Table 1: Community Detection Results: It can be seen that the detected communities are meaningful (as evident by modularity scores that are comparable to the ones obtained by the spectral clustering algorithm) while at the same time being *smooth* (since the NMI scores are considerably higher) thereby validating our claim.

DATASET	MODULARITY			NMI		
	SPECTRAL	iELSM (OURS)	ELSM (OURS)	SPECTRAL	iELSM (OURS)	ELSM (OURS)
SYNTHETIC	0.479	**0.489**	0.488	0.769	0.851	**0.864**
ENRON-FULL (WEIGHTED)	0.506	**0.597**	0.590	0.455	0.722	**0.823**
ENRON-FULL (BINARY)	0.540	**0.555**	0.551	0.529	0.767	**0.779**
ENRON-50	0.396	**0.419**	0.414	0.560	0.819	**0.838**
NIPS-110	0.497	**0.601**	0.595	0.249	0.804	**0.863**
INFOCOM	0.283	**0.288**	0.270	0.443	0.643	**0.662**

Table 2: Link Prediction Results: Our method outperforms other approaches on both metrics. We were unable to obtain an implementation for DMMG and hence the performance numbers of DMMG on Enron-50 are missing.

	ENRON-50		INFOCOM		NIPS-110	
	AUC	F1	AUC	F1	AUC	F1
BAS	0.874	0.585	0.698	0.317	0.703	0.161
LFRM	0.777	0.312	0.640	0.248	0.398	0.011
DRIFT	0.910	0.578	0.782	0.381	0.672	0.084
DMMG	-	-	0.804	0.392	0.732	0.196
iELSM (OURS)	0.913	0.600	0.868	**0.489**	**0.754**	0.248
ELSM (OURS)	**0.911**	**0.596**	**0.871**	**0.489**	0.742	**0.251**

model overfitting to the training data to get good embeddings? These questions get answered, if the observed data can be extrapolated to predict an unseen network snapshot using our model. This task is known as link prediction.

Formally, given network snapshots up to time t, $\{\mathbf{A}^{(1)}, \mathbf{A}^{(2)}, ..., \mathbf{A}^{(t)}\}$, we want to predict the next network snapshot $\mathbf{A}^{(t+1)}$. Note that this involves predicting the appearance of new links as well as removal of existing links. We use binary networks in this experiment to compare against other approaches. We use the well known AUC score and F1 score for the purpose of comparison. Values close to 1 indicate good performance for both the scores.

To predict $\mathbf{A}^{(t+1)}$, we train the inference network for iELSM and ELSM on $\{\mathbf{A}^{(1)}, \mathbf{A}^{(2)}, ..., \mathbf{A}^{(t)}\}$. We update the predicted latent embeddings $\mathbf{Z}^{(t)}$ using (5) and (6) to get $\mathbf{Z}^{(t+1)}$. Then, $P(a_{ij}{}^{(t+1)} = 1|\mathbf{Z}^{(t+1)})$ is computed using (2) (or the decoder, if a decoder network has been used). Note that for ELSM, while updating the latent embeddings we set $h_i^{(t+1)} = 0$ for all nodes.

We compare our performance against a simple baseline (BAS) in which the probability of an edge is directly proportional to the number of times it has been observed in the past (**?**). We also compare against existing approaches - LFRM (**?**) (using only the last snapshot), DRIFT (**?**) and DMMG (**?**) (Table 2). Maximum F1 score over all thresholds is selected at each snapshot as it was done in (**?**). The scores reported here have been obtained by averaging the snapshot wise scores. It can be seen that our method outperforms other methods on both metrics. Visualization of latent embeddings and predicted output matrices for Enron-full can be found in supplementary material.

6 Conclusion and Future Work

In this paper, we proposed ELSM, a generative model for dynamically evolving networks. We also proposed a neural network architecture that performs approximate inference in a simplified version of our model, iELSM (inference for ELSM is in supplementary material) and highlighted the flexibility of this approach. Our model is capable of: (i) Generating synthetic dynamic networks with gradually evolving communities and (ii) Learning meaningful latent embeddings of nodes in a dynamic network. We demonstrated the quality of learned latent embeddings on downstream tasks like community detection and link prediction in dynamic networks.

In this paper we focused on undirected, positive influence based, gradually changing, assortative networks with a fixed number of nodes. Though, these properties are exhibited by a large number of real world networks, however there are other important classes of networks that do not follow these properties. For example, one can also extend this idea to directed networks. One can also consider the case where the number of nodes is allowed to change over time. Considering networks that are not necessarily assortative (like hierarchical networks) also poses interesting questions.

Tempore et magni deserunt rem id, repellat nulla nemo praesentium minima exercitationem architecto dicta ad, quis eaque eum facere optio, corporis harum quasi exercitationem ratione.Modi corrupti architecto tempora voluptatibus, quo porro quos fugiat ipsum asperiores quibusdam delectus inventore obcaecati voluptas voluptatum, ducimus facere ut iure vero unde eius, cupiditate blanditiis porro optio nesciunt explicabo sint in culpa, atque asperiores ratione nihil voluptas.Eligendi voluptate quis doloremque rerum architecto beatae, tempore sit magnam illum quis eligendi ut.Quas rerum qui facilis voluptas quia tenetur tempora itaque, quia possimus laboriosam quod laudantium amet a id vitae cupiditate minus, quam nulla similique, natus sint sed unde voluptate esse error a, est ab