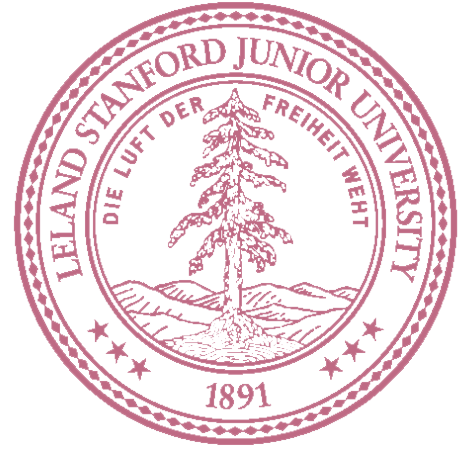


INTERACTIVE REFINEMENT OF SUPERVISED AND SEMI-SUPERVISED SOUND SOURCE SEPARATION ESTIMATES



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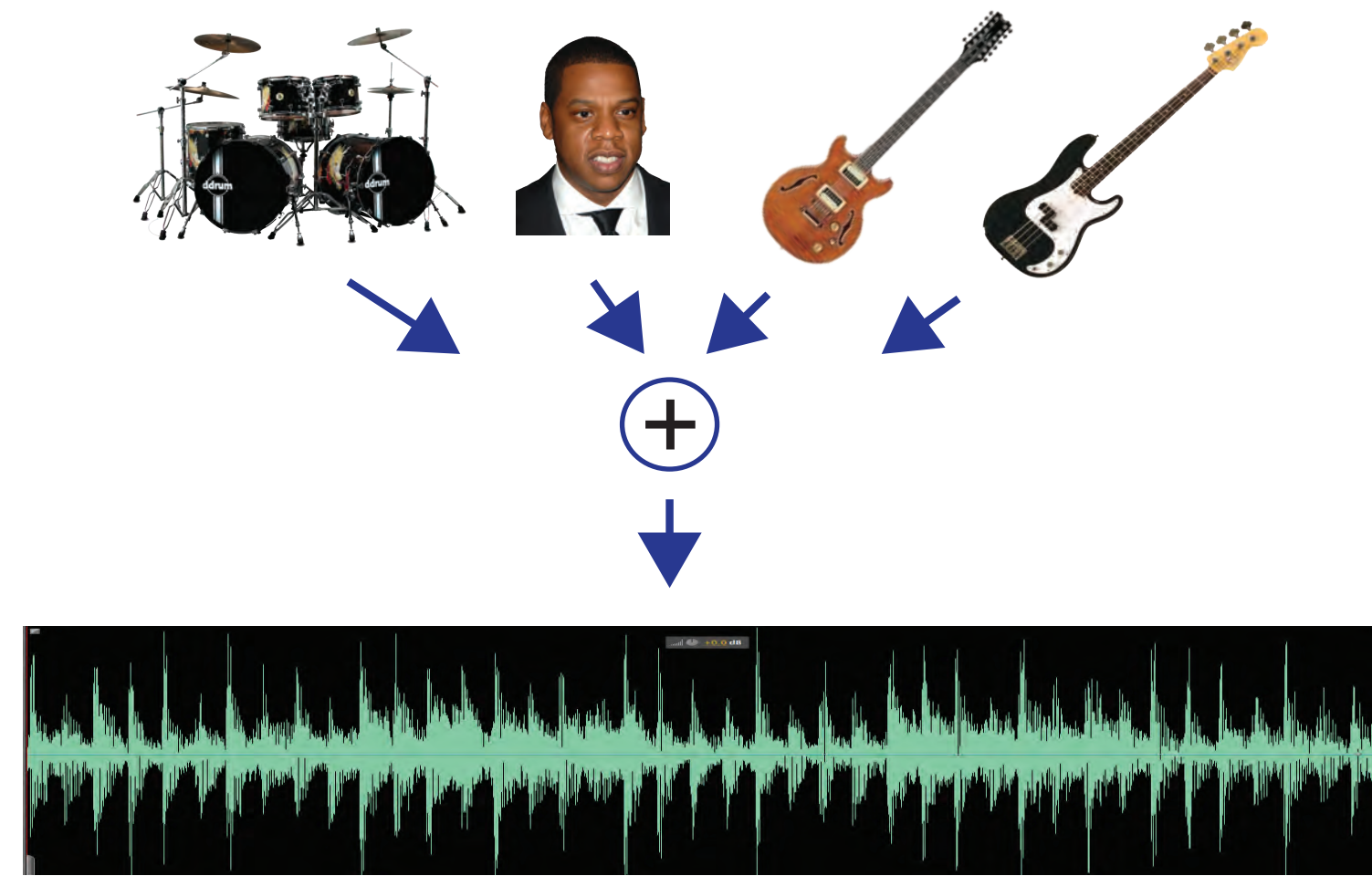
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²Adobe Research



Introduction

- Real world sounds are mixtures of many individual sounds



- It's useful to separate a mixture into its respective sources

music transcription

audio denoising

audio-based forensics

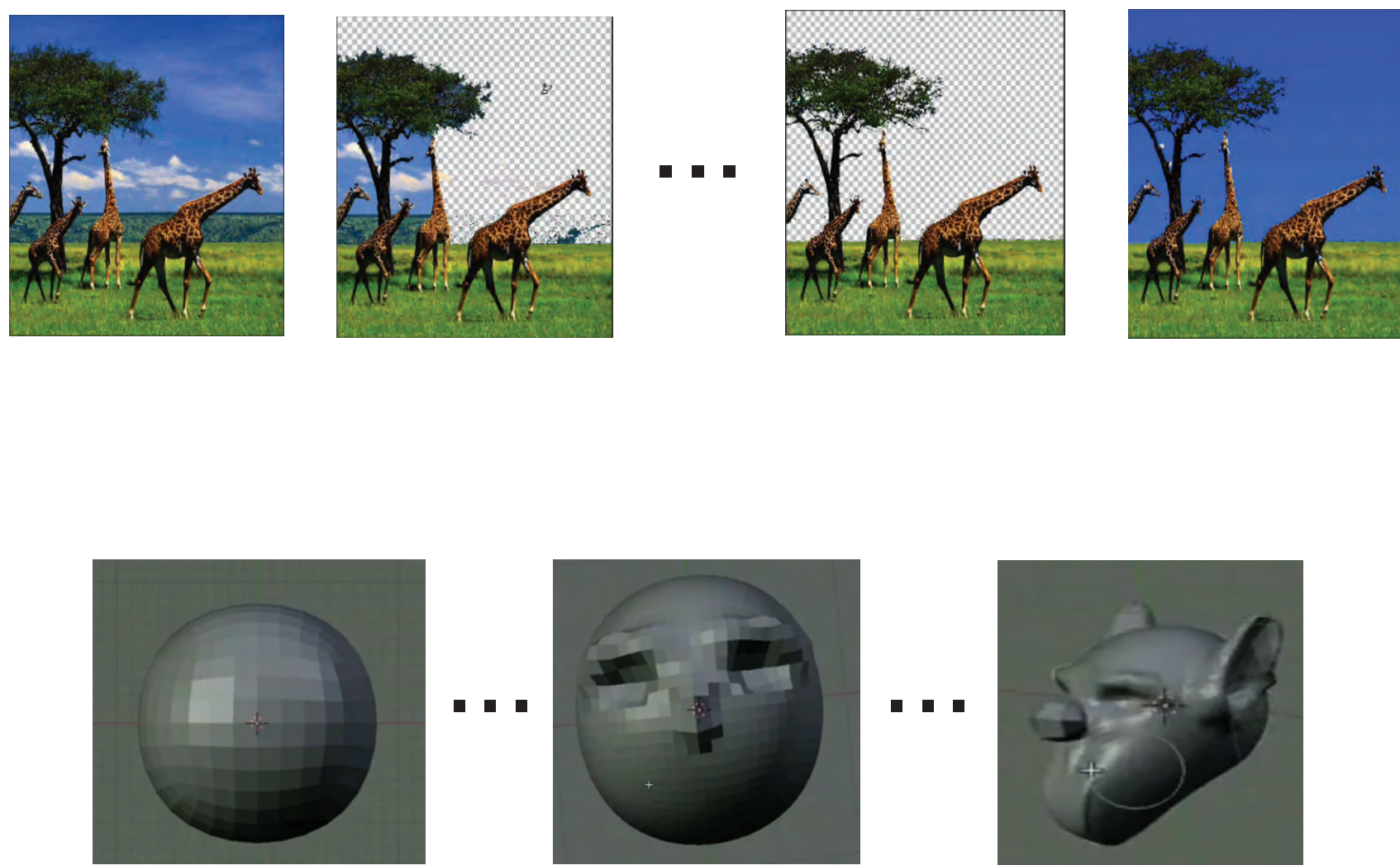
music remixing

- Current supervised and semi-supervised NMF-based methods can perform well, but:

- may also yield poor results
- are typically a one-shot process
- have no user-feedback or method of refinement

Idea

- A layers-sculpting-like environment for audio

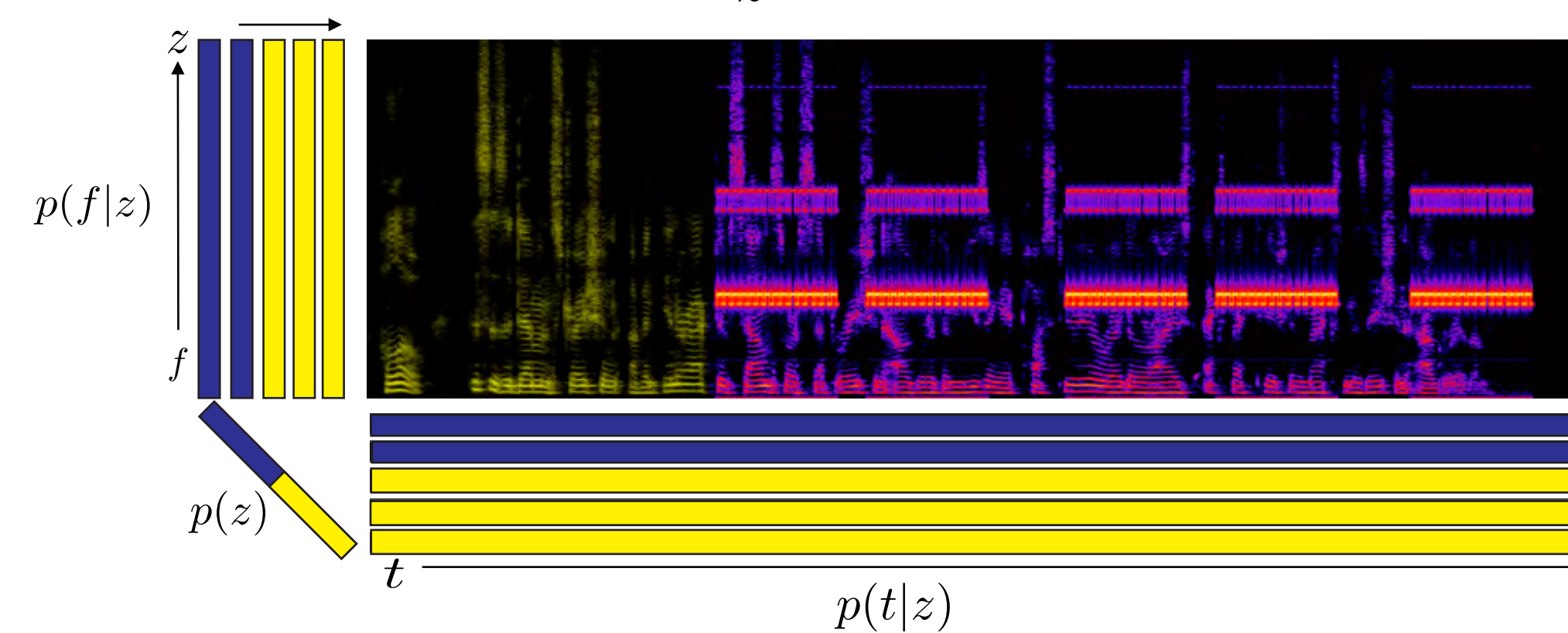


- Remove burden of being perfect the first time
- Focus on the professional

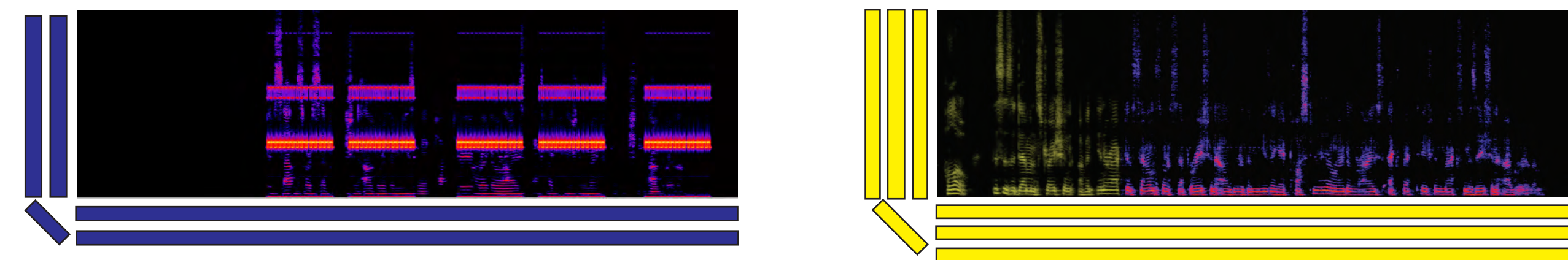
Proposed Method

- Probabilistic latent component analysis model

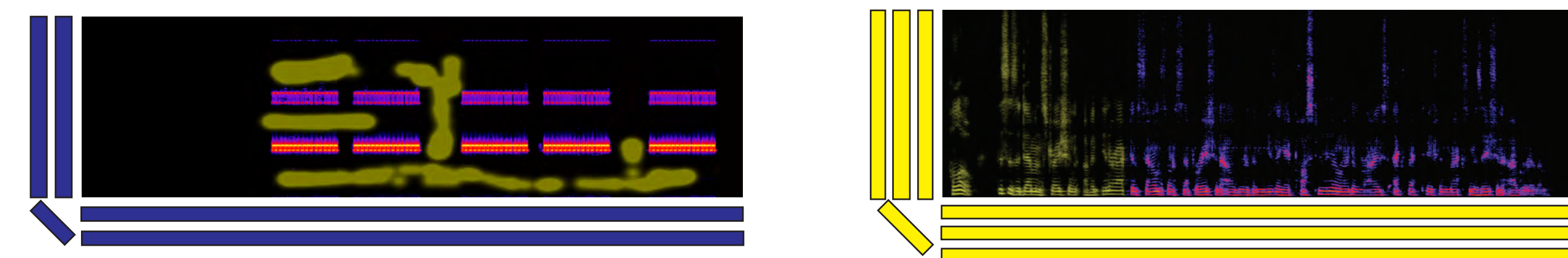
$$p(f, t) = \sum_z p(z) p(f|z) p(t|z)$$



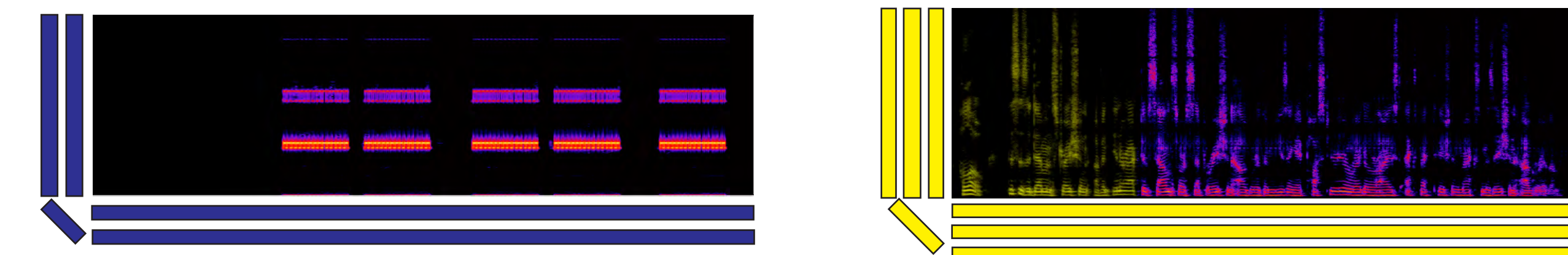
- Initial separation (semi-supervised)



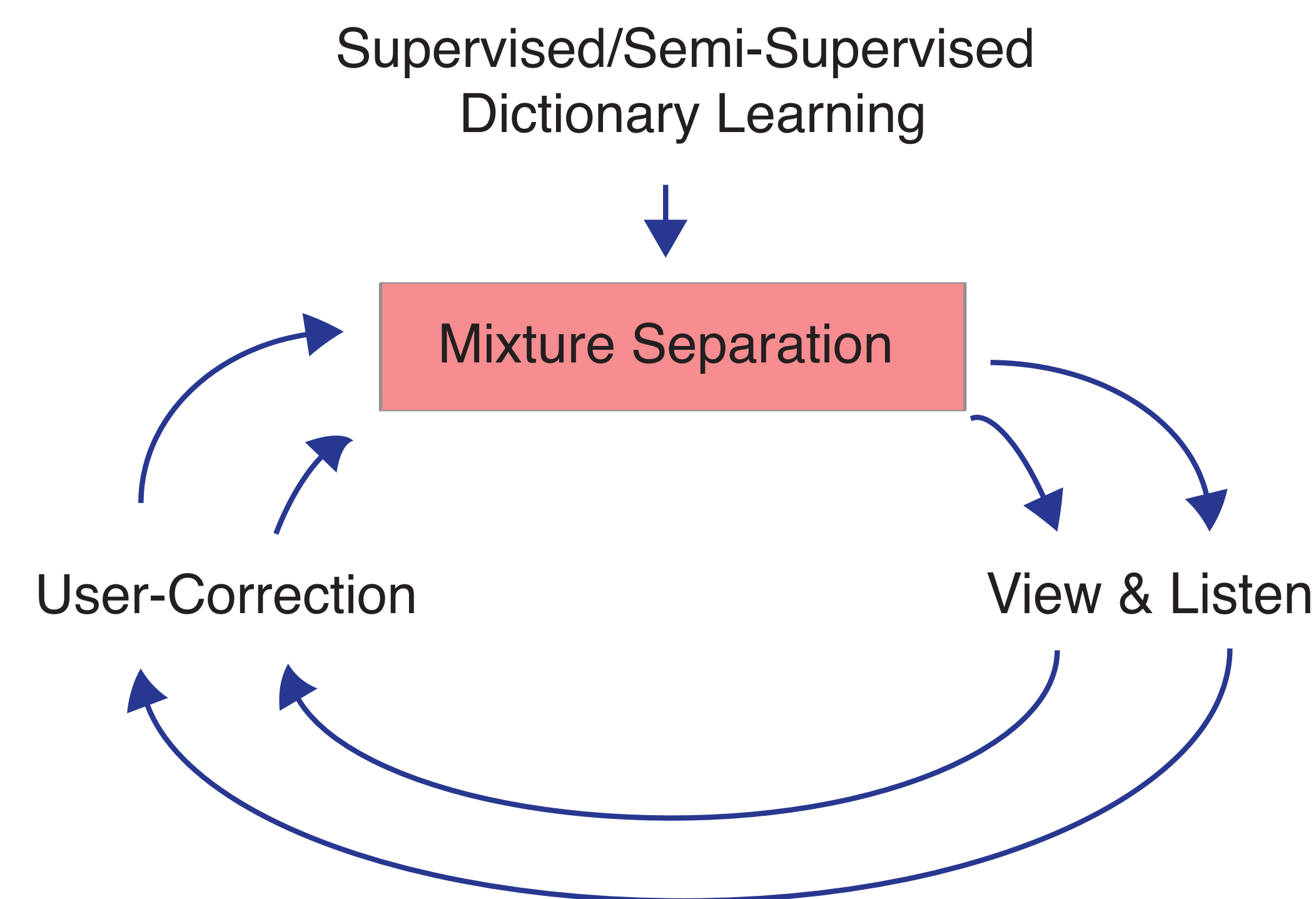
- User correction



- Refined results



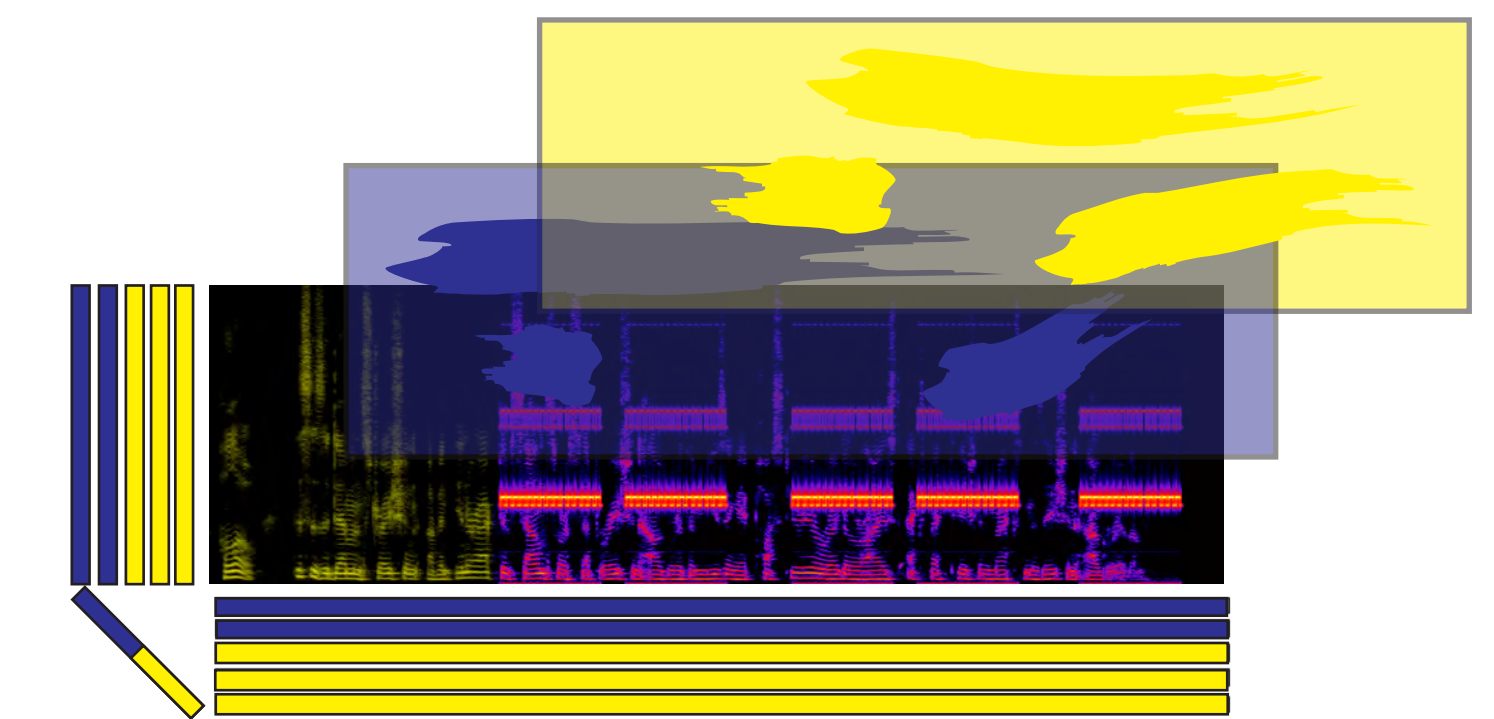
Block Diagram



Posterior Regularization

- Incorporate painting annotations as penalty constraints
- Difficult to encode time-frequency-source constraints via priors

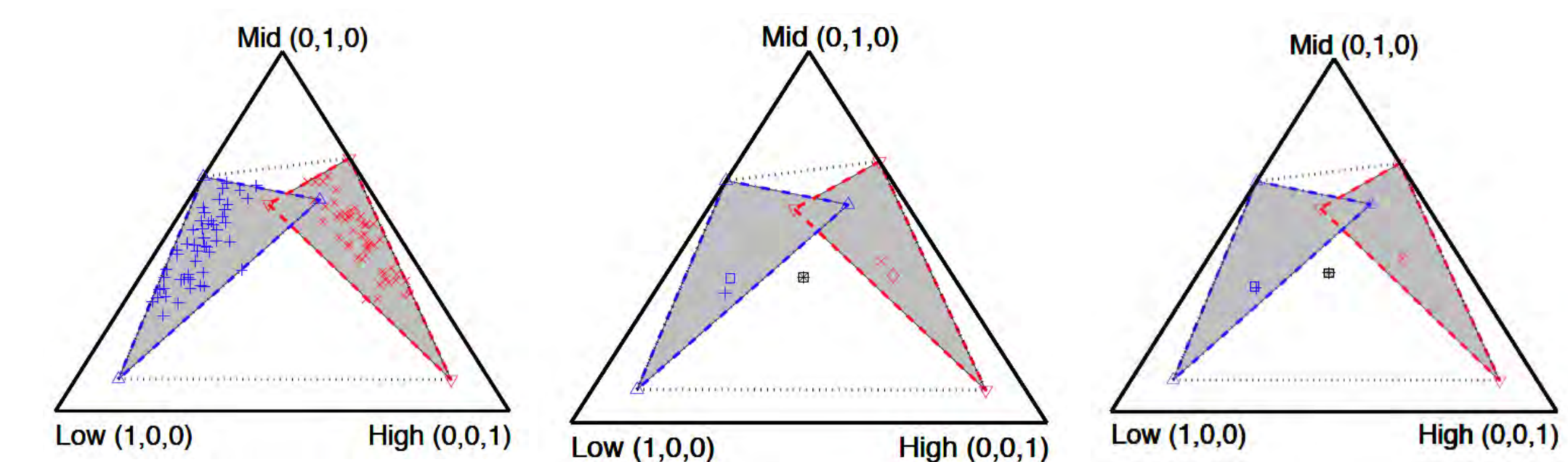
$$p(f, t) = \sum_z \tilde{p}(z) \tilde{p}(f|z) \tilde{p}(t|z)$$



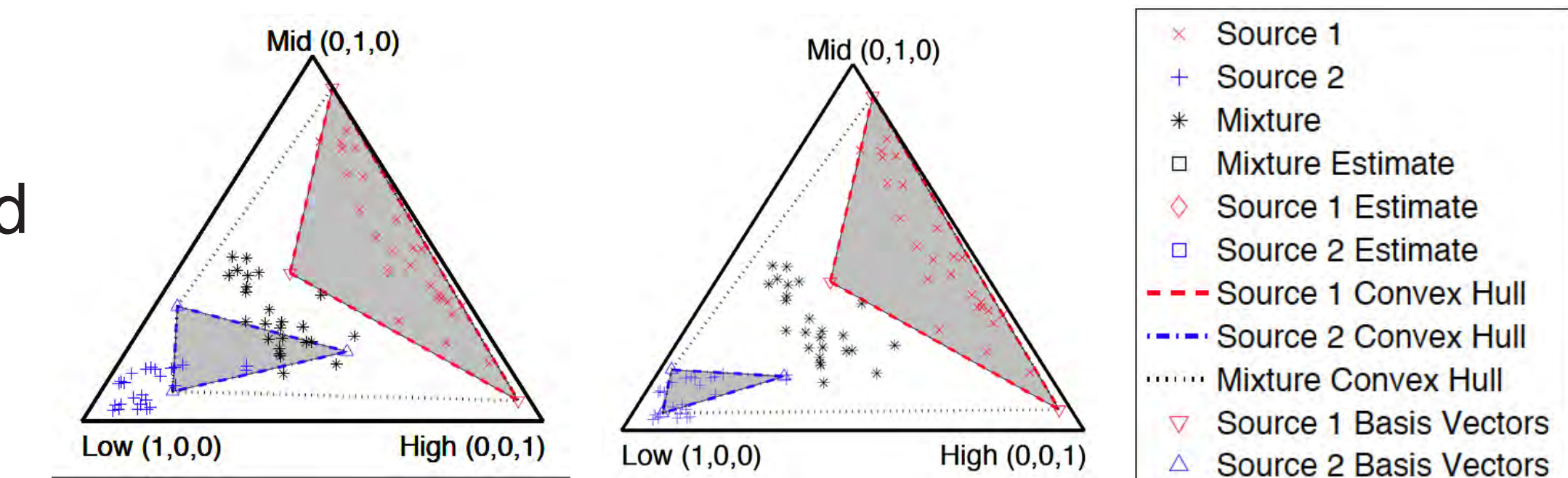
- Use framework of posterior regularization for EM algorithms
- Applies constraints on the posterior (E step) that would otherwise not be possible via standard priors (M step)

Geometric Perspective

Supervised Separation



Semi-Supervised Separation



Conclusions

- Source separation algorithm that allows:
 - time-frequency constraints via posterior regularization
 - interactive refinement
 - improved results over baseline methods



- For audio and video demonstrations, please see <https://ccrma.stanford.edu/~njb/research/iss>