Singer Identity Representation Learning using Self-Supervised Techniques

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Introduction

Goal: obtain time-invariant identity representations from singing voice

Existing models from speech literature

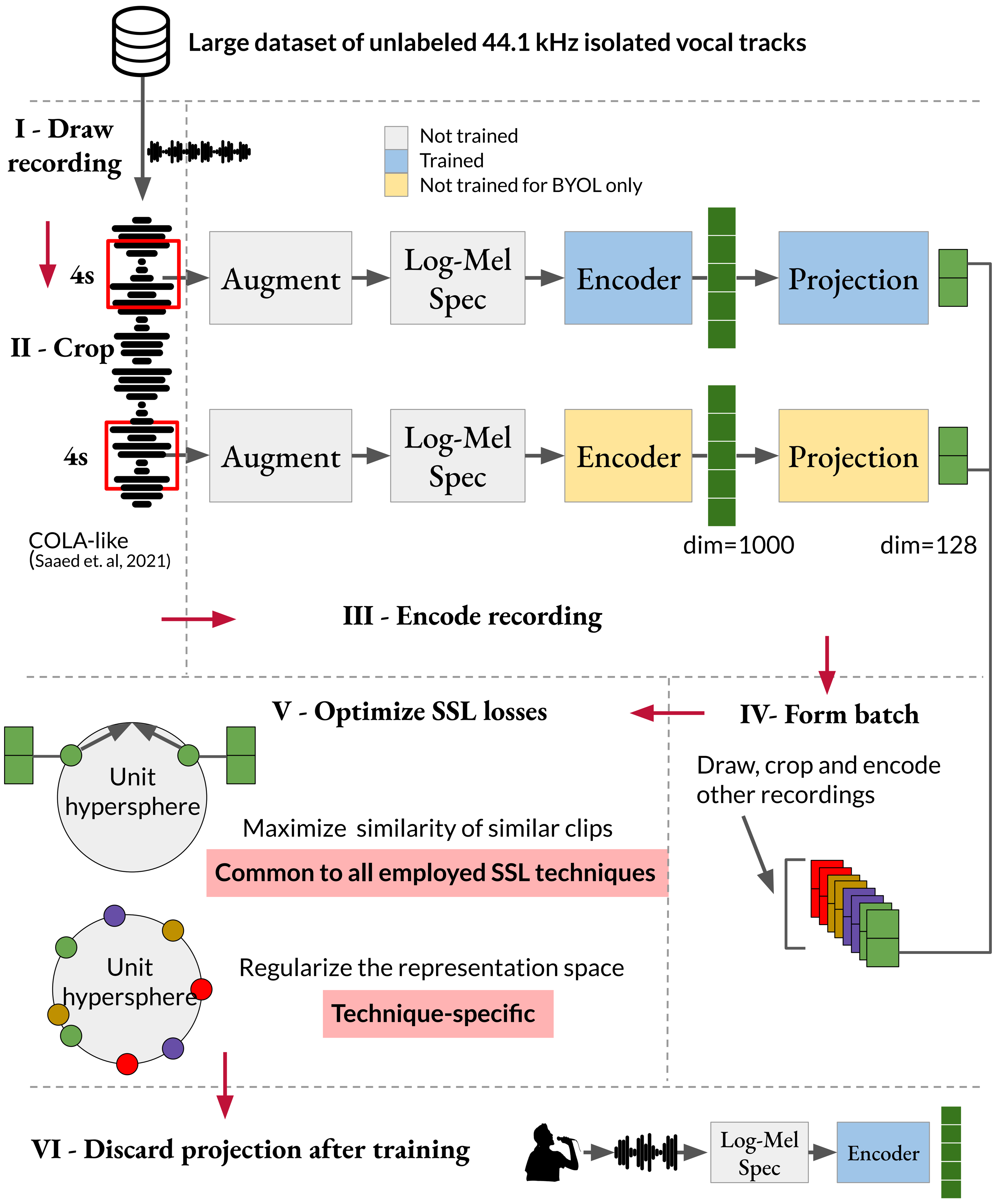
How well do models trained on speech generalize to singing voice?

Train identity extraction encoders

Lack of large labelled singing voice datasets

Can we train better models using Self-supervised Learning (SSL)?

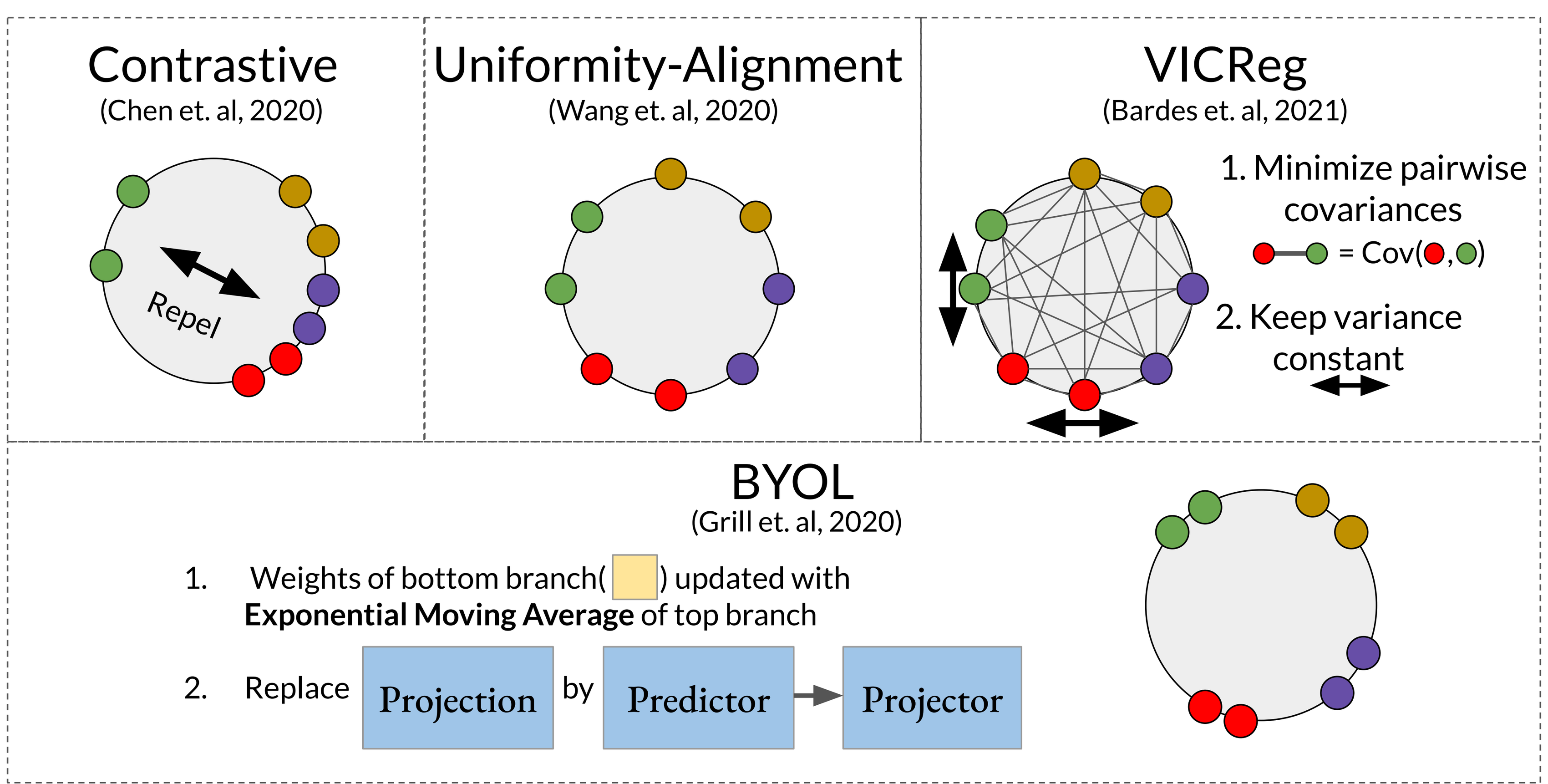
Overview and training



Self-supervised techniques

Common idea: representations from the same recording should be close

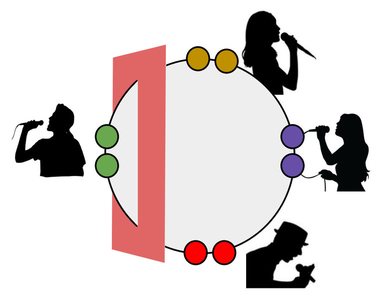
We trained models with the following SSL techniques:



Evaluation

Singer identification

Linear classifier



Trained on embedding space (frozen encoder)
Test accuracy of N-fold cross validation

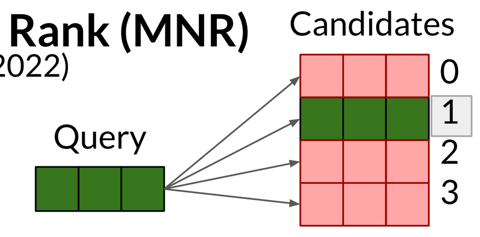
Singer similarity

Equal Error Rate (EER)

same/different binary classification

Mean Normalized Rank (MNR) (Lattner, 2022)

Rank ground-truth match by similarity with query



Evaluation on out-of-domain public datasets

Corpus	Language	#Hours	#Singers	Type	
VCTK	English	44	110	Speech	Yamagishi et. al, 2019
NUS-48E	English	1.91	12	Speech/Singing	Duan et.al, 2013
VocalSet	English	10.1	20	Singing	Wilkins et al., 2018
M4Singer	Chinese	29.77	20	Singing	Zhang et. al, 2022

Baselines

Pre-trained, publicly available speech models → Supervised speaker verification; General purpose SSL

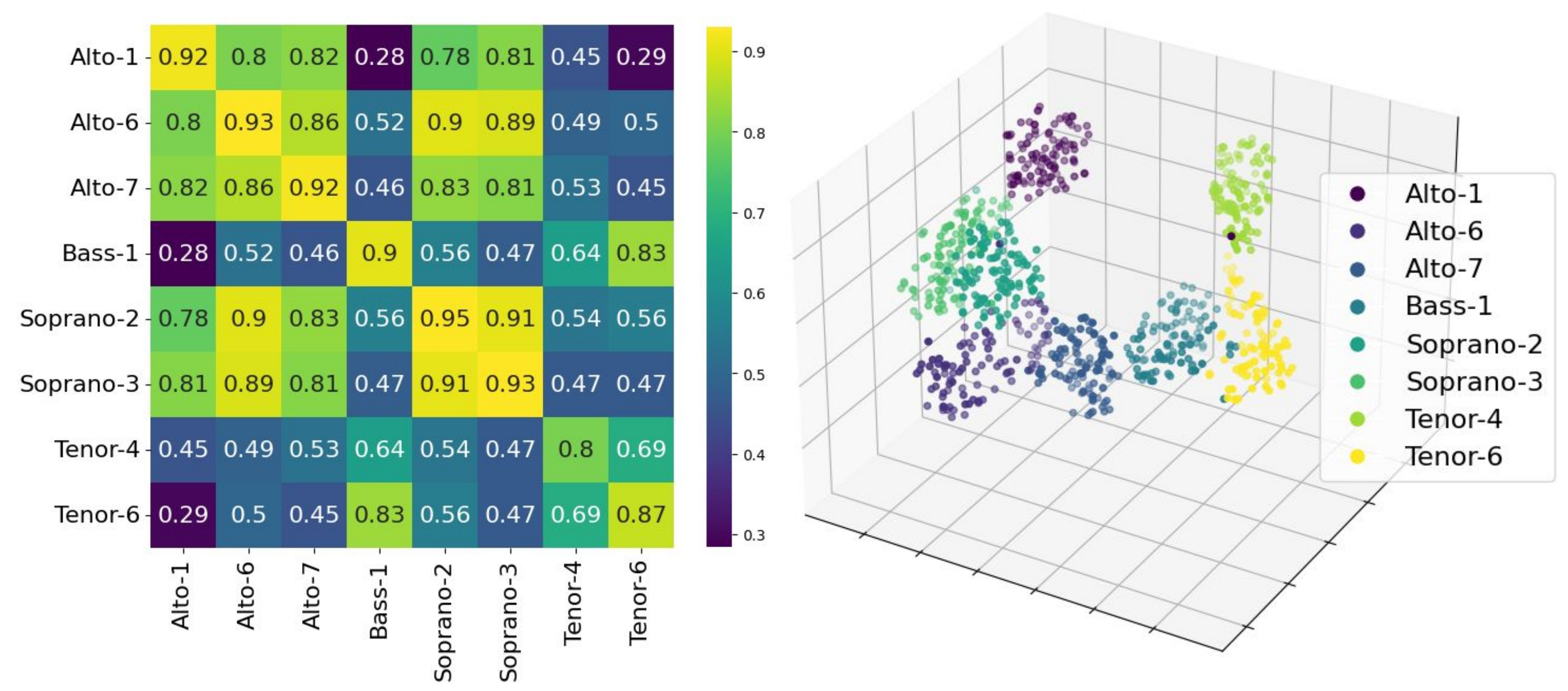
Model	#Params	SR	Dim.	Backbone	
GE2E	1.4M	16	256	LSTM	Wan et. al, 2018
F-ResNet	1.4M	16	512	ResNet-34	Chung et.al, 2020
H/ASP	8.0M	16	512	ResNet-34	Kwon et al., 2022
Wav2Vec-base	95M	16	12X768	Wav2Vec 2.0	Baevski et. al, 2020
XLSR-53	300M	16	24X1024	Wav2Vec 2.0	Conneau et. al, 2021
Ours	5.0M	44.1	1000	EfficientNet-B0	

Results

Speech baselines on singing voice

- ↓ compared to speech data.
- Still work reasonably well; except for VocalSet
- SSL baselines: performed bad on similarity, well on identification

Trained SSL identity encoders



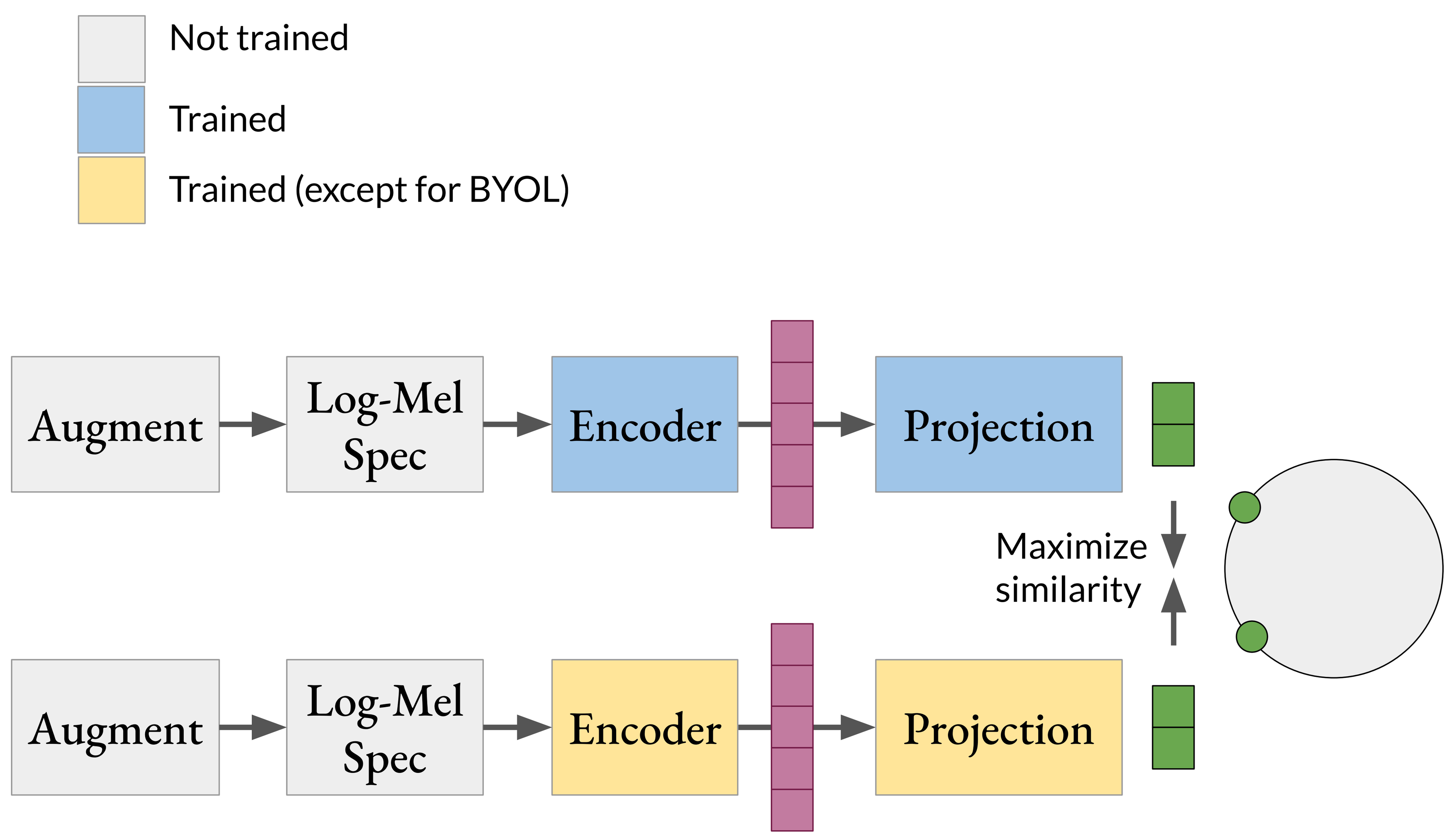
Left: Average similarity score between singers over 100 4s clip draws for each singer (M4Singer dataset)
Right: T-SNE visualization for the same embeddings in 3D (original dimensionality is 1000)

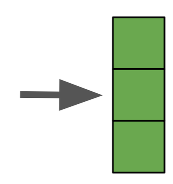
The trained SSL models were comparable or superior to baselines

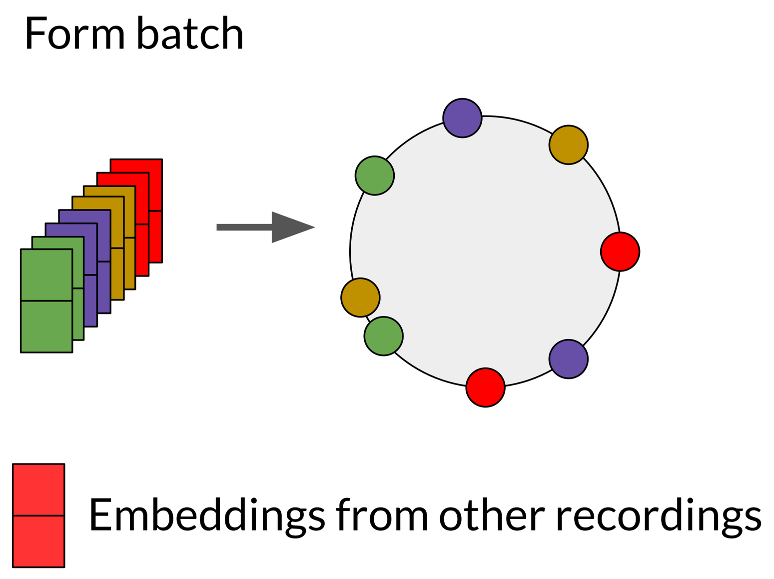
Comparison of SSL techniques → Best on out-of-domain: **BYOL**; Best In-domain: **Contrastive**

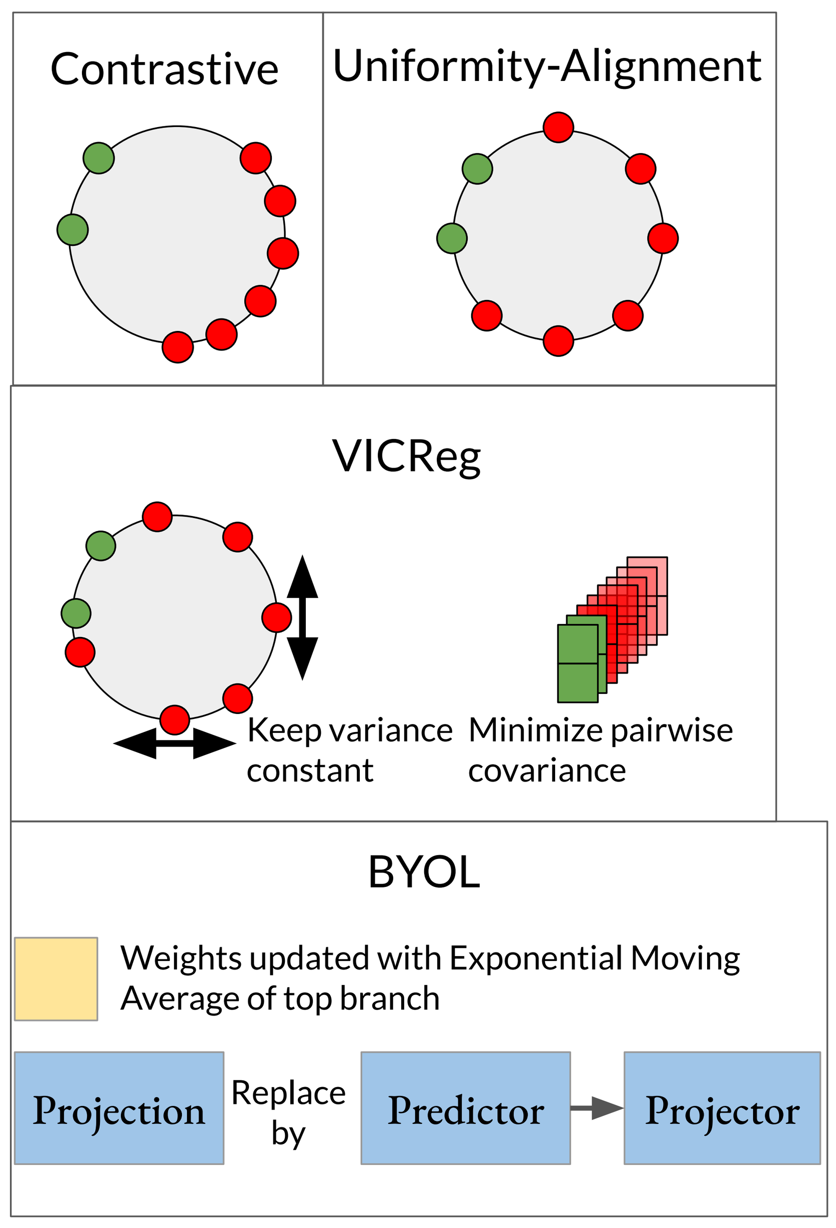
Conclusion

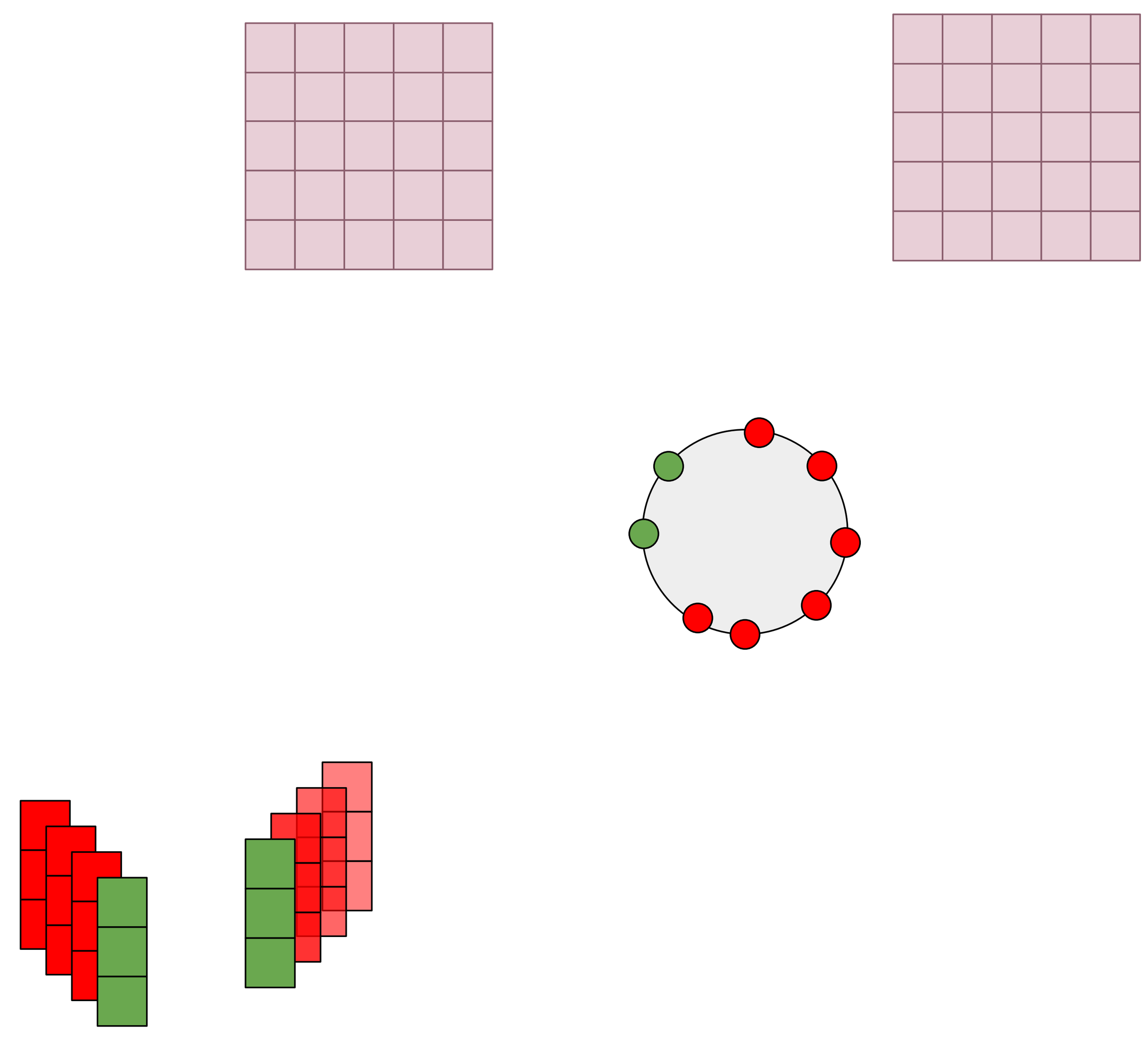
- **Trained** identity encoders using **Self-Supervised Learning (SSL)**
- **Dataset**: large unlabeled singing voice isolated recordings
- **Comparison** with publicly available pre-trained speech models
- **Evaluation** on singer identification and similarity tasks
- A big gap still exists for challenging datasets
- Release of code and trained models











Augment	Random noise, gain, time mask, formant preserving pitch shifting
Encoder	Generic encoder: EfficientNet-B0 (Tan and Lee, 2019)
Projection	Linear layer + nonlinearity

Retrieval

Mean Normalized Rank (MNR)

Identification | Similarity

Big drop on singing voice

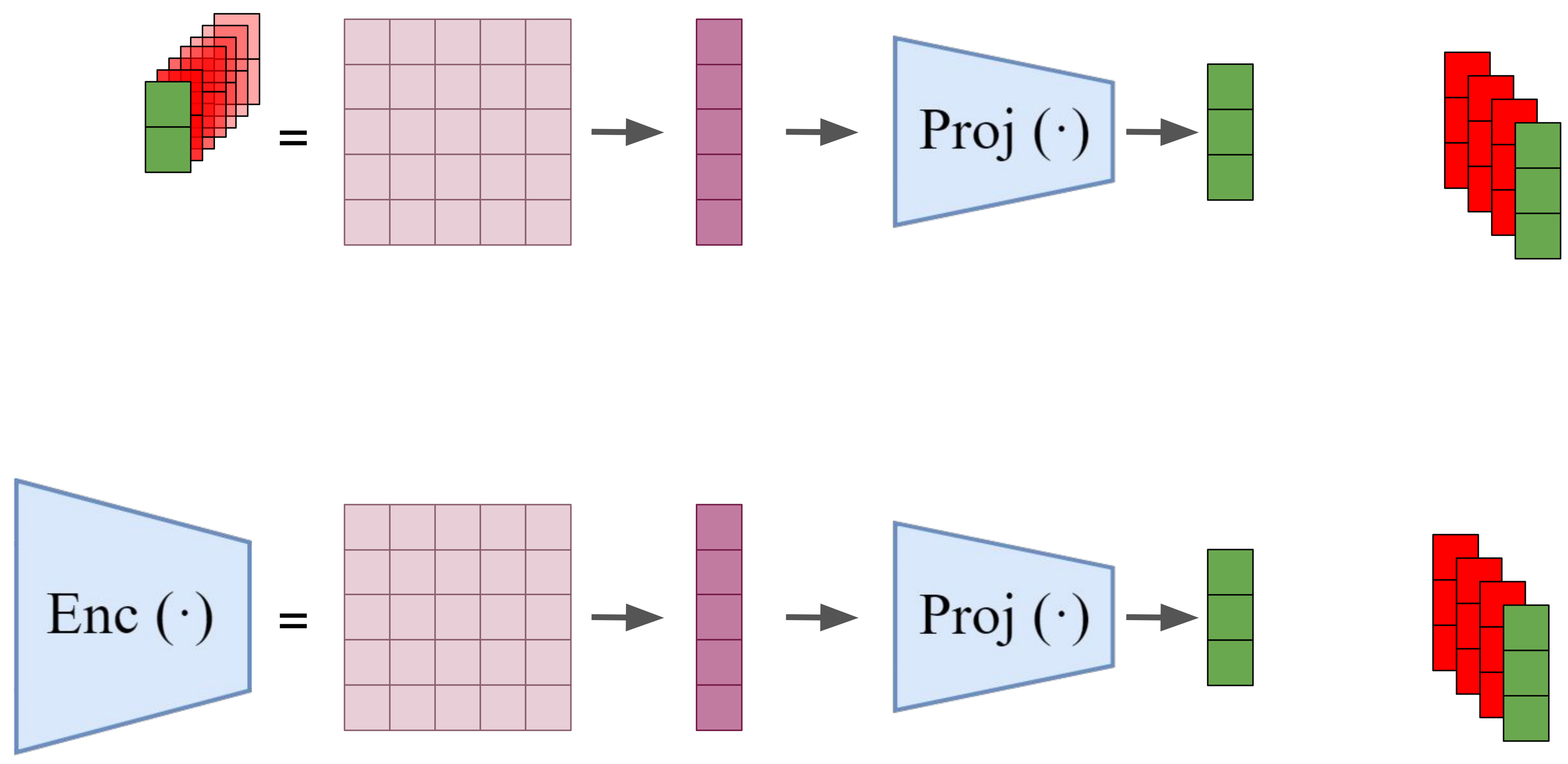
Supervised | SSL

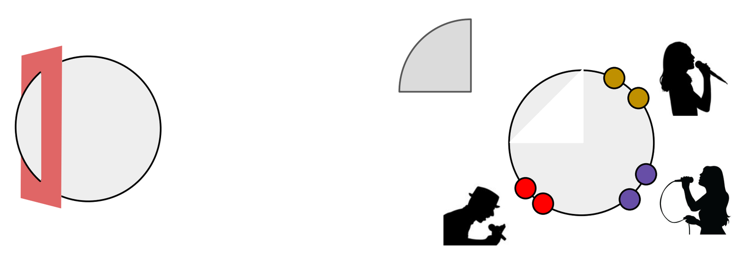
Still work reasonably well

Well | Not well

Trained models

Comparable or superior





Main results for singing voice

- ↓ compared to evaluation on speech data
- They still work reasonably well; except for VocalSet
- SSL baselines: performed well on identification, bad on similarity

- **The trained SSL models were comparable or superior to baselines**
- A big gap still exists for challenging datasets

- **Trained** identity encoders using **Self-Supervised Learning (SSL)**
- **Dataset**: large unlabeled singing voice isolated recordings
- **Evaluation** on singer identification and similarity tasks
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Motivation