Radio galaxy classification with scattering-transform-based generative augmentation



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With great data comes great responsibilities



In the context of my PhD



Radio galaxy generation and classification

FIRST Data



Credit: FIRST dataset, Rustige+23

Diffuse cluster radio emission generation and classification

- MGCLS and MERGHERS data
- X-ray, optical, polarisation, spectral index





Morlet wavelets are sinusoids with Gaussian envelopes

 $\psi_{j,\ell}(u) = 2^{-2j} \psi(2^{-j} r_{\theta} u) \text{ for } 0 \le \ell < \overline{L, \ \theta} = \ell \pi / L, \ 0 \le j < \overline{J}$

Wavelet kernels are localised and extract features

Scattering transform is a cascade of wavelet transforms

Order 0

Input image

Scattering transform is a cascade of wavelet transforms

Order 0

Order 1

Input image

Multidimensional dependency require variable mixing

Tensor fitting

Scattering coefficients are dependent

Multidimensional dependency require variable mixing

Tensor fitting

Variational Autoencoder

Scattering coefficients are dependent

Latent variables are independent

FIRST dataset is a popular radio galaxy benchmark

- 2158 radio galaxies
 - FRI: 495
 - FRII: 924
 - Compact: 391
 - Bent: 348
- 300x300 pixels (greyscale) Compa
- No noise or artefacts

Models capture general features of FRII galaxies

Galaxy10 provides less sparse sources and is easier

Reconstructions			Generations - similar				Generations - free								
Original	٦	٠		٩	o	٦	٠	•	٩	o					
Dual	٥	۰	۰	۲	•	•	•	•	۰	•	•	۰	۰	•	•
CNN	۰	•	•	٠	۰	۰	٠	•	۹	•	٠	•	•	۰	٠
STMLP	۰	۰	•	۰	•	•	•	•	۰	•	ø	۰	0	۰	•
Lavg STMLP	۰	•	۰	۰	0	۰	۰	•	۰	•	۰	۰	۰	٠	•
Ldiff STMLP	۰	•	•	۰	0	•	۰	•	۹	0	•	٥	•	•	•

The VAEs capture Galaxy10 peak pixels well

Reconstructions of Galaxy10

The VAEs capture Galaxy10 peak pixels well

Reconstructions of Galaxy10

Reconstructions of FIRST

Peak intensity is worse for irregular sources

Peak intensity is worse for irregular sources

MSE scales with asymmetry

24

Difficult reconstructions are asymmetric, faint and spread out

Originals

Filtering reduces risk of faint constructions

Filtered

Scattering transform saves training time

Using Dual VAE no classification improvement is made

λ=0

Model: ProjectModel Total accuracy: 76.38%

0.0%

7.2%

18.0%

₽ - 74.8%

0.8

-0.6

Generated images facilitate classification of FRII and bent sources

λ=0

Conclusions

- VAE-generated images are smooth, faint, but overall realistic
- Classification performance seems to be only marginally improved by artificial augmentation
- More tests with different VAEs and levels of artificial generation will be made
- This method will soon be applied on diffuse cluster radio emission

Thank you! Questions?

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Backup slides

Scattering transforms are iterative wavelet transforms

$$\begin{split} \Psi_{J,L}(x) &= [X, |X \star \psi_{j,\ell}|, ||X \star \psi_{j,\ell}| \star \psi_{j',\ell'}|]_{1 \le \ell,\ell' \le L, \ 1 \le j < j' \le J} \\ \phi_J(u) &= 2^{-2J} \phi(2^{-J}u) \\ S_{J,L}(X) &= \Psi_{J,L}(X) \star \phi_J \\ &= [X \star \phi_J, |X \star \psi_{j,\ell}| \star \phi_J, ||X \star \psi_{j,\ell}| \star \psi_{j',\ell'}| \star \phi_J]_{1 \le j < j' \le J, 1 \le \ell,\ell' \le L} \end{split}$$

 $X \star \phi_2 = |X \star \psi_{0,0}| \star \phi_2 = |X \star \psi_{0,1}| \star \phi_2 = |X \star \psi_{1,0}| \star \phi_2 = |X \star \psi_{1,1}| \star \phi_2 = |X \star \psi_{0,0}| \star \psi_{1,0}| \star \phi_2 = |X \star \psi_{0,0}| \star \psi_{1,1}| \star \phi_2 = |X \star \psi_{0,1}| \star \psi_{1,0}| \star \phi_2 = |X \star \psi_{0,1}| \star \psi_{1,1}| \star \psi_2 = |X \star \psi_{0,1}| \star \psi_2 = |X \star \psi_2 =$

Low pass filter for scattering transform

Littlewood-Paley equality

Conservation of energy

$$\sum_{j=-\infty}^{+\infty} |\hat{\psi}(2^j\omega)|^2 = 1 , \ \forall \omega > 0$$

Capture lower frequencies of signal $~[-2^{-J}\pi,2^{-J}\pi]$

With low-pass filter
$$\hat{\Phi}_J(\omega) = \left(\sum_{j=J+1}^{+\infty} |\hat{\psi}(2^j \omega)|^2\right)^{1/2}$$
 satisfying $\int \Phi_J(t) dt = 1$

 \rightarrow preserves norm and is therefore invertible

The scattering transform is an iterative wavelet transform

Wavelet transform $WX = X \star \overline{\psi_{j,l}(t)}$ Scattering transform SX = W|WX|

$S_0 = X \star \Phi$ $S_1(j_1, l_1) = \langle |X \star \psi_{j_1, l_1}| \star \Phi \rangle$ $S_2(j_1, j_2, l_1, l_2) = \langle ||X \star \psi_{j_1, l_1}| \star \psi_{j_2, l_2}|\Phi \rangle$

Convolutional neural networks encodes features

Scattering transform is an iterative wavelet transform

Performance improves with number of scattering coefficients $a_{1} = 2^{-2l(1 + l + l + 2^{l(l-1)})}$

VAEs learns total pixel distribution well for galaxy10

Radial profiles are smoother and steeper than originals

Two plots from te left one. Logarithmic x-axis.

Filtering was an important part in the generative modelling

J=2

Reconstructions of FRII Generations of FRII Real (n=1312) Real (n=1312) 100 CNN (n=6560) CNN (n=5000) 100 lavgSTMLP (n=6560) — lavgSTMLP (n=5000) Dual (n=6560) Dual (n=5000) STMLP (n=6560) STMLP (n=5000) ≥ ¹⁰⁻ Frequency IdiffSTMLP (n=6560) IdiffSTMLP (n=5000) Value of Frequen brightest 10-2 10^{-2} pixel 10 10-0.2 0 2 0.4 0.6 0.8 1.0 0.4 0.6 0.8 X (Real - Gen) Real + Gen (Real – Gen) Real + Gen 1 0 0 -1 × N N 0.2 0.4 0.8 0.2 0.4 0.8 0.6 0.6 1.0 Peak Intensity Peak Intensity Reconstructions of FRII Generations of FRII Real (n=21495808) — Real (n=21495808) 100 100 CNN (n=107479040, RMAE=0.240) CNN (n=81920000, RMAE=0.457) — lavgSTMLP (n=107479040, RMAE=0.275) lavgSTMLP (n=81920000, RMAE=0.452) 10- 10^{-1} Dual (n=107479040, RMAE=0.216) Dual (n=81920000, RMAE=0.450) STMLP (n=107479040, RMAE=0.273) STMLP (n=81920000, RMAE=0.458) <u></u>לי 10⁻∕ Frequency 10-IdiffSTMLP (n=107479040, RMAE=0.329) IdiffSTMLP (n=81920000, RMAE=0.478) Frequen Values of 10all pixels 10^{-4} 10^{-4} 10-5 10^{-5} 10-6 10-6 0.0 02 0.4 0.6 0.8 1.0 0.0 02 0.4 0.6 0.8 1.0 – Gen) + Gen - Gen) + Gen 1 × (Real (Real Real × N N 00 0.2 0.4 0.6 0.8 1.0 0.0 0.2 0.4 0.6 0.8 1.0 Total Intensity Total Intensity

J=2

Reconstructions of FRII Generations of FRII Real (n=1312) Real (n=1312) 100 CNN (n=6560) CNN (n=5000) 100 lavgSTMLP (n=6560) — lavgSTMLP (n=5000) Dual (n=6560) Dual (n=5000) STMLP (n=6560) STMLP (n=5000) ک^{10−} Frequency IdiffSTMLP (n=6560) IdiffSTMLP (n=5000) Value of Frequer brightest 10- 10^{-2} pixel 10 10 0.2 0 2 04 0.6 0.4 0.6 X (Real - Gen) Real + Gen (Real – Gen) Real + Gen 1 0 0 -1 × N N 0.2 0.4 0.8 0.2 0.4 0.8 0.6 0.6 1.0 Peak Intensity Peak Intensity Reconstructions of FRII Generations of FRII Real (n=21495808) — Real (n=21495808) 100 100 CNN (n=107479040, RMAE=0.240) CNN (n=81920000, RMAE=0.457) — lavgSTMLP (n=107479040, RMAE=0.275) lavgSTMLP (n=81920000, RMAE=0.452) 10-3 10^{-1} Dual (n=107479040, RMAE=0.216) Dual (n=81920000, RMAE=0.450) STMLP (n=107479040, RMAE=0.273) STMLP (n=81920000, RMAE=0.458) Frequency 10-Frequency 10-IdiffSTMLP (n=107479040, RMAE=0.329) IdiffSTMLP (n=81920000, RMAE=0.478) Values of all pixels 10^{-4} 10^{-4} 10^{-5} 10^{-5} 10-6-10-6 0.0 02 04 0.6 0.0 02 0.4 0.6 – Gen) + Gen - Gen) + Gen 1 × (Real (Real Real × N N 00 0.2 0.4 0.6 0.8 1.0 0.0 0.2 0.4 0.6 0.8 1.0 Total Intensity Total Intensity

Value of brightest pixel

J=3

Values of all pixels

brightest pixel

J=4

Values of all pixels

Filtering helps but is difficult

Thresholds and filtering

Non-filtered vs filtered

Filtered

Reconstructed FRII sources

Filtered

Original Dual CNN STMLP Lavg STMLP Ldiff STMLP

1 1	0-0 0 0	8	۰	° °
1	••	8	N	1
1	••	8	-	8
1	••	8	~	8
1	•••	8	•	2

Generated FRII sources

Original	00	0-0	8	٩.,	y
Dual	1	•••	8	•.	- į
CNN	1	••	8	~	Ľ
STMLP	1	-	8	×.	Ţ
Lavg STMLP	*	••	8	×.	1
Ldiff STMLP	1	• -	8	•	1

Filtered

Generated FRII sources

Filtered

