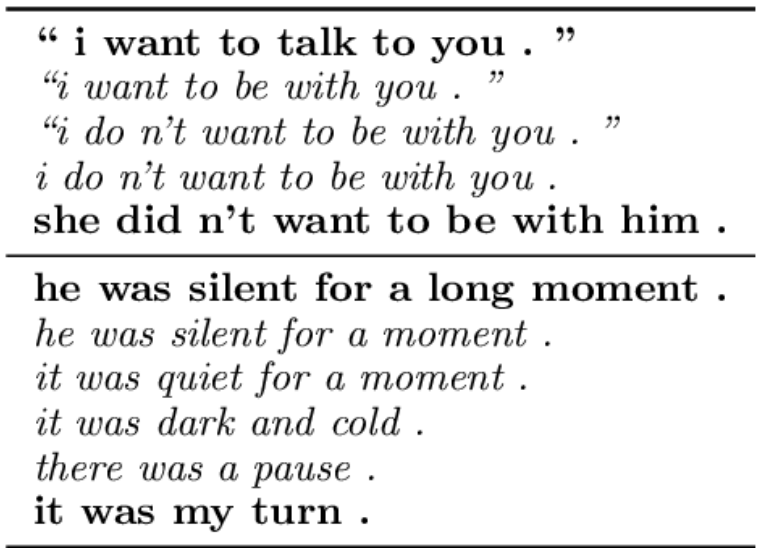
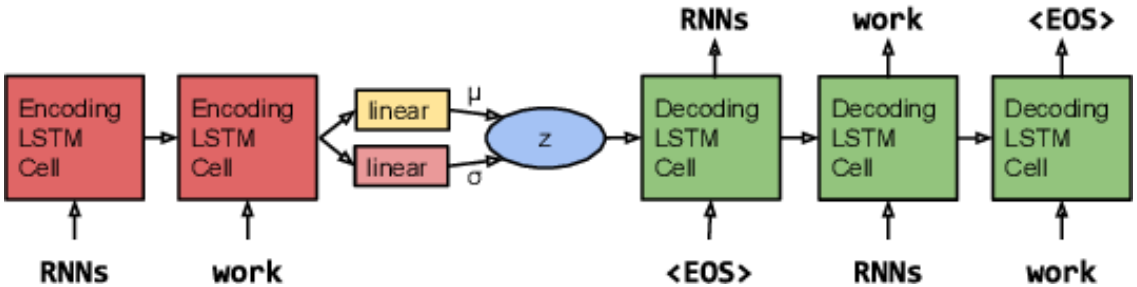


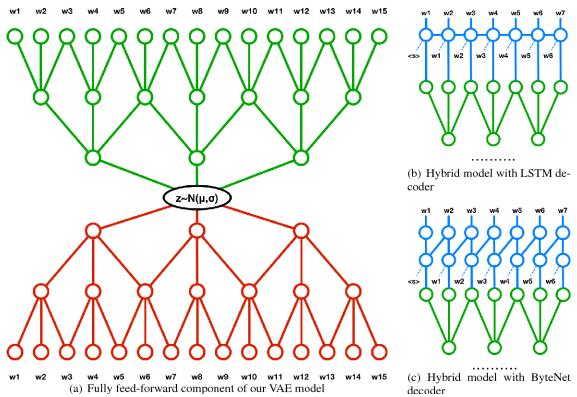
Figure: Paths between pairs of random points in VAE latent space

VAE for text-generation

- (Bowman et al. 2015) proposed using LSTM-RNN to form a sequence autoencoder with the Gaussian prior acting as a regularizer on the hidden code.



- (Semeniuta, Severyn, and Barth 2017) proposed a convolutional architecture similar to the models in the vision domain



- (Kikuchi et al. 2016) attempted to control output length for abstractive summarization

Challenges

- **Over-regularization**
  - Difficult for the simple Gaussian prior to indicate the semantic structure among sentences or text
  - Reduce the generative power of the decoder
- **Posterior collapse**
  - A strong decoder network $p(x|z)$ ignore the information from the latent code and merely depends on previous generated tokens for prediction
  - Signal from input x to posterior parameters is either too weak or too noisy

Overview

Introduction

- (Wang et al. 2019) proposed a topic-guided variational autoencoder (TGVAE) to generate semantically-meaningful sentences from different topics
- Attepmts to address the previous two challenges by:
  - Permitting text generation with designated topic by specifies a Gaussian mixture model (GMM) as the prior of the latent code
  - Householder flow is introduced to transform the mixture distribution into a flexible approximate posterior
- Comprised of two modules, a neural topic model (NTM) and a neural sequence model (NSM)

Neural Topic Model (NTM)

- Use a bag-of-words representation of the document, such that $d \in \mathbb{Z}_+^D$
- Let $\theta \in \mathcal{N}(0, I)$ and $t = g(\theta)$, where $g(\theta) = \mathrm{softmax}(\hat{W}\theta + \hat{b})$ is the function that maps sample θ to topic embedding t
- Let a_n be the topic assignment for word w_n, and $\beta_{a_n} \in \mathbb{R}^D$ represents the distribution over words for topic a_n. Then the marginal likelihood for document d, $p_\theta(d|\beta)$ is

$$
\begin{aligned}
p_\theta(d|\beta) &= \int_t p(t) \prod_n \sum_{a_n} p(w_n|\beta_{a_n}) p(a_n|t) dt \\
&= \int_t p(t) \prod_n p(w_n|\beta, t) dt \\
&= \int_t p(t) p(d|\beta, t) dt = \int_\theta p(\theta) p(d|\beta, \theta) d\theta
\end{aligned}
$$

- Note that $a_n \sim \mathrm{discrete}(t)$ so $p(w_n|\beta, t) = \sum_{a_n} p(w_n|\beta_{a_n}) p(a_n|t)$

Neural Sequence Model (NSM)

- Assumes each z is sampled from a topic dependent GMM using word distribution β and topic usage t from NTM, such that

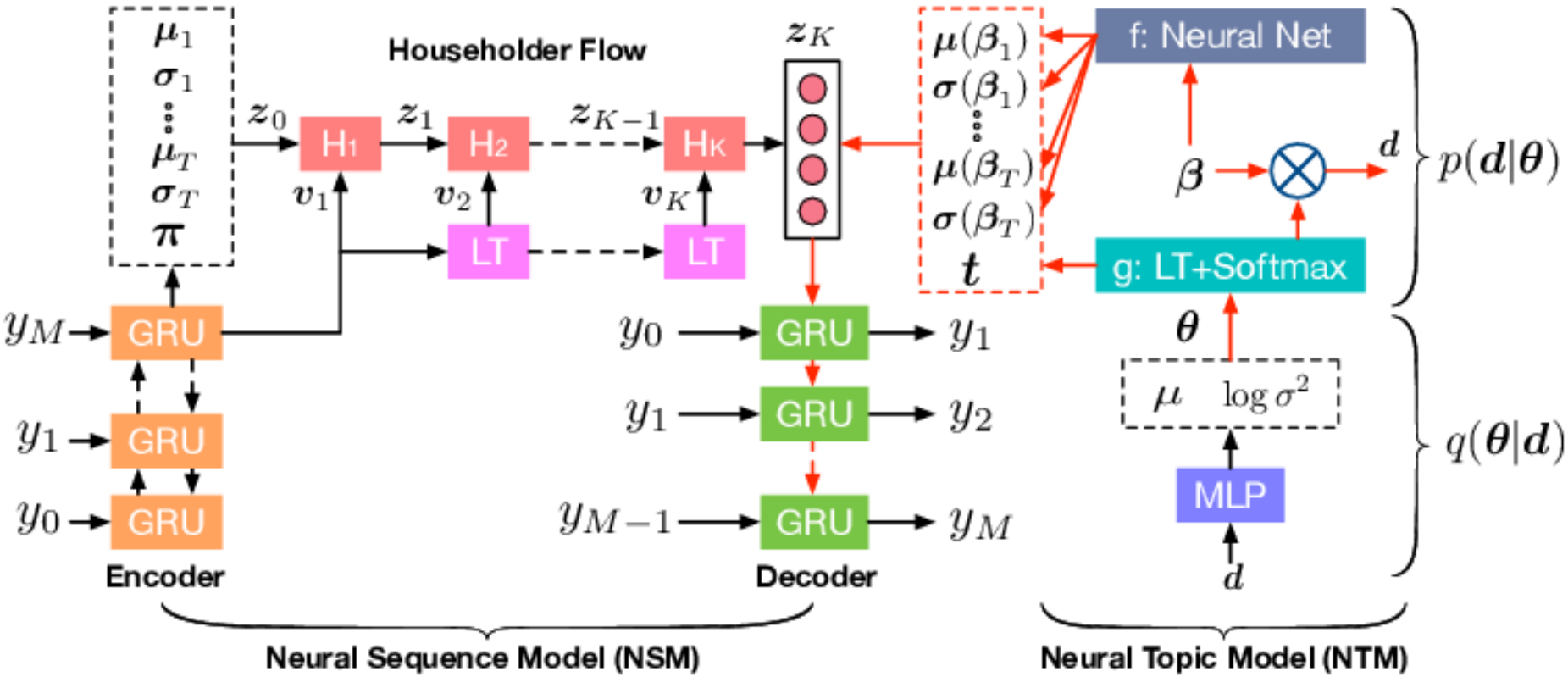
$$p(z|\beta, t) = \sum_{i=1}^{T} t_i \, \mathcal{N}(\mu(\beta_i), \sigma^2(\beta_i))$$
$$\mu(\beta_i) = f_\mu(\beta_i)$$
$$\sigma^2(\beta_i) = \mathrm{diag}(\exp(f_\sigma(\beta_i)))$$

- Both f_μ and f_σ are MLPs parameterized by W_μ and W_σ, respectively
- **Decoder**: The likelihood of a word sequence $p(\hat{x}|z)$ is

$$p(\hat{x}|z) = p(\hat{x}_1|z) \prod_{m=2} p(\hat{x}_m|h_m)$$

  - Where $h_m = \mathrm{GRU}(h_{m-1}, \hat{x}_{m-1}, z)$

Architecture



Inference

- The joint marginal likelihood can be written as

$$p(\hat{x}, d|\beta) = \int_{\theta} \int_{z} p(\theta) p(d|\beta, \theta)\ p(z|\beta, \theta) p(\hat{x}|z) d\theta dz$$

- Since direct optimization is intractable, use variation distribution of θ and z given by $q(\theta|d)$ and $q(z|x)$
- Variational objective ELBO given as

$$\begin{aligned}\mathcal{L} = &\mathbb{E}_{q(\theta|d)} \left[\log\, p(d|\theta\beta)\right] - \mathrm{KL}(q(\theta|d)||p(\theta)) \\ &+ \mathbb{E}_{q(z|x)} \left[\log\, p(x|z)\right] - \mathbb{E}_{q(\theta|d)} \left[\mathrm{KL}(q(z|x)||p(z|\beta, \theta))\right]\end{aligned}$$

  - Under the assumption that $q(\theta|d) \sim \mathcal{N}(\theta|g_{\mu}(d), \mathrm{diag}(\exp(g_{\sigma}(d))))$

Householder Transformation

- We know that any hyper plane can be defined by a orthogonal vector v such that $\|v\|_2 = 1$ (orthonormal)
- Let z_k be the reflection of vector z_{k-1} about the hyperplane defined by v_k, then we have $z_k = z_{k-1} - 2v_k^T z_{k-1} v_k$
- To capture the transformation as a matrix, we have

$$z_k = (I - 2\frac{v_k^T v_k}{\|v_k\|^2})z_{k-1} = H_k z_{k-1}$$

  - Where $H_k = (I - 2\frac{v_k^T v_k}{\|v_k\|^2})$ is called the Householder matrix
- For $k = 1, \ldots, K$, vector v_k is produced by a linear layer with input v_{k-1}, and $v_0 = h$ is the last hidden vector of the encoder RNN sentence y

Householder Flow for Approximate Posterior

- (Tomczak and Welling 2016) showed that Householder flow can transform a simple posterior to an arbitrarily complex distribution
- To construct posterior $p_K(z_K|x)$ from z_0, we can use the property of Jacobians of invertible functions and apply chain rule

$$\log q_K(z_K|x) = \log q_0(z_0|x) - \sum_{k=1}^{K} \log|\det \frac{\partial f_k}{\partial z_{k-1}}|$$

Here we have $q_O(z_0|x)$ is specified as a GMM, where

$$q_O(z_0|x) = \sum_{i=1}^{T} \pi_i(x)\, \mathcal{N}(\mu_i(x), \sigma^2(x))$$

  - Where mixture components π, μ, and σ are produced by the encoder network with respect to h

Extension to Text Summarization

- For text summarization, interested in modelling $p(y, d|x)$ where (x, y) denotes the document-summary pair, where

$$p(y, d|x) = \int_{\theta} \int_{z} p(\theta)p(d|\beta, \theta)p(z|\beta, \theta)p(y|x, z)d\theta dz$$

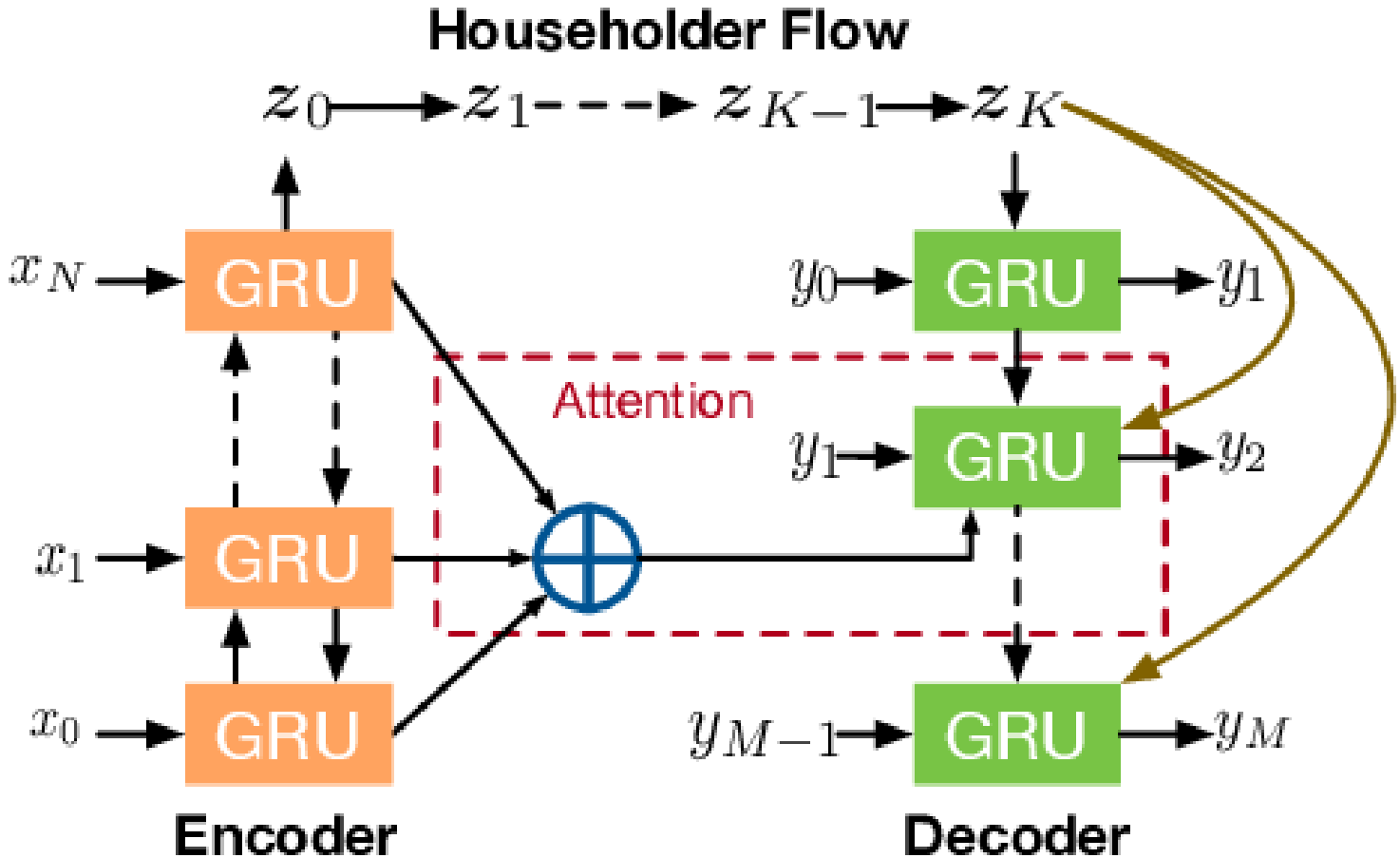
- The ELBO loss is reconstructed as

$$\mathcal{L} = \mathcal{L}_t + \mathbb{E}_{q(z|x)} \left[\log p(y|x, z)\right] - \mathbb{E}_{q(\theta|d)} \left[\mathbf{KL}(q(z|x)||p(z|\beta, \theta))\right]$$

  - Where $\mathcal{L}_t$ is the NTM loss as earlier

- The main difference compared to the unconditioned text generation being the usage of z_K to generate y at every time-step to provide topic guidance

Text Summarization Architecture



Experiments: Text Generation

Metric	Methods	APNEWS				IMDB				BNC			
		B-2	B-3	B-4	B-5	B-2	B-3	B-4	B-5	B-2	B-3	B-4	B-5
test-BLEU	VAE	0.564	0.278	0.192	0.122	0.597	0.315	0.219	0.147	0.479	0.266	0.169	0.117
	VAE+HF (K=1)	0.566	0.280	0.193	0.124	0.593	0.317	0.218	0.148	0.475	0.268	0.165	0.112
	VAE+HF (K=10)	0.570	0.279	0.195	0.123	0.610	0.322	0.221	0.147	0.483	0.270	0.169	0.110
	TGVAE (K=0, T=10)	0.582	0.320	0.203	0.125	0.627	0.362	0.223	0.159	0.517	0.282	0.181	0.115
	TGVAE (K=1, T=10)	0.581	0.326	0.202	0.124	0.623	0.358	0.224	0.160	0.519	0.282	0.182	0.118
	TGVAE (K=10, T=10)	0.584	0.327	0.202	0.126	0.621	0.357	0.223	0.159	0.518	0.283	0.173	0.119
	TGVAE (K=10, T=30)	0.627	0.335	0.207	0.131	**0.655**	0.369	**0.243**	**0.165**	0.528	**0.291**	0.182	0.119
	TGVAE (K=10, T=50)	**0.629**	**0.340**	**0.210**	**0.132**	0.652	**0.372**	0.239	0.160	**0.535**	0.290	**0.188**	**0.120**
self-BLEU	VAE	0.866	0.531	0.233	-	0.891	0.632	0.275	-	0.851	0.51	0.163	-
	VAE+HF (K=1)	0.865	0.533	0.241	-	0.899	0.641	0.278	-	0.854	0.515	0.163	-
	VAE+HF (K=10)	0.873	0.552	0.219	-	0.902	0.648	0.262	-	0.854	0.520	0.168	-
	TGVAE (K=0, T=10)	0.847	0.499	0.161	-	0.878	0.572	0.234	-	0.832	0.488	0.160	-
	TGVAE (K=1, T=10)	0.847	0.495	0.160	-	0.871	0.571	0.233	-	0.828	0.483	0.150	-
	TGVAE (K=10, T=10)	0.839	0.512	0.172	-	0.889	0.577	0.242	-	0.829	0.488	0.151	-
	TGVAE (K=10, T=30)	0.811	0.478	0.157	-	0.850	0.560	0.231	-	0.806	0.473	0.150	-
	TGVAE (K=10, T=50)	**0.808**	**0.476**	**0.150**	-	**0.842**	**0.559**	**0.227**	-	**0.793**	**0.469**	**0.150**	-

Generation on Given Topic

Data	Topic	Sentences
APNEWS	education	• the commission has approved a bill that would make state funding available for the city 's new school .
	animal	•the feline did n't survive fence hangars at the lake .
	crime	• the jury found the defense was not a <unk> , <unk> 's ruling and that the state 's highest court has been convicted of first-degree murder .
	weather	• forecasters say they 're still trying to see the national weather service watch for the latest forecast for friday evening .
	lottory	• she hopes the jackpot now exceeds $ 9 million .
	education+law	• an alabama law professor thomas said monday that the state's open court claims it takes an emotional matter about issuing child molesters based on religion.
	animal+medicine	• the study says the animal welfare department and others are not sure to make similar cases to the virus in the zoo.
IMDB	war	• after watching the movie , there is a great documentary about the war in the years of the israeli war .
	children	• the entire animation was great at times as to the readings of disney favorites .
	epsiode	• the show would have warranted for 25 episodes and it does help immediately .
	name	• she steals the other part where norma 's <unk> husband (crawford) (as at his part , sh*t for the road) .
	detective	• holmes shouted just to be as much as the movie 's last scene where there were <unk> pills to nab the <unk> .
	horror + negative	• the movie about a zombie is the worst movie i have ever seen.
	detective + children	• my favorite childhood is that rochester takes the character in jane's way, playing the one with hamlet.
BNC	medical	• here mistaking ' causes ' drugs as the problem although both economically ill patients arising from a local job will be in traumatic dangers .
	education	• he says the sale is given to five students ' award off : out at a laboratory after the three watts of the hours travelling in and chairman store the bank of the <unk> sutcliffe .
	religion	• schoolchildren will either go or back to church in his place every year in the savoy .
	entertainment	• 100 company and special lace with <unk> garland for tea our garden was filmed after a ceremony
	IT	• ibm also has shut all the big macs in the 60mhz ncube , represent on the acquisition and mips unix .
	environment + crime	• the earth's environmental protection agency said that the government was still being shut down by the police.
	education+entertainment	• the school is 55 and hosts one of a musician's theme charities festival.

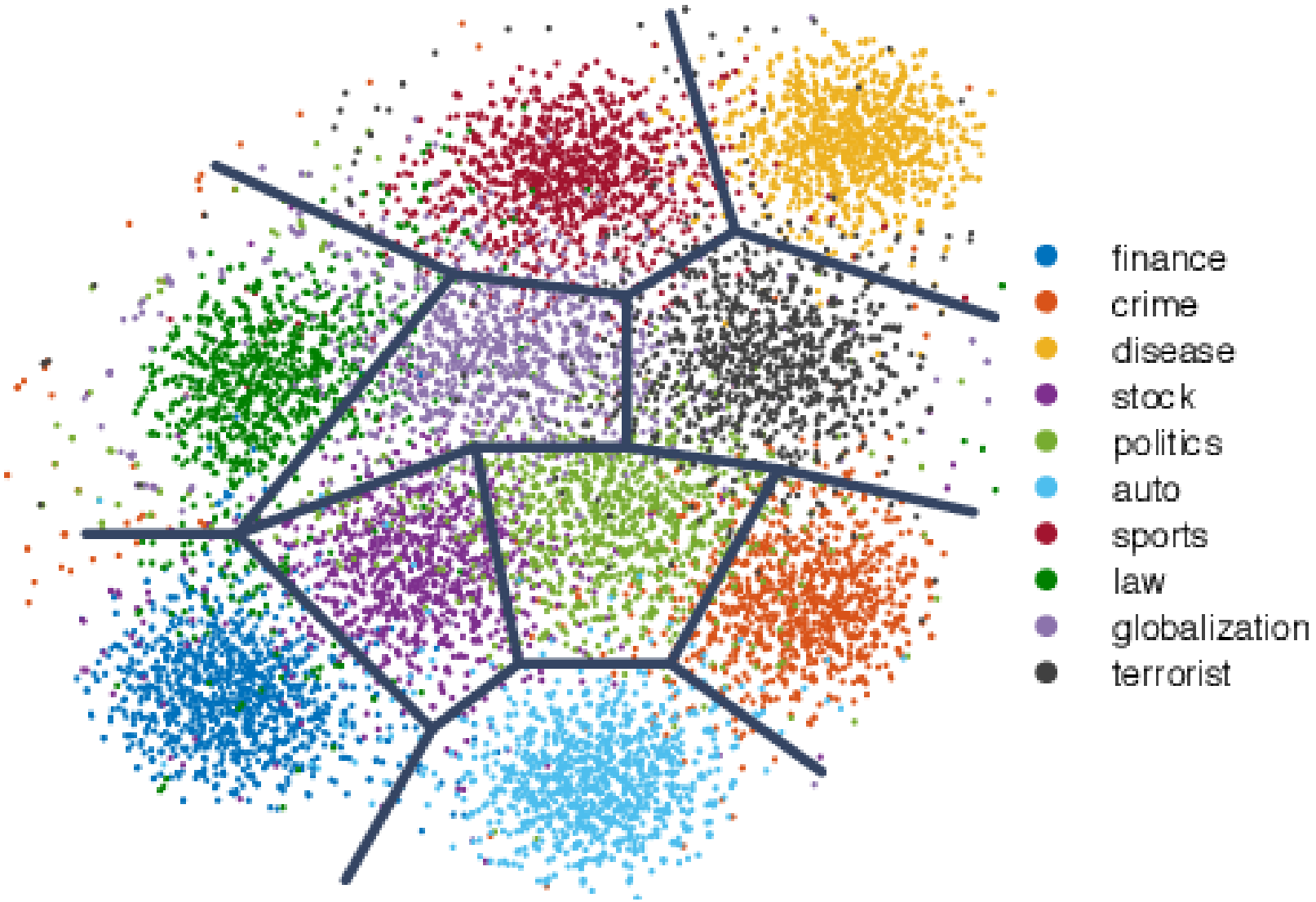
Summarization Results

Methods	GIGAWORDS			DUC-2004		
	RF-1	**RF-2**	**RF-L**	**RR-1**	**RR-2**	**RR-L**
ABS	29.55	11.32	26.42	26.55	7.06	22.05
ABS+	29.78	11.89	26.97	28.18	8.49	23.81
RAS-LSTM	32.55	14.70	30.03	28.97	8.26	24.06
RAS-Elman	33.78	15.97	31.15	27.41	7.69	23.06
lvt2k-lsent	32.67	15.59	30.64	28.35	9.46	24.59
lvt5k-lsent	35.30	16.64	32.62	28.61	9.42	25.24
ASC+FSC	34.17	15.94	31.92	26.73	8.39	23.88
Seq2Seq	34.03	15.93	31.68	28.39	9.26	24.83
Var-Seq2Seq	34.00	15.97	31.85	28.11	9.24	24.86
Var-Seq2Seq-HF (K=1)	34.04	15.98	31.84	28.18	9.27	24.84
Var-Seq2Seq-HF (K=10)	34.22	16.10	32.13	28.78	9.11	24.96
TGVAE (K=0, T=10)	35.34	16.68	32.69	28.99	9.21	24.89
TGVAE (K=1, T=10)	35.35	16.70	32.64	29.02	9.24	24.93
TGVAE (K=10, T=10)	35.40	16.77	32.71	29.07	9.32	25.17
TGVAE (K=10, T=30)	35.59	17.18	32.89	29.38	**9.60**	25.22
TGVAE (K=10, T=50)	**35.63**	**17.27**	**33.02**	**29.65**	9.55	**25.38**

Summarization Examples

Sample of Summaries
D: a court here thursday sentenced a ##-year-old man to ## years in jail after he admitted pummelling his baby son to death to silence him while watching television . **R**: man who killed baby to hear television better gets ## years. **Seq2Seq**: man sentenced to ## years after the son 's death **Ours**: a court sentenced a man ## years in jail
D: european stock markets advanced strongly thursday on some bargain-hunting and gains by wall street and japanese shares ahead of an expected hike in us interest rates , dealers said **R**: european stocks bounce back UNK UNK with closing levels **Seq2Seq**: european stocks advance ahead of us interest rate hike **Ours**: european stocks rise on bargain-hunting, dealer said friday
D: the democratic people 's republic of korea whitewashed south korea in the women 's team semi-finals at the world table tennis championships here on sunday **R**: dpr korea sails into women 's team final **Seq2Seq**: dpr korea whitewash south korea in women 's team final **Ours**: dpr korea beat south korea in table tennis worlds

Latent Space Visualization



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Overview

The End