Generative Adversarial Network for Approximating the Chameleon Scalar Field

William Charles

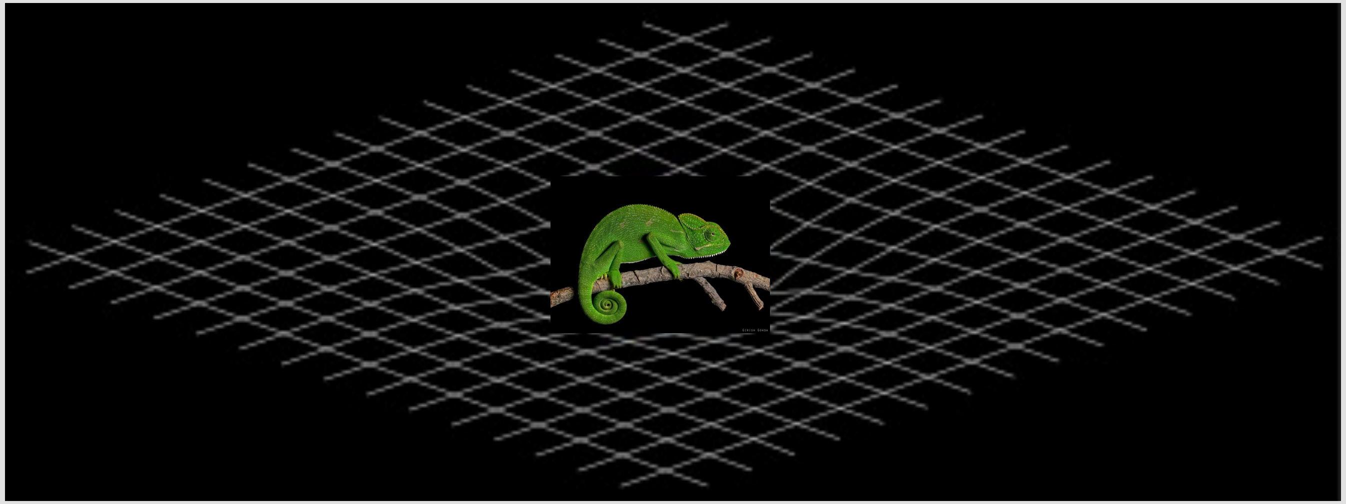
Washington University in St. Louis

Chameleon Gravity

- Chameleon scalar particle: proposed by Khoury and Weltman (2004) as a possible dark energy candidate
  - 5th force screened by mass, so not seen in locally dense regions
- Chameleon equation of motion in the Einstein frame has form:

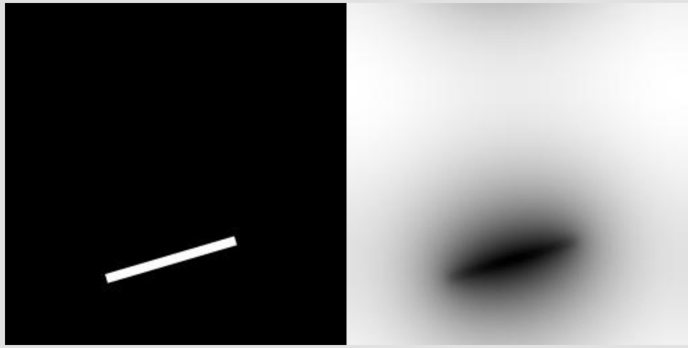
$$\nabla^2\phi = V'_{eff}(\phi)$$

$$V_{eff}(\phi) = V(\phi)A(\phi)\rho_m = \lambda^4 + \lambda^5/\phi + \rho_m/M$$

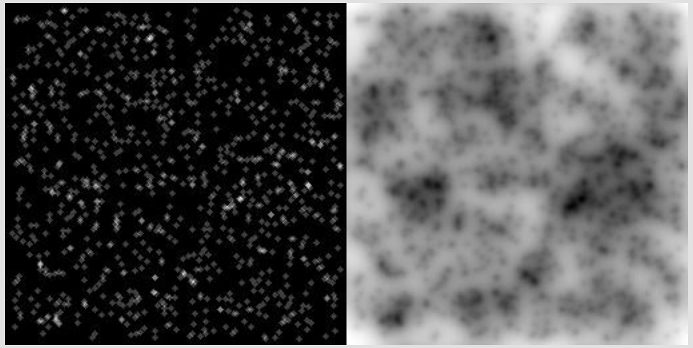


Chameleon Gravity

- Good representative model for family of other types of modified gravity (symmetron gravity)
  - Relatively easy to work with, proof of concept
- The chameleon is a scalar-tensor modification of gravity that mediates a fifth force
- Numerics:
  - Solving for a fifth force potential like the chameleon scalar field is expensive
  - Want to integrate into n-body simulations



$$\nabla^2\phi = -\lambda^5/\phi^2 + \rho_m/M$$



Chameleon Gravity

- One ok numerical method – matrix inversion

$$\phi = \phi_0 + \delta\phi$$

$$\nabla^2(\phi_0 + \delta\phi) = -\lambda^5(\phi_0 + \delta\phi)^{-2} + \rho_m/M$$

$$\nabla^2(\phi_0 + \delta\phi) = -\lambda^5(1/\phi_0^2 - 2\delta\phi/\phi_0^3) + \rho_m/M$$

$$[\nabla^2 - 2\lambda^5(1/\phi_0^3)]\delta\phi = -\nabla^2\phi_0 - \lambda^5/\phi_0^2 + \rho_m/M$$

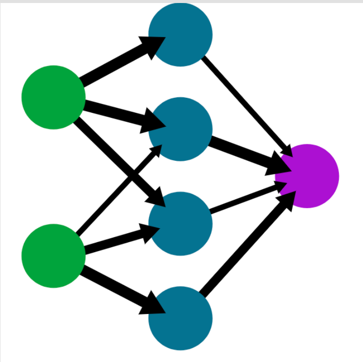
$$\delta\phi = -[\nabla^2 - 2\lambda^5(1/\phi_0^3)]^{-1}[\nabla^2\phi_0 - \lambda^5/\phi_0^2 + \rho_m/M]$$

- ∃ alternatives (like typical relaxation method)
  - Also expensive
- Computational expense not unique to chameleon

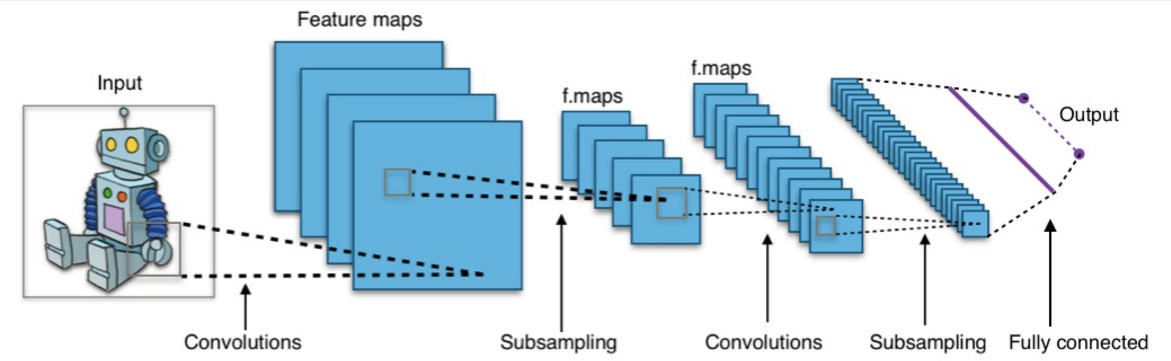
Machine Learning

- Physicists are lazy
- Neural nets: cheap, clever, black box

- Dense neural network:



- Convolutional neural network:

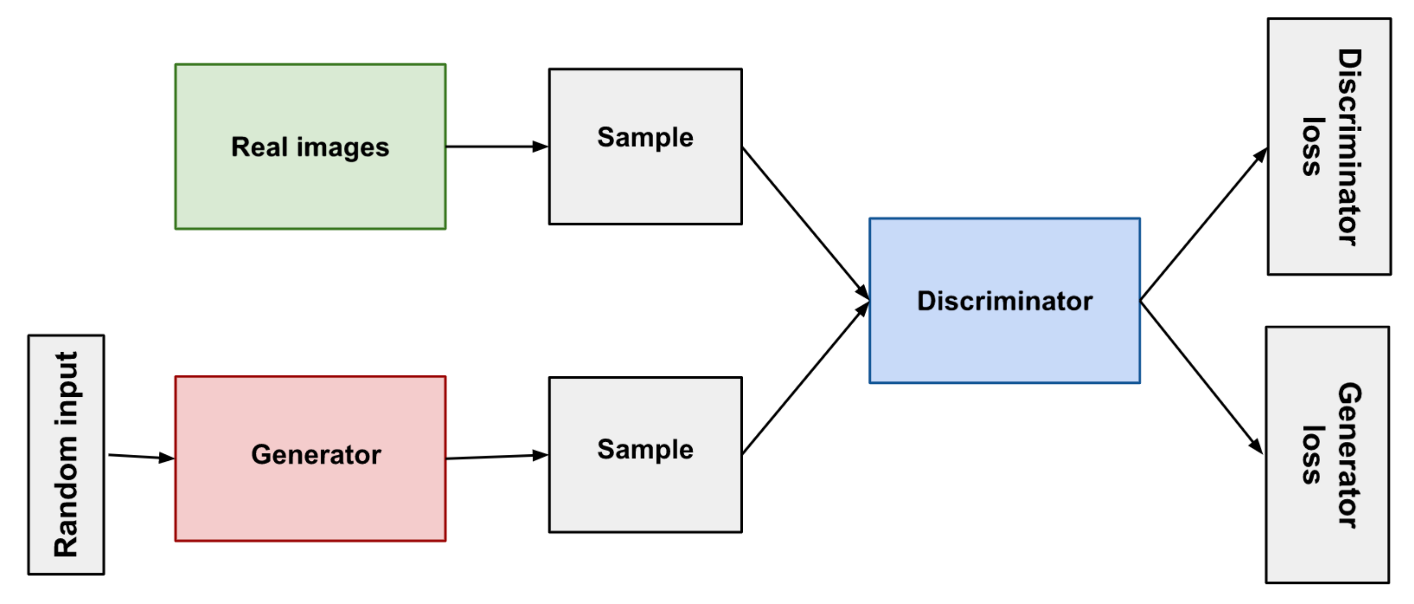


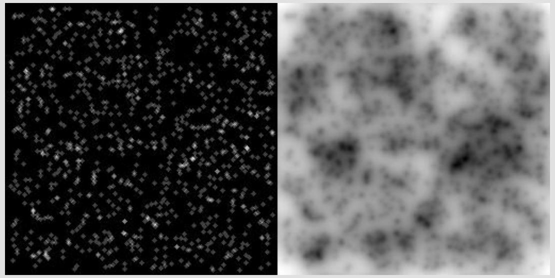
- **Backpropagation**: process of calculating each weight's contribution to the total loss, and updating it

Machine Learning

$$\nabla^2\phi = -\lambda^5/\phi^2 + \rho_m/M$$

- Generative adversarial network:





ρ Φ

- Generator loss: L1 plus KL divergence

$$D_{\mathrm{KL}}(P \parallel Q) = \int_{-\infty}^{\infty} p(x) \log\left(\frac{p(x)}{q(x)}\right) dx$$

- Discriminator loss: classification error

https://developers.google.com/machine-learning/gan

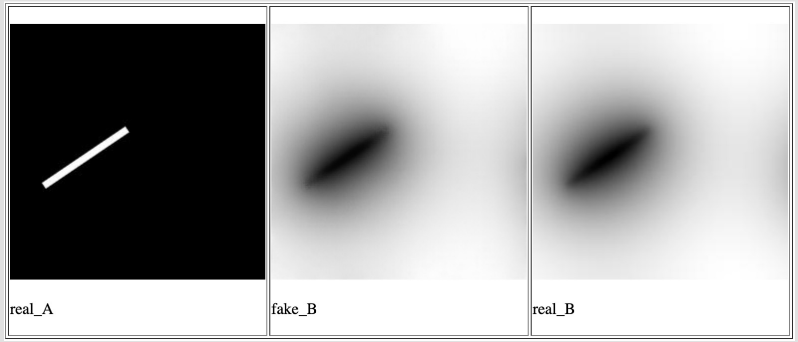
GAN Training Results

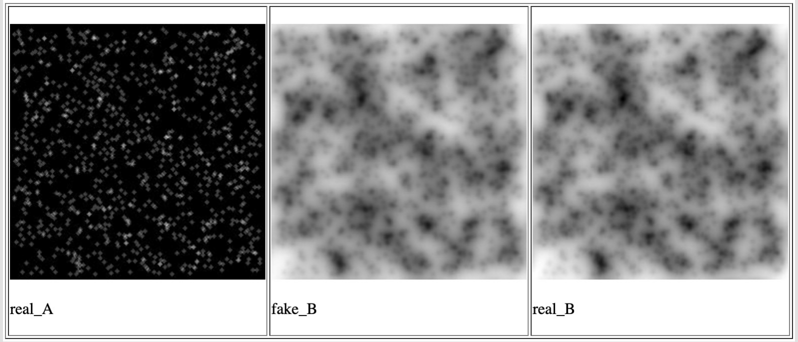
- Generator and discriminator losses over a few rounds of training on different data sets

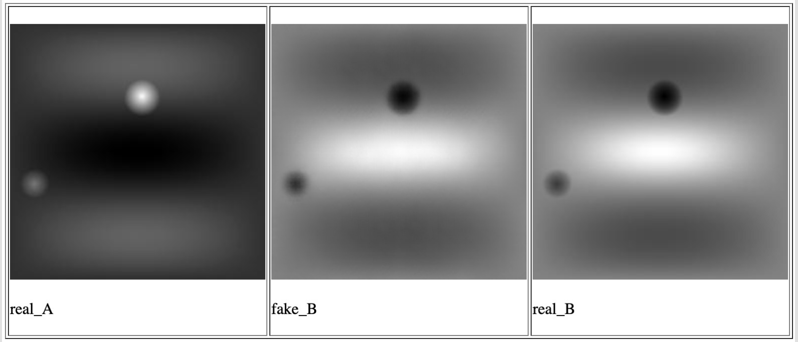
Seeing is Believing

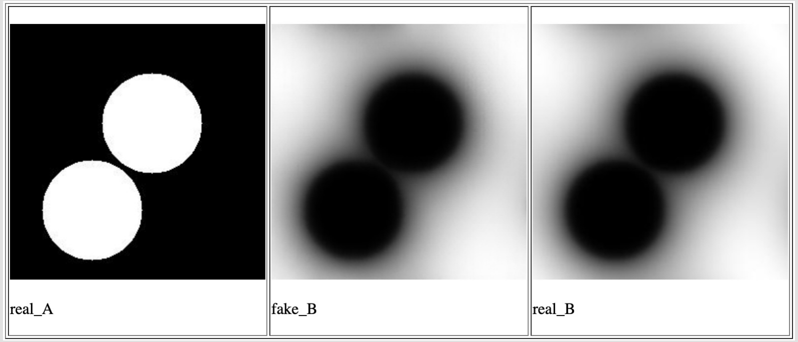
$$\nabla^2\phi = -\lambda^5/\phi^2 + \rho_m/M$$

- Testing on unseen data - no overfitting









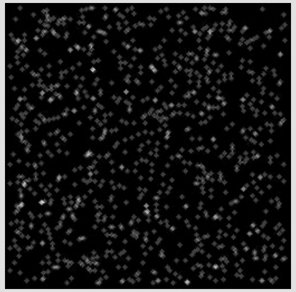
- Pixel-to-pixel error between 0.1% and 5%

Running Time

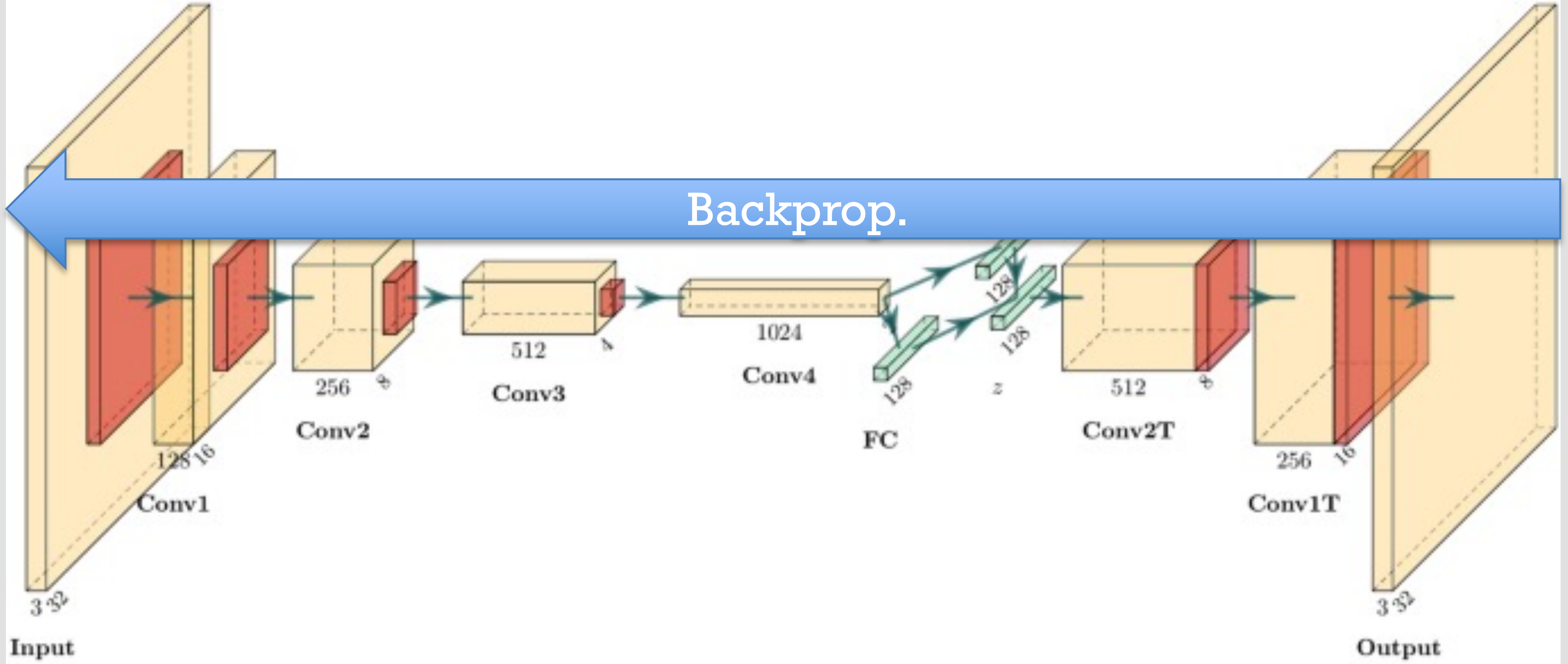
- 2.3 GHz 8-Core Intel Core i9:
  - GAN:
    - 0.19 ± 0.03 seconds per evaluation
  - Matrix Inversion:
    - 30.42 ± 5.80 seconds per evaluation
- ~150x speed up for 5% error

Experimental Motivation

- Best part: we can backpropagate all the way *through* the input



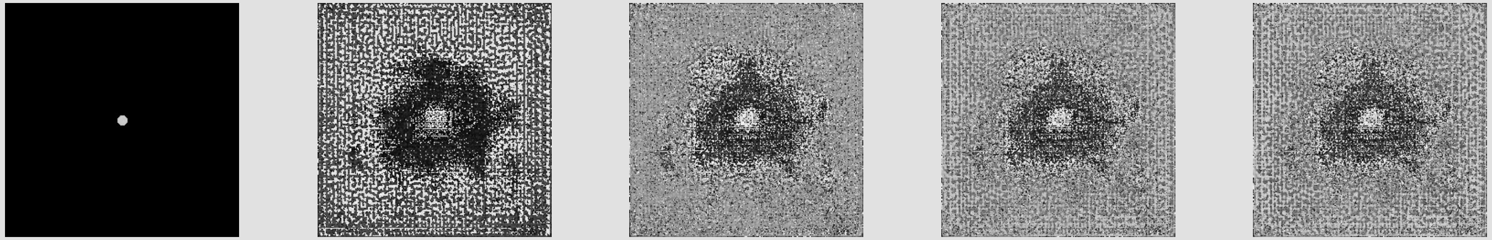
N-body input



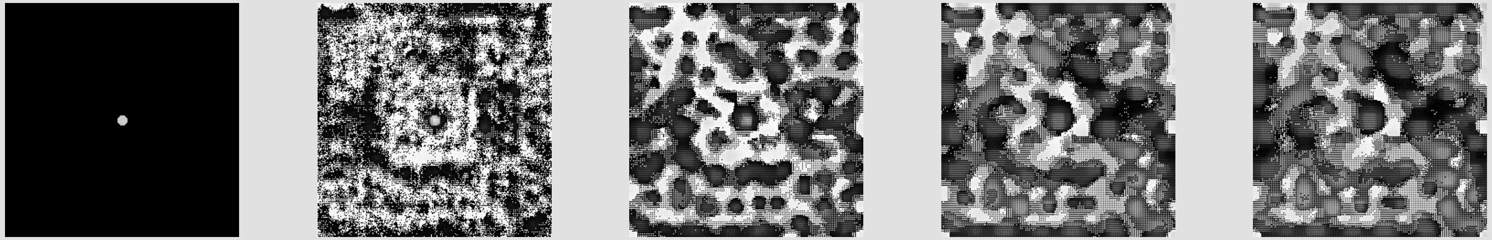
Generator

Experimental Motivation & Results

- We choose a new loss function – we would like to find a continuous, smooth mass distribution which maximizes observable 5th forces – then update the input distribution **ρ** to optimize output
  - Help to direct experimental searches for chameleon / other scalar fields



Objective function: maximize mean of scalar field Φ



Objective function: minimize gradients in **ρ**, and maximize [gradients in Φ + mean of Φ]

References

- Khoury, Justin; Weltman, Amanda (2004). "Chameleon cosmology". Physical Review D. 69 (4): 044026. arXiv:astro-ph/0309411
- T. P. Waterhouse: “An Introduction to Chameleon Gravity”, 2006; arXiv:astro-ph/0611816
- Isola, P., Zhu, J.-Y., Zhou, T., & Efros, A. A. (2016). Image-to-image translation with conditional adversarial networks.

Thank you! I will take any questions at this time.