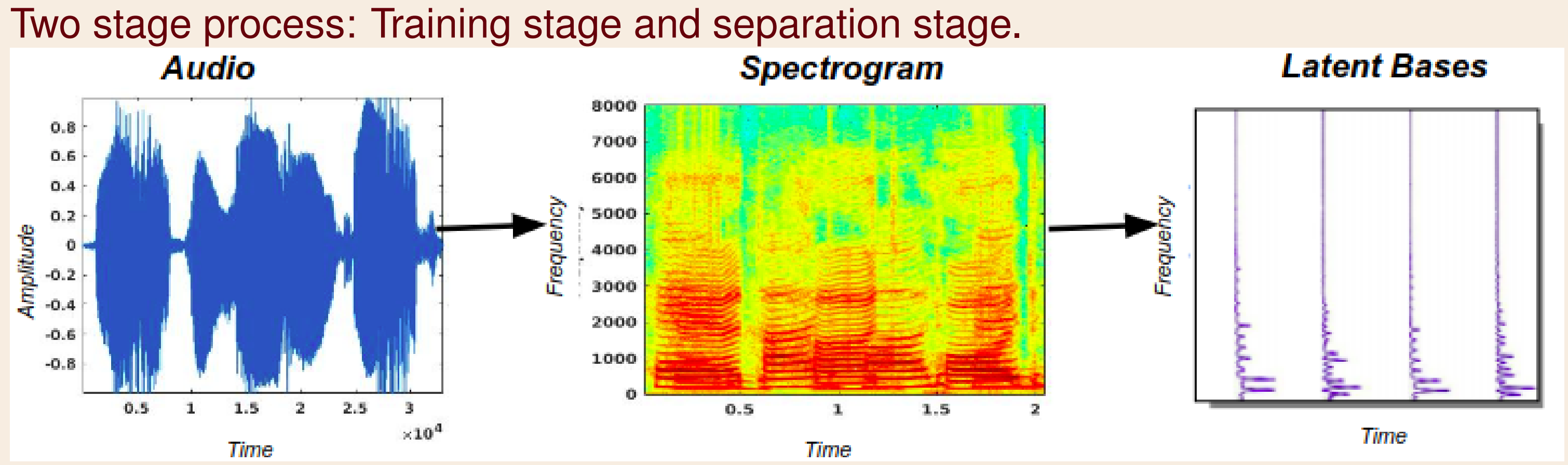
# A DYNAMIC LATENT VARIABLE MODEL FOR SOURCE SEPARATION

*Anurendra Kumar*[1], *Tanaya Guha*[1], *Prasanta Ghosh*[2]

[1]Indian Institute of Technology,Kanpur [2]Indian Institute of Science, Bangalore

## Introduction

- **Latent Variables**: Unobserved variables that explain the observed variables.
- **Supervised source separation**: Assumes small training data ( 15 sec) for each source.
  Popular methods: Latent Variable Model (LVM) and the Nonnegative Matrix Factorization (NMF).
  Two stage process: Training stage and separation stage.



- The latent bases for each sources are utilized to separate the sources.
- Latent variable models assumes mixture multinomial as likelihood and can be seen as probabilistic counterpart of non-negative matrix factorization.
- **Dynamic Modeling**: LVM and NMF assumes no temporal correlation in spectrogram. In past, exponential distribution as a dynamic prior [1]. Imperative to use Dirichlet as a prior since it is conjugate to multinomial. However, Dirichlet in its basic form yields negative updates

## Proposed model

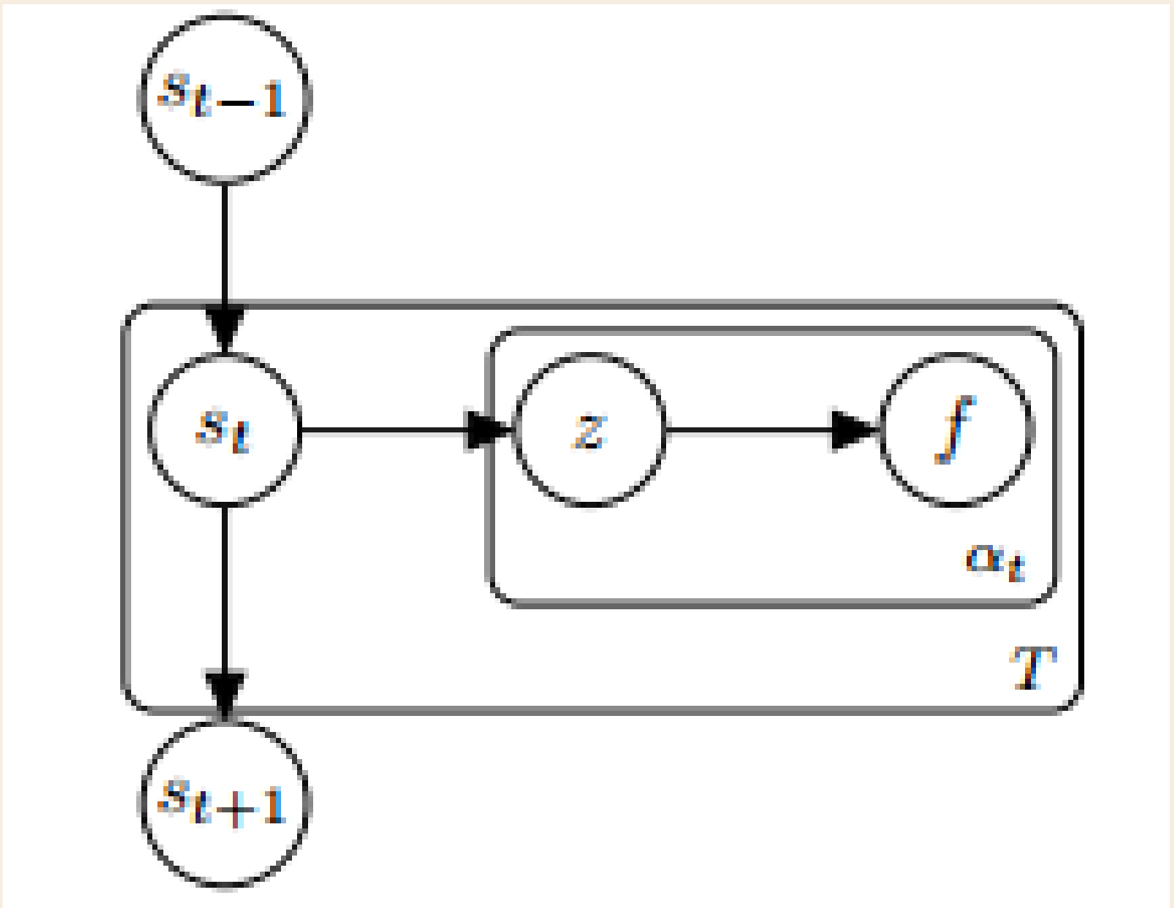


Figure : Plate notation for the proposed dynamic DLVM.

- $x(t) \Rightarrow$ signal, $\mathbf{X} \Rightarrow$ spectrogram, $\mathbf{N} \Rightarrow$scaled spectrogram

$$\mathbf{N} = \gamma|STFT(x(t))| = \gamma \mathbf{X} \tag{1}$$

- $\mathbf{N}$ as a surrogate of $\mathbf{X}$ for all analysis.
- Each count of frequency modeled as a mixture multinomial,

$$P_t(f) = \sum_{k=1}^{K} P_t(f, z_k) = \sum_{k=1}^{K} P_t(z_k) P(f|z_k) \tag{2}$$

- Let state $\mathbf{s}_t$

$$\mathbf{s}_t = [P_t(z_1), ..., P_t(z_K)]^{\mathsf{T}} = [s_t(1), s_t(2)..., s_t(K)]^{\mathsf{T}} \tag{3}$$

- We impose a Markovian dependence between states, which follows a dynamic Dirichlet distribution.

$$P(\mathbf{s}_t|\mathbf{s}_{t-1}, \mathbf{D}) = \mathrm{Dir}(\alpha_{t-1}\mathbf{D} \ \ \mathbf{s}_{t-1} + \mathbf{1}) \tag{4}$$

$$\text{where, } \ \alpha_t = \sum_f \mathbf{N}_{ft}, \ P(\mathbf{s}_1) = \mathrm{Dir}(\mathbf{1})$$

$\mathbf{D}_{kk} = d_k$, $1 \le k \le K$, where $d_k \in \mathbb{R}^+$ denotes the temporal dependence between two consecutive time instants for the $k$-th latent basis.

- Let pseudo-observation for each basis $k$ as $\mathbf{m}_{tk} = \alpha_{t-1}\mathbf{d}_k\mathbf{s}_{t-1}(k)$

## Properties of Dynamic Dirichlet Distribution

- Spectrogram at time $t$ is modeled as count data over $K$ bases. The dynamic Dirichlet prior allows us to have $\mathbf{m}_{tk}$ extra pseudo-observations for each basis $k$ .
- Variance of each entry decreases as total number of observations at previous time instant increases.

$$Var(\mathbf{s}_t(k)|\mathbf{s}_{t-1}) \propto \frac{1}{(\sum_k \mathbf{m}_{tk} + K)^2 (\sum_k \mathbf{m}_{tk} + K + 1)}$$

- PLCA as a special case when no temporal dependence i.e. $\mathbf{D}$=0

## Dynamic DLVM as dynamic version of NMF

- The EM algorithm can be viewed as a dynamic NMF algorithm.
- $\mathbf{W}_{fk} = P(f|\mathbf{z}_k)$; $\mathbf{S}_{kt} = P_t(z_k)$
- $\mathbf{X}_{F\times T} = \mathbf{W}_{F\times K}\mathbf{S}_{K\times T}\mathbf{G}_{T\times T} = \mathbf{W}_{F\times K}\mathbf{H}_{K\times T}$;

**Algorithm 1** Dynamic DLVM as Dynamic NMF

```
Input: $\mathbf{X}$
Output: $\mathbf{W}, \mathbf{S}, \mathbf{d}$
Randomly initialize $\mathbf{W}, \mathbf{S}, \mathbf{d}$
while Not converged do
    $\mathbf{W}_{fk} = \mathbf{W}_{fk} \sum_t \frac{\mathbf{X}_{ft}}{(\mathbf{WS})_{ft}} \mathbf{S}_{kt}$
    $\mathbf{W}_{fk} = \mathbf{W}_{fk} / \sum_k \mathbf{W}_{fk}$
    while Not converged do
        $\mathbf{m}_{tk} = \alpha_{t-1}\mathbf{d}_k\mathbf{s}_{t-1}(k)$
        $\mathbf{S}_{kt} = \mathbf{S}_{kt} \sum_f \mathbf{W}_{fk} \frac{\mathbf{X}_{ft}}{(\mathbf{WS})_{ft}} + \mathbf{m}_{tk}$
        $\mathbf{S}_{kt} = \mathbf{S}_{kt} / \sum_t \mathbf{S}_{kt}$
        Update $\mathbf{d}$
    end
end
```

## Experimental Setup

- Speaker source separation and Speech noise separation.
- **Speaker source separation:** Around 25 seconds of speech (8 to 9 sentences) from 10 speakers (5 male, 5 female) from TIMIT. First 17 seconds for training. Tested on 45 synthetic mixtures by digitally adding the speech from two speakers.
- **Speech noise separation:** Five noise types: Babble, Factory, White, Pink and Cockpit.
- Evaluation Metric: Signal to noise ratio improvement (SNRI), Source to Distortion ratio (SDR), Source to interference ratio (SIR), Source to Artifact ratio (SAR). SDR, SIR and SAR are perceptual metrics.

## References

1. N. Mohammadiha, P. Smaragdis, G. Panahandeh, and S. Doclo, A state-space approach to dynamic nonnegative matrix factorization, IEEE Transactions on Signal Processing, vol. 63, no. 4, pp. 949959, 2015
2. P. Smaragdis, B. Raj, and M. Shashanka, A probabilistic latent variable model for acoustic modeling, NIPS, vol. 148, pp. 81, 2006.
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## Results & Discussion

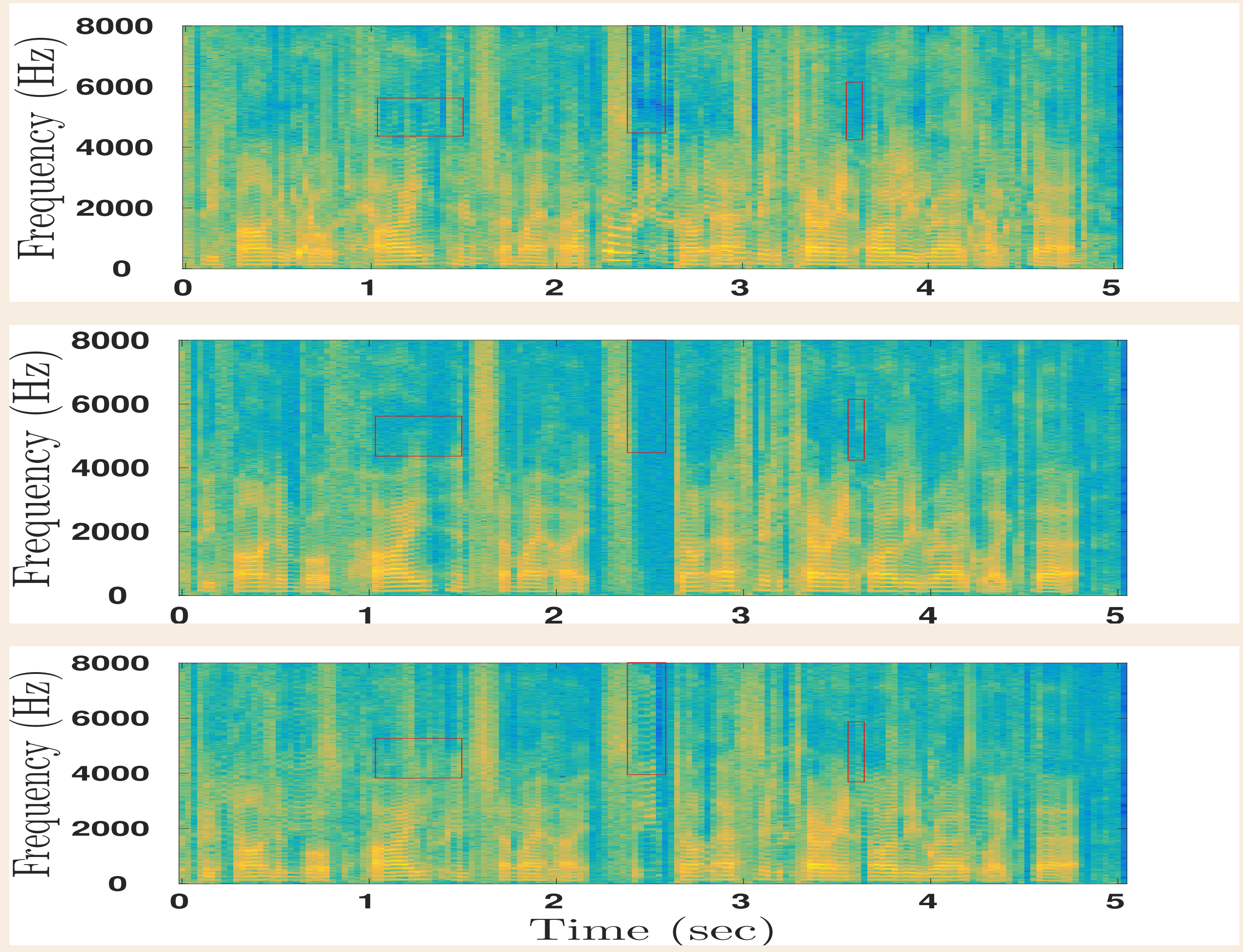

Figure : Original source, recovered source using PLCA, and recovered source using dynamic DLVM. Dynamic DLVM recovers a smoother spectrogram (areas of significant differences are highlighted).

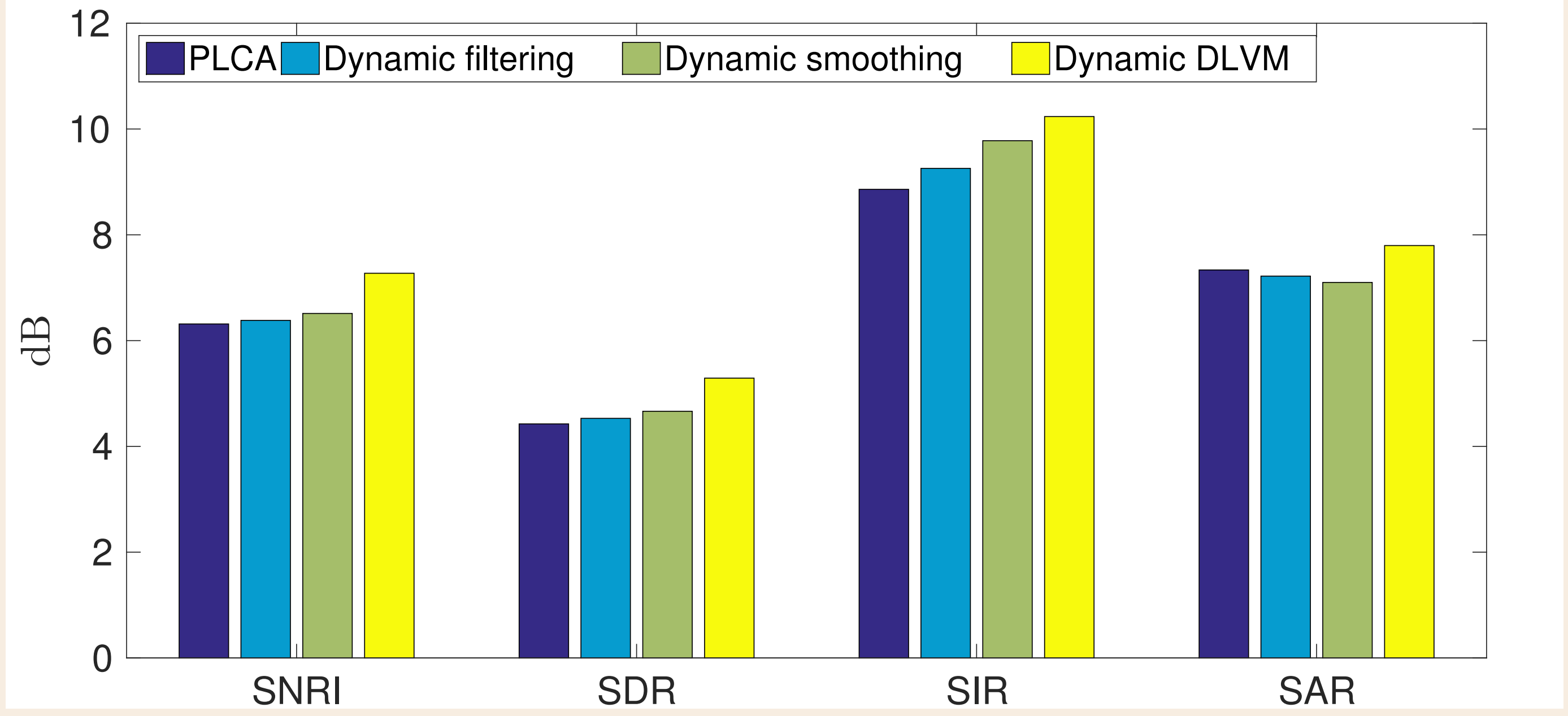

Figure : Results on speaker separation: Dynamic DLVM compared with three existing techniques in terms of four evaluation metrics. Our model outperforms PLCA by $0.96$ dB in SNRI, $0.87$ dB in SDR, $1.38$ dB in SIR, and $0.46$ dB in SAR.

Table : Comparison of different methods for noise separation

| | Average SNRI | | | | |
|---|---|---|---|---|---|
| | Babble | Factory | White | Pink | Cockpit |
| PLCA [2] | 5.63 | 2.60 | 5.07 | 2.04 | 2.78 |
| Dynamic filtering [3] | 4.93 | 2.87 | **5.83** | 2.06 | 2.70 |
| Dynamic smoothing [3] | 4.30 | 2.99 | 5.36 | 2.14 | 2.38 |
| **Dynamic DLVM** | **5.83** | **5.30** | 3.90 | **4.60** | **3.03** |
| | Average SAR | | | | |
| PLCA [2] | 6.69 | 8.14 | 8.30 | 7.82 | 7.84 |
| Dynamic filtering [3] | 6.44 | 7.73 | 5.25 | 5.97 | 4.36 |
| Dynamic smoothing [3] | 5.65 | 7.73 | 3.98 | 7.44 | 3.21 |
| **Dynamic DLVM** | **7.22** | **8.75** | **9.92** | **8.66** | **9.13** |

## Conclusion

1. Proposed a dynamic Dirichlet distribution particularly suitable for dynamic non-negative data.
2. Dynamic DLVM can be interpreted as dynamic NMF.
3. Our model does not require any free parameter apart from K.

https://anurendra.github.io/Homepage/

anu.ankesh@gmail.com, tanaya@iitk.ac.in,prasantg@iisc.ac.in