

fnet

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outline

complex output

adversarial network

attention

evaluation

stft

$$fs = 16,000$$

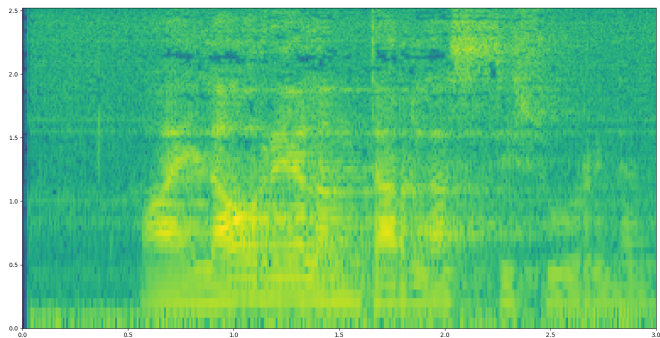
$$x: [-1, 1)^{3fs}$$

```
from scipy.signal import stft  
f, t, s = stft(x, fs)
```

$$s: \mathbb{C}^{129,376}$$

mel

```
plt.pcolormesh(t, np.log1p(f/700), np.log(np.abs(s)))
```



istft

```
from scipy.signal import istft  
t2, x2 = istft(s, fs)  
assert np.allclose(x, x2)
```

frames vs samples

- ▶ predicting frames takes much fewer steps
- ▶ an individual sample has no interpretable meaning
- ▶ a model predicting samples has to model much more complicated dependencies across a much longer time

vocoder

- ▶ most of the models we've seen has a trainable vocoder (wavenet, samplernn)
- ▶ to reconstruct the samples from frames
- ▶ which is unnecessary when we have complex-valued frames

complex network for speech

- ▶ 2016 Drude et al. “inappropriate for speech enhancement”
- ▶ 2016 Hu et al. “initial investigation”
- ▶ 2017 Fu et al. “complex spectrogram enhancement”
- ▶ 2018 Nakashika et al. “complex-valued rbm”

objective

- ▶ output expected complex-valued frames

	min	max	mean
s.real	-0.08	0.10	0.00
s.imag	-0.14	0.12	0.00
s.abs	6.65^{-09}	0.14	0.17^{-02}

- ▶ how to define the loss?

adversary

frames	$s :$	$\mathbb{C}^{f,t}$
generator	$g :$	$? \rightarrow \mathbb{C}^{f,t}$
discriminator	$d :$	$\mathbb{C}^{f,t} \rightarrow \{0, 1\}$

- ▶ zero-sum game $\arg \min_g \max_d v(g, d)$
- ▶ payoff $v(g, d) = \mathbb{E}_{s \sim p_{data}} \log d(s) + \mathbb{E}_{s \sim p_{model}} \log (1 - d(s))$

attenttion

- ▶ lots of attention

problem

- ▶ how to evaluate

baby steps

- ▶ not to explode
- ▶ to drop the loss
- ▶ to output more than noises