Emotion and Theme Recognition in Music with Frequency-Aware Receptive Field Regularized CNNs



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Agenda

- Overview
- Approaches
 - What worked
 - What didn't work
- Results
- Conclusion



Takeaways

Insights

Make the network see less of the input to avoid overfitting.

Frequency context helps.

Ensembling helps.

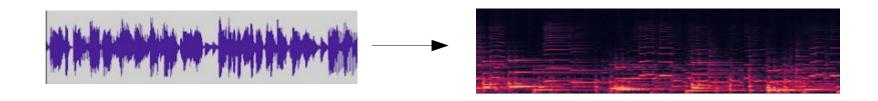
Results

<u>Validation PR-AUC</u>	Testing PR-AUC
0.1189	0.1546
_	0.1077 (baseline)



Overview

- Emotion and theme recognition task instance of auto-tagging.
- Current state-of-the-art in many audio tasks, including audio-tagging uses
 CNNs in a VGG-like architecture.
- Input: Time-Frequency representation of audio (Spectrograms)





Overview

- The success of CNNs started in computer vision tasks.
- Later improvements on CNNs architectures made the networks deeper.
- Deeper architectures such as ResNet and DenseNet don't perform as well in audio processing tasks.



Approach: Baseline Models

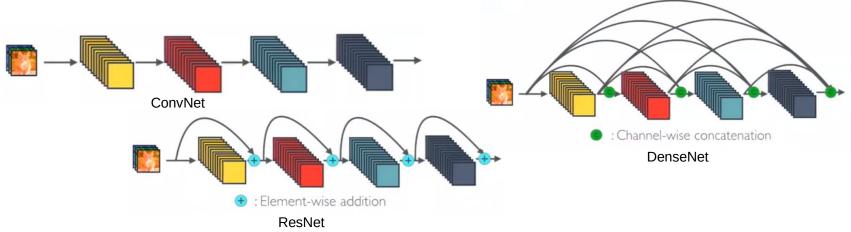
- VGG-like
- ResNet18, ResNet34, ResNet50
- CRNN Convolutional Recurrent Neural Network

Model	Validation PR-AUC	Testing PR-AUC
VGG-like	-	0.1077
ResNet34	0.0924	0.1021
CRNN	0.0924	0.1172



Deeper = Better?

- ResNet [1] and DenseNet [2] variants outperform earlier (and shallower)
 VGG-based [3] variants by a significant margin (Vision tasks).
- They address shortcomings of VGG such as the vanishing gradient.





Deeper = Better? Can lead to overfitting

Hershey et al. [8] compared various vision CNNs on a large-scale dataset of 70M audio clips from YouTube.

- ResNet-50 can perform very well.
- However, training such deep architectures on smaller datasets results in heavy overfitting on the training samples.



The Receptive Field in CNNs

- In fully-connected layers, each neuron is affected by the whole input. In contrast, in convolutional layers each neuron has a strictly limited 'field of view' (RF).
- Input values outside of this RF cannot influence the neuron's activation.
- The maximum RF can be calculated:

$$S_n = S_{n-1} * s_n$$

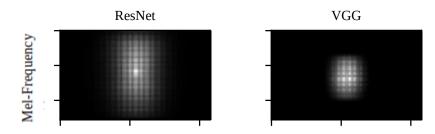
 $RF_n = RF_{n-1} + (k_n - 1) * S_n$

 s_n , k_n are stride and kernel size of layer n, respectively, and S_n , RF_n are cumulative stride and RF of a unit from layer n to the network input.



The Effective Receptive Field in CNNs

- A neuron may not actually use all the available receptive field.
- The set of input pixels or units that effectively influence a neuron is called its Effective Receptive Field (ERF) by Luo et al. [14]



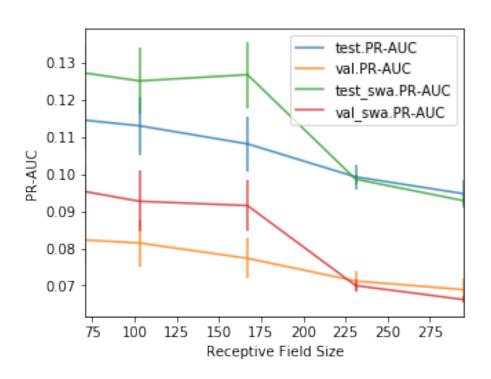


Adapting the RF of Vision Architectures

- Changing filter sizes to change the maximum receptive field.
- We changed some filter sizes from 3×3 to 1×1 .
- Filter size is a hyperparameter.



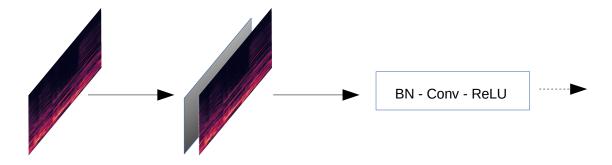
Results with Receptive Field Adaptation





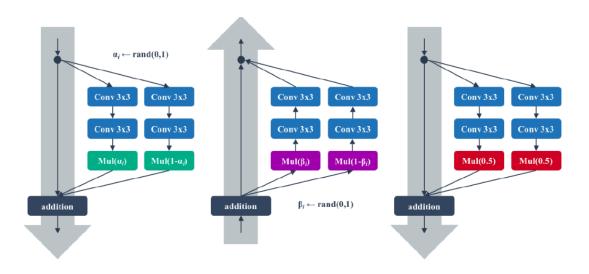
Frequency Aware Networks

- Drawback of CNN for audio domain: lack of spatial ordering in convolutional layers.
- Solution: Add a channel that encodes frequency as a value in [-1, 1].





Shake-Shake Regularization



Left: Forward training pass. **Center:** Backward training pass. **Right:** At test time.

Image source: Gastaldi, X., 2017. Shake-shake regularization. arXiv preprint arXiv:1705.07485.



Ensembling

- Stochastic Weight Averaging
 - Maintain a paired network with running average of weights
- Snapshot Averaging
 - Average the predictions of the 5 snapshots of the model during training
- Multi-model averaging
 - Average predictions from models with different initializations, RFs, etc.



Results

Submission	Validation PR-AUC	Testing PR-AUC
ShakeFAResNet*	.1132	.1480
FAResNet*	.1149	.1463
Avg_ensemble*	.1189	.1546
ResNet34	.0924	.1021
CRNN	.0924	.1172
CP_ResNet	.1097	.1325
VGG-ish-baseline	-	.1077
popular baseline	-	.0319

^{*:} indicates an ensemble.



Conclusions

- Receptive field regularization is useful to avoid overfitting.
- Frequency-aware networks improve performance (spectrogram as input).
- Ensembling improved results.

- Future work:
 - Temporal context?
 - Perceptual features?





Thank you! Questions?





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