



Seeing Faces in Things: A Model and Dataset for Pareidolia

ECCV 2024



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DuTell¹



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Harrington¹



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Corbett¹



Ruth
Rosentholtz⁴



William T.
Freeman¹



Face Pareidolia

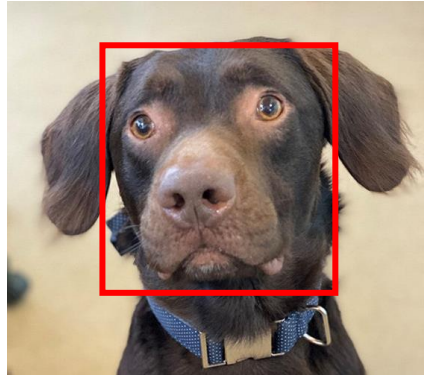


Our Contributions

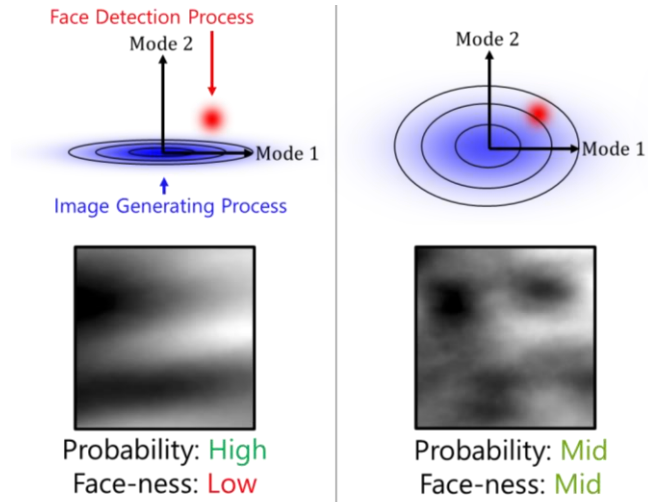
The Faces in Things Dataset



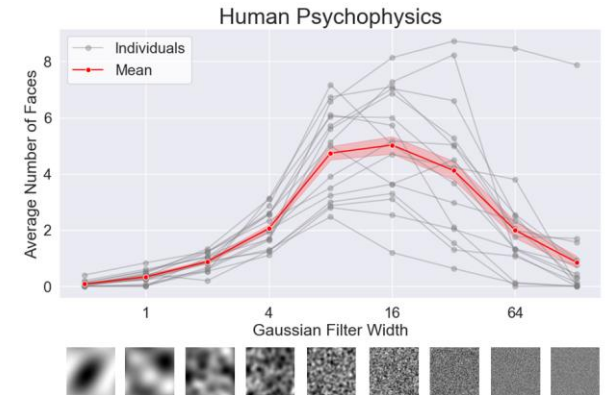
Animal Faces → Pareidolia



Mathematics of Pareidolia



Human and Machine Verification of Theory

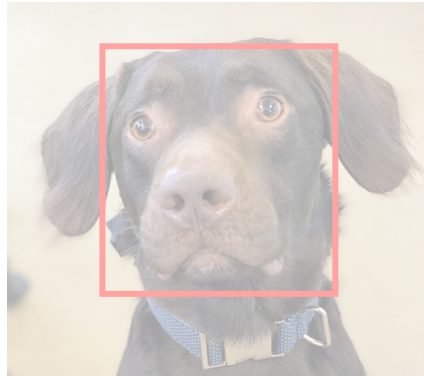


Our Contributions

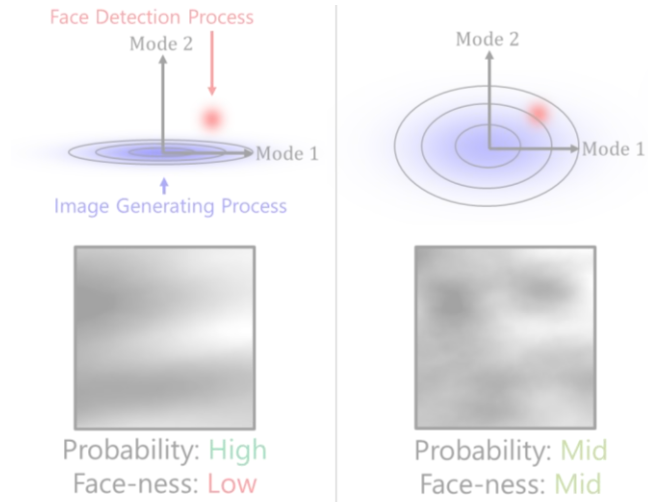
The Faces in Things Dataset



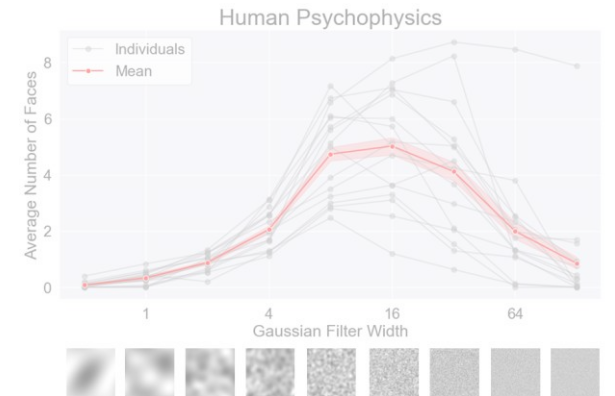
Animal Faces → Pareidolia



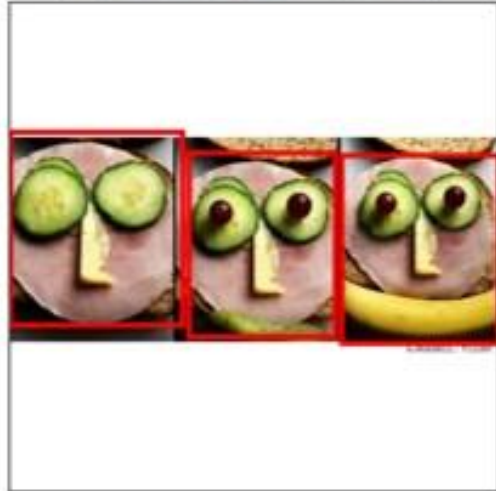
Mathematics of Pareidolia



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Faces in Things Dataset

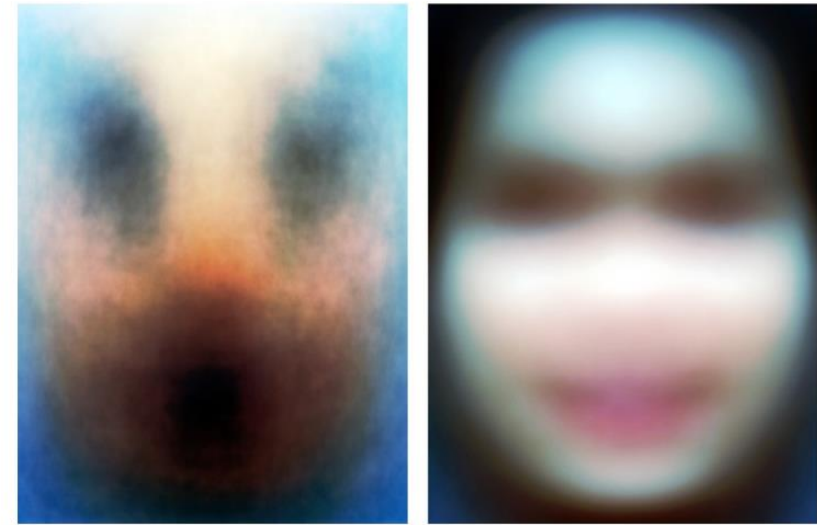


Faces in Things Dataset

- 5,000 Images
- Human Labeled Bounding Boxes

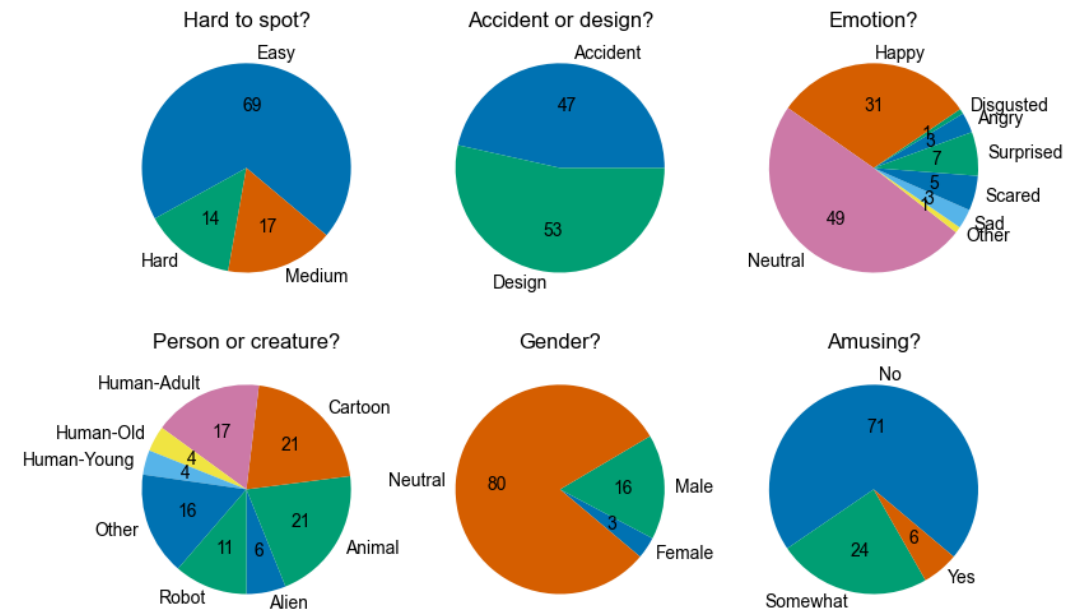


Average Faces



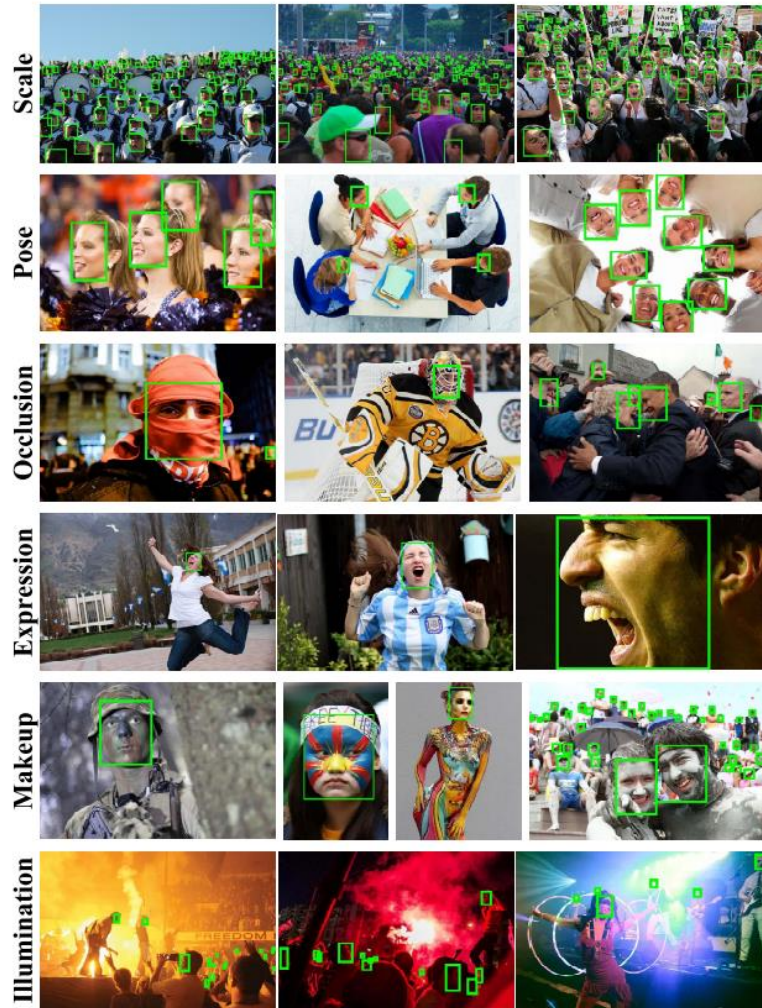
Pareidolic

Human

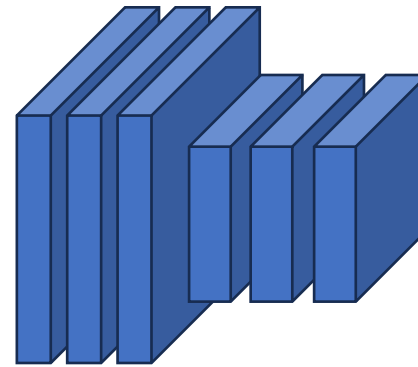


Do SOTA face detectors experience pareidolia?

WIDER FACE: A Face Detection Benchmark



Retina Face

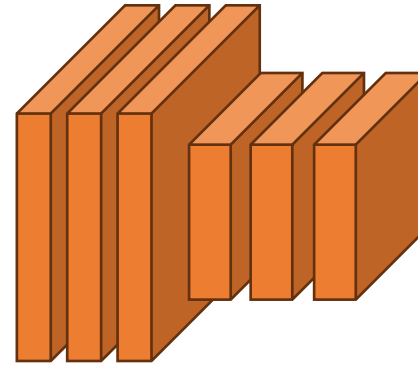


Do SOTA face detectors experience pareidolia?

Faces in Things Dataset



Retina Face



9% AP

36% AP

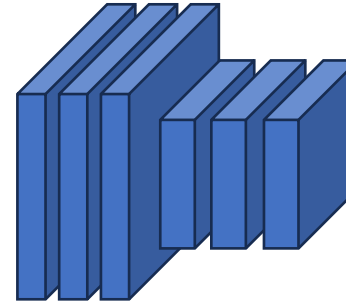
When Trained on
Pareidolic Images

Measuring the Effect of Training Data Intervention

Control Group Dataset



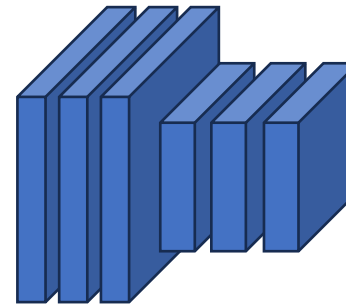
Retina Face



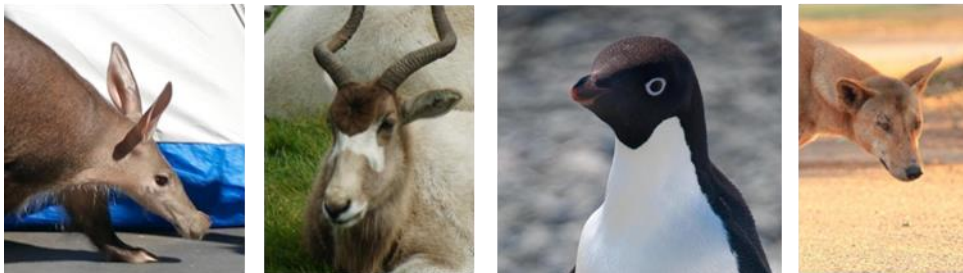
Treatment: Sobel Filtering



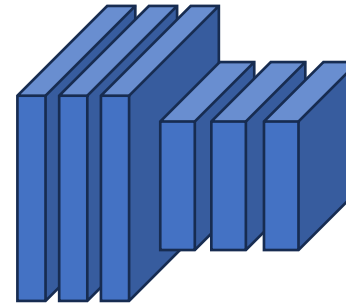
Retina Face



Treatment: Animal Faces



Retina Face

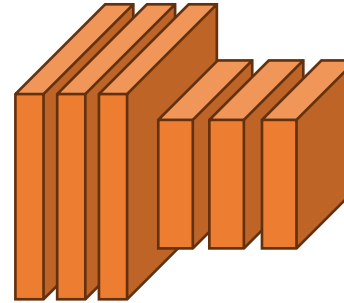


Measuring the Effect of Training Data Intervention

Faces in Things Dataset



Control Retina Face

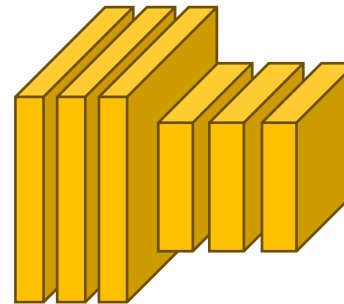


↑ 0%

Faces in Things Dataset



Retina Face + Sobel

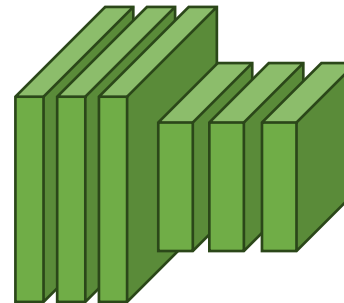


↑ 21%

Faces in Things Dataset

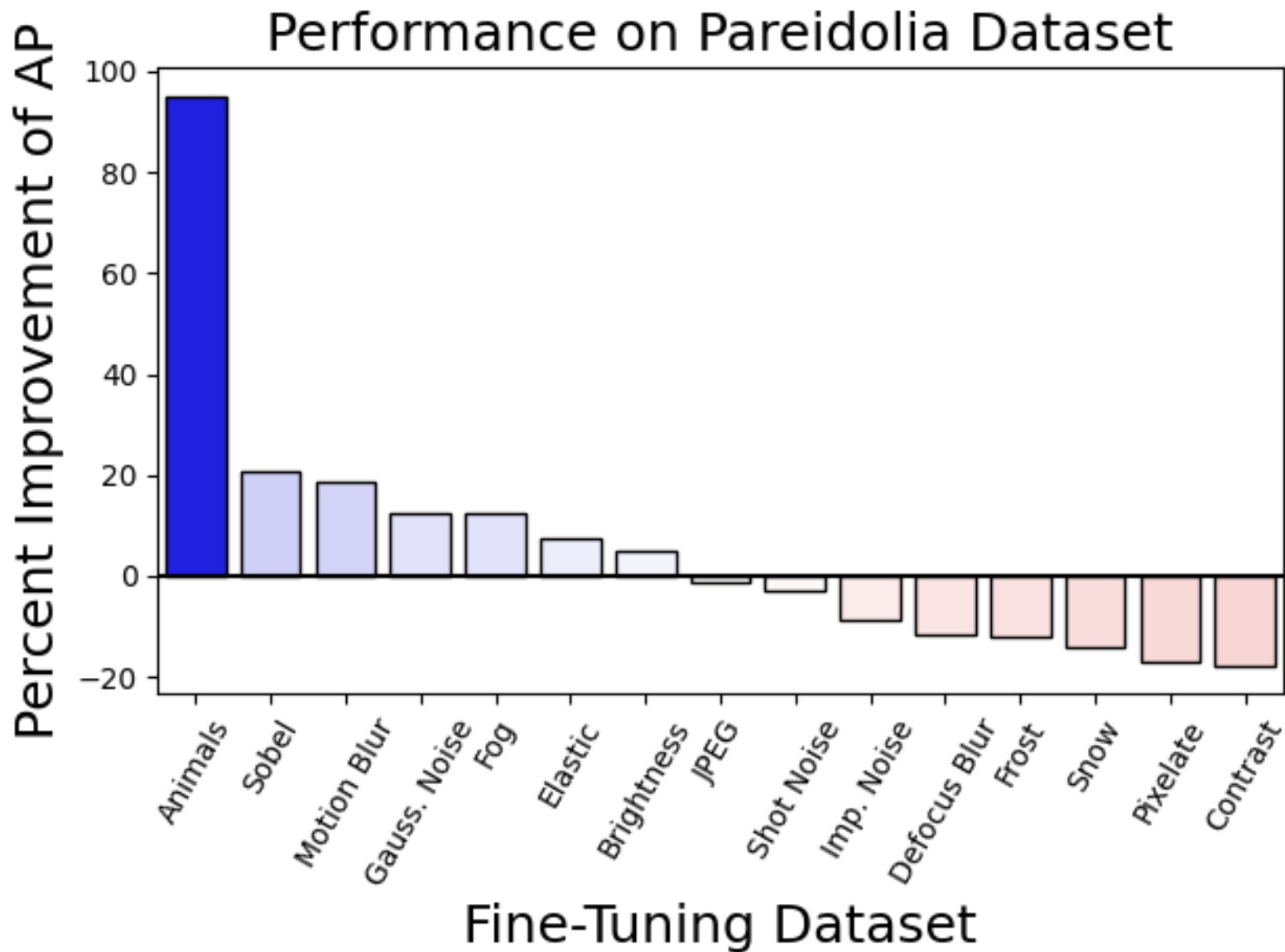


Retina Face + Animal

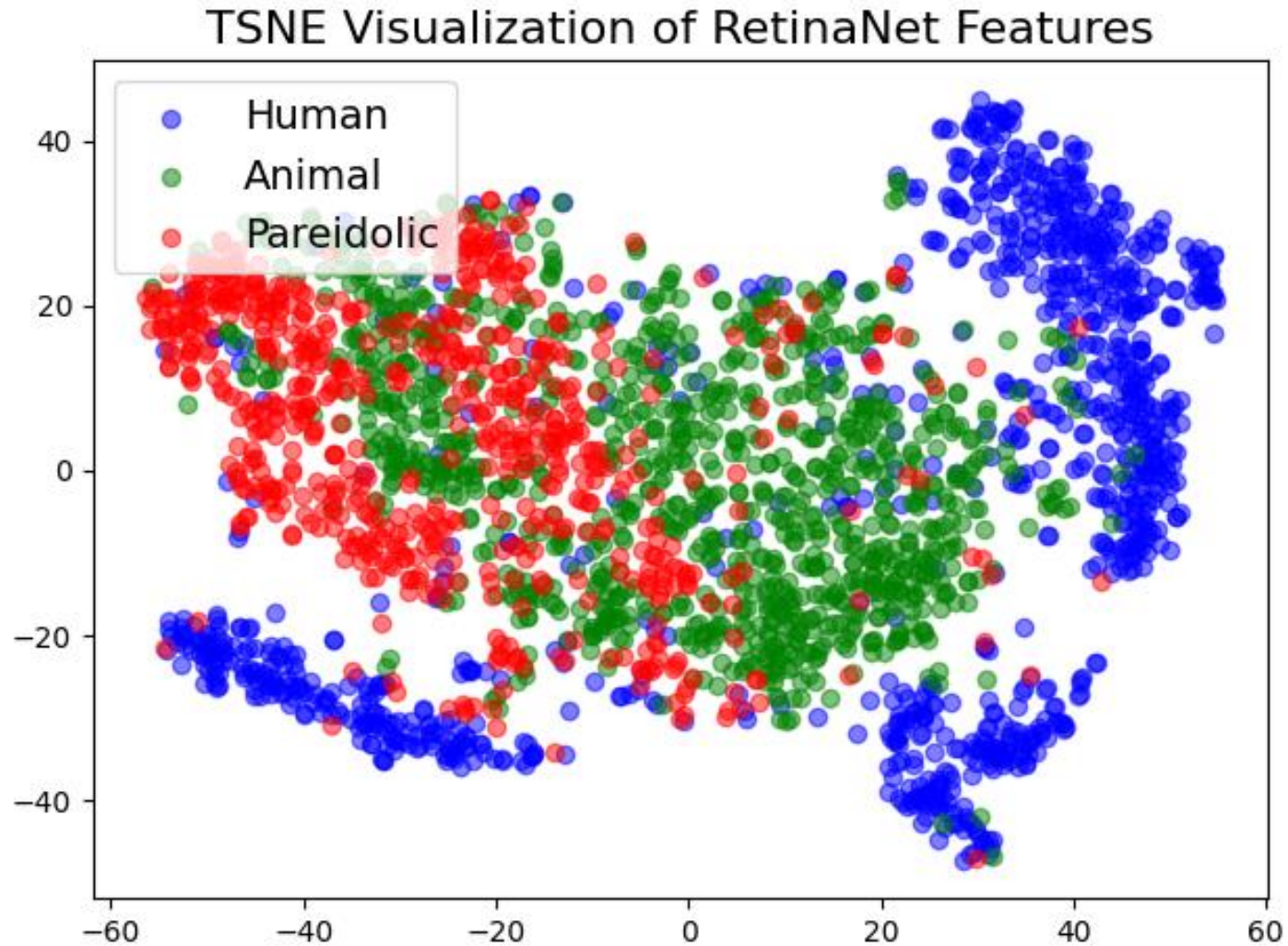


↑ 92%

Measuring the Effect of Training Data Intervention

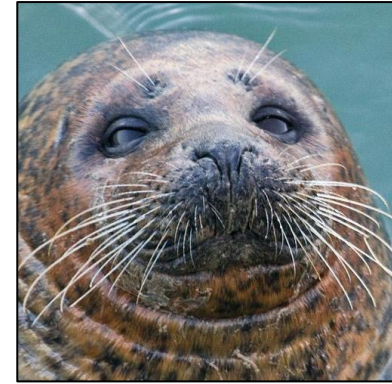
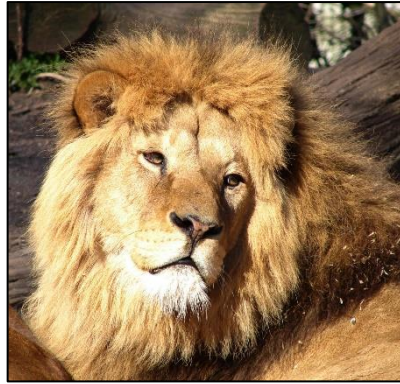


Trained Networks Group Animal and Pareidolic Faces Together



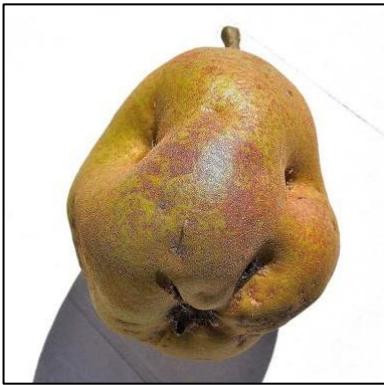
Finding Pareidolic Doppelgangers

Animal Face



Closest

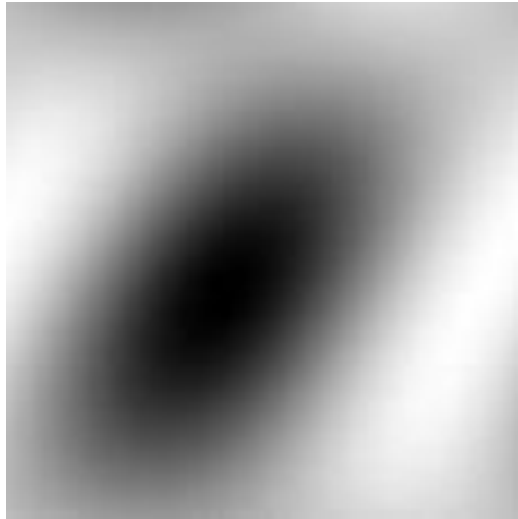
Pareidolic Face



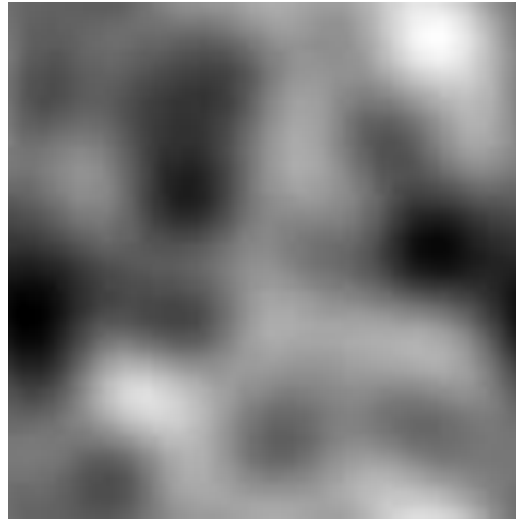
A Simple Mathematical Model of Pareidolia

“What should the frequency of my image generator be to maximize pareidolia?”

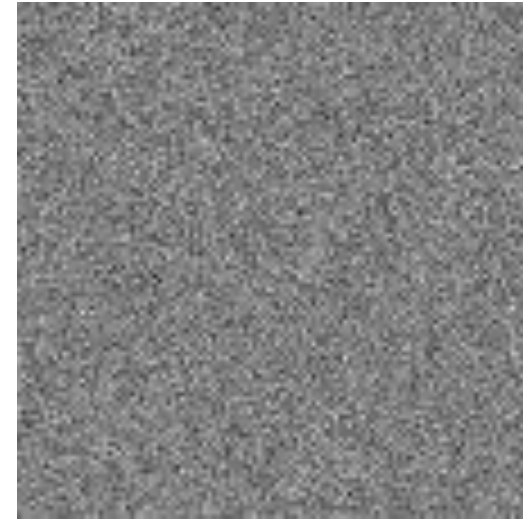
Low Frequency



Mid Frequency



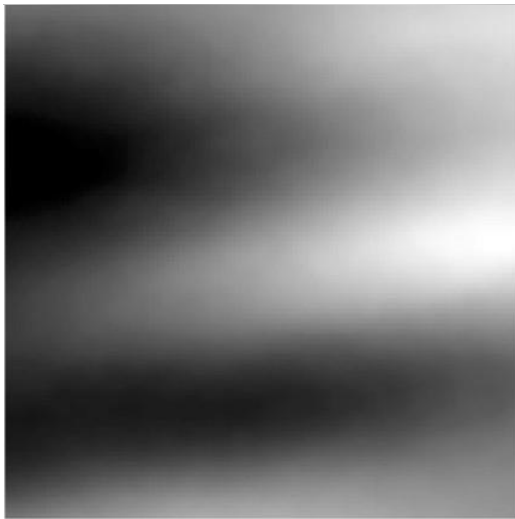
High Frequency



A Simple Mathematical Model of Pareidolia

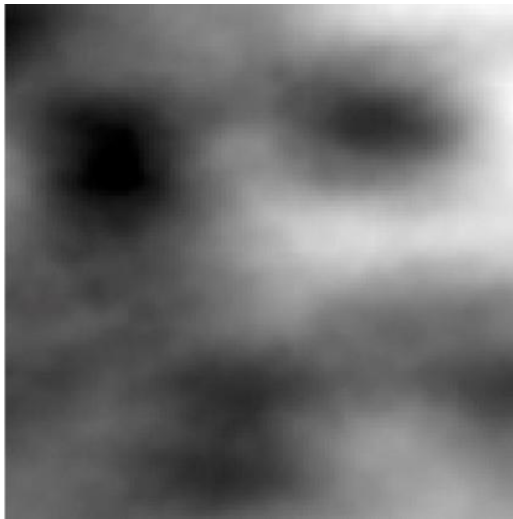
“What should the frequency of my image generator be to maximize pareidolia?”

Low Frequency



Not rich enough to generate faces!

Mid Frequency



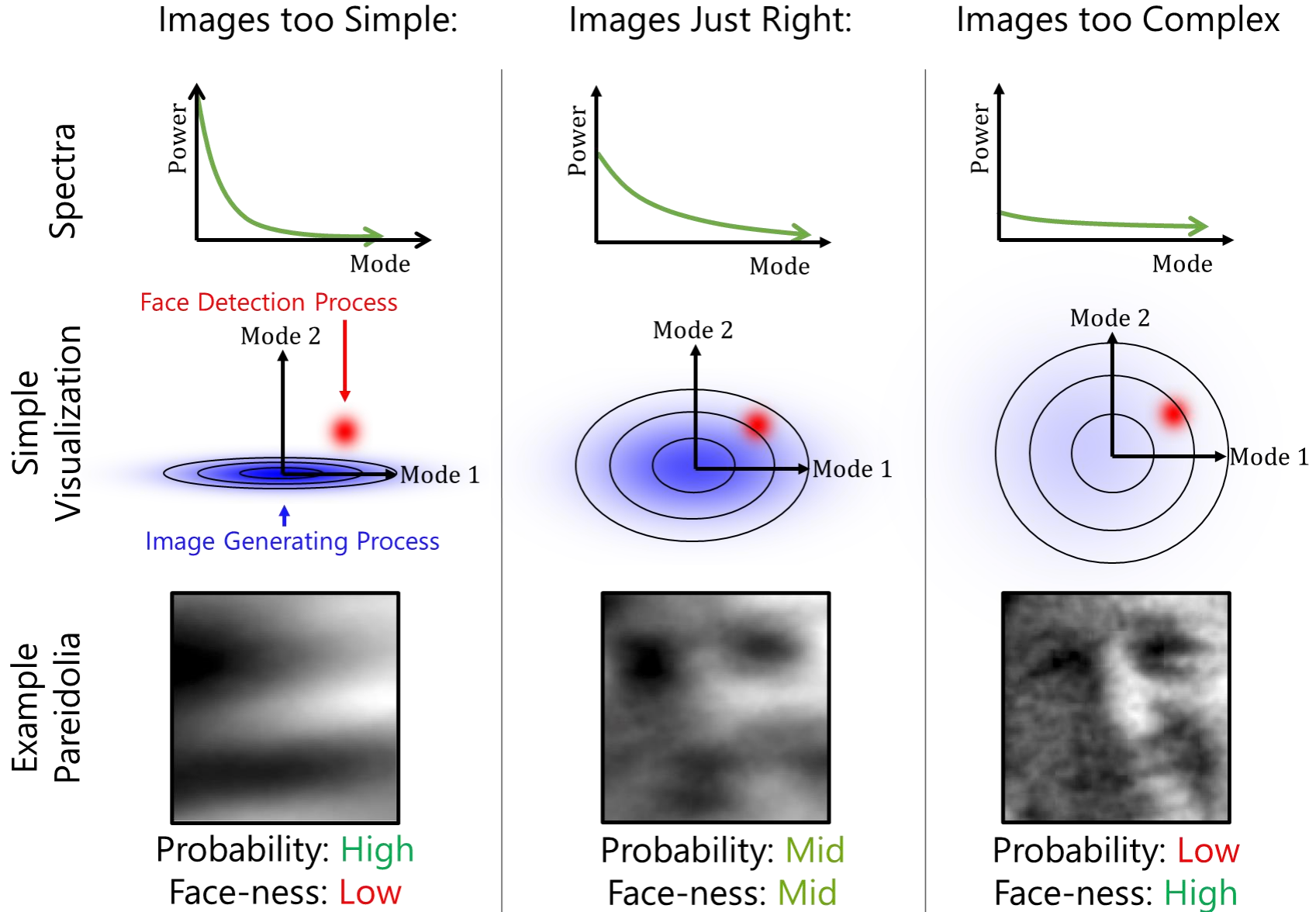
Rich enough to form faces, likely enough to happen.

High Frequency



Very rich distribution, but faces are very unlikely!

Intuition behind the



A Simple Mathematical Model of Pareidolia

Too Simple



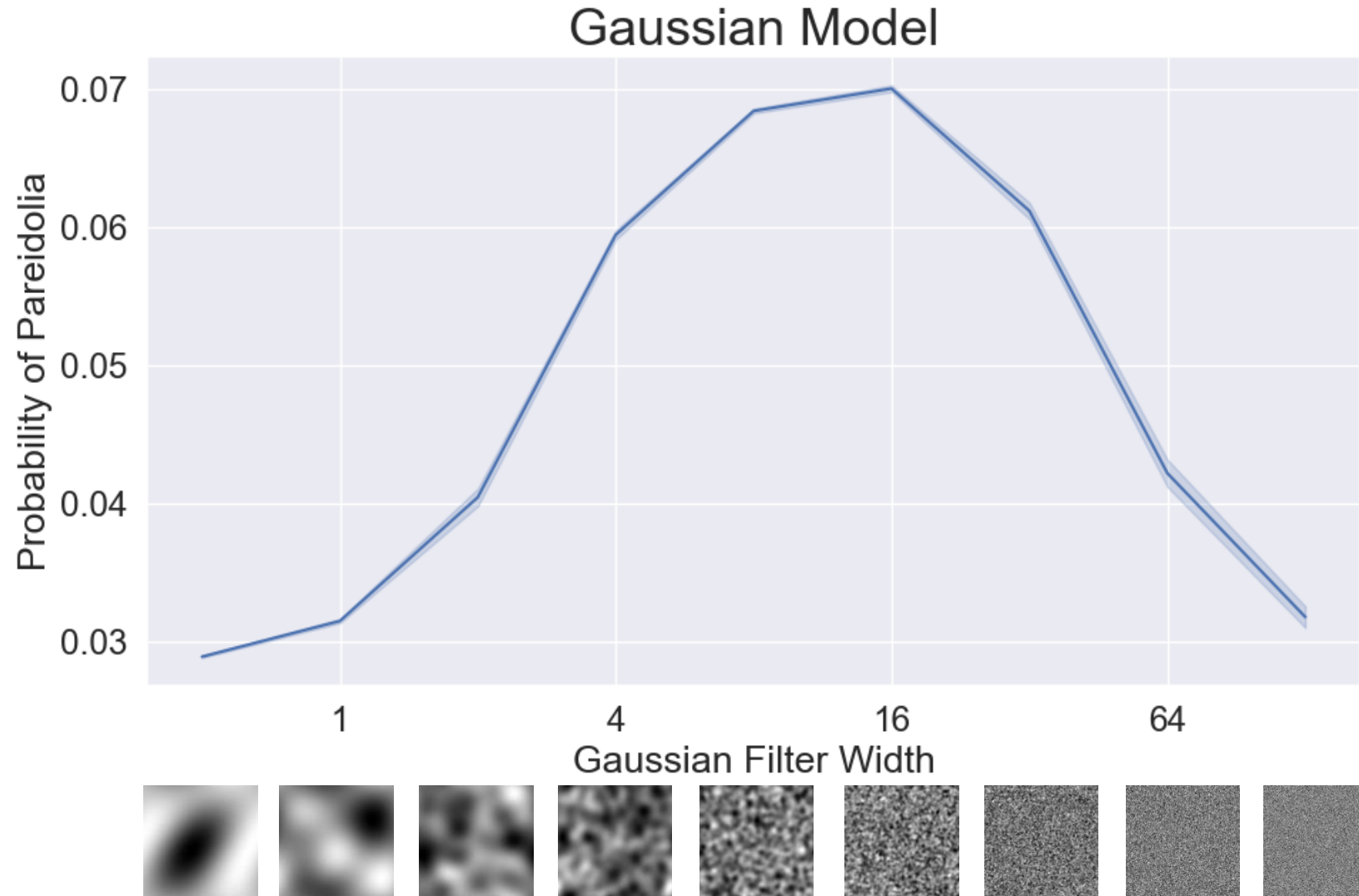
Just Right



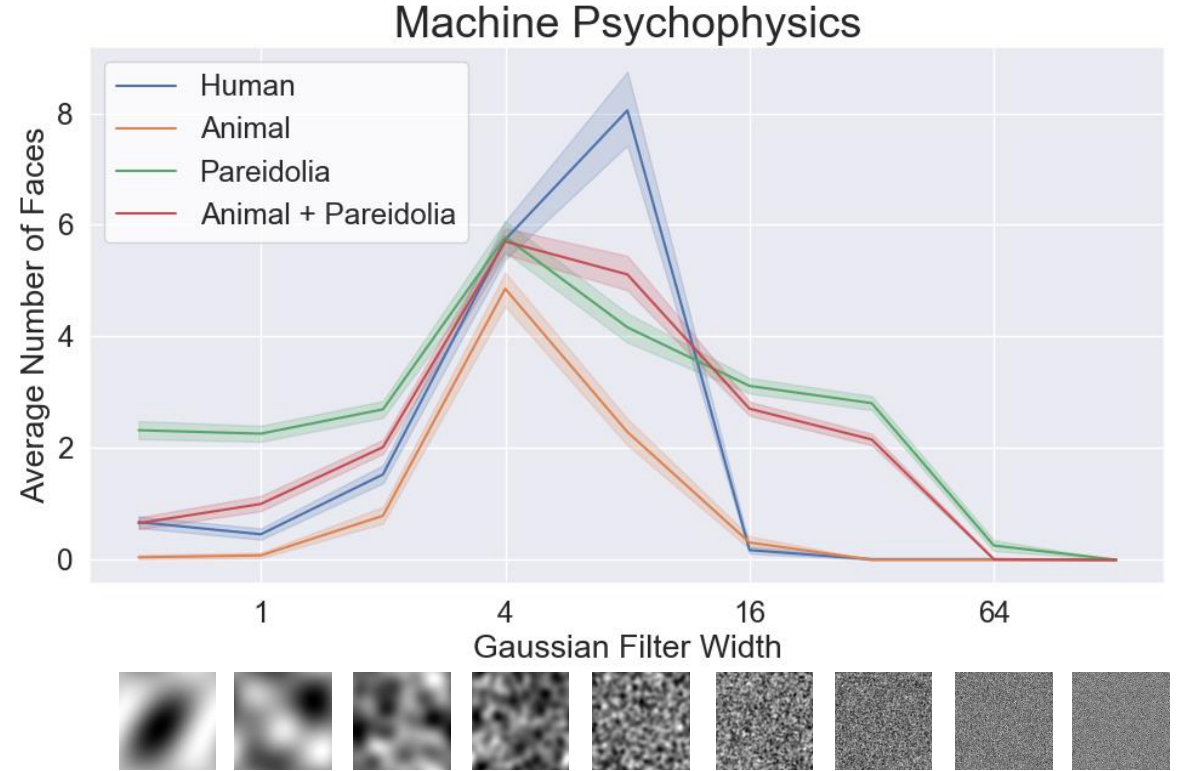
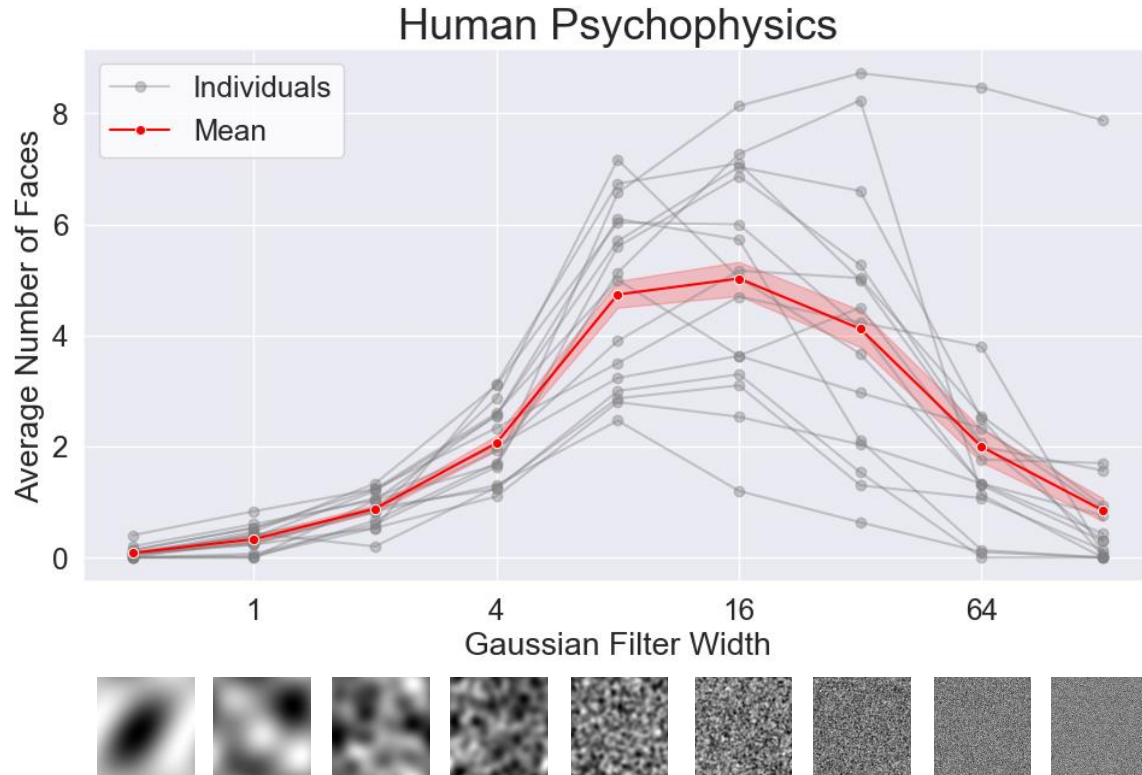
Too Complex



What the Model Says:



What the Data Says:

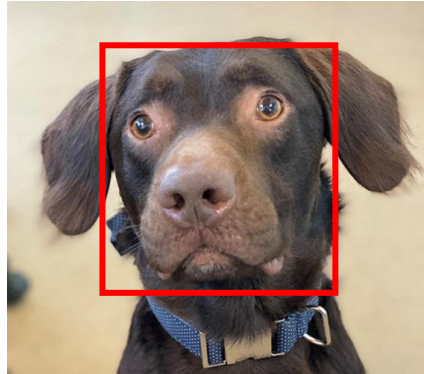


Our Contributions

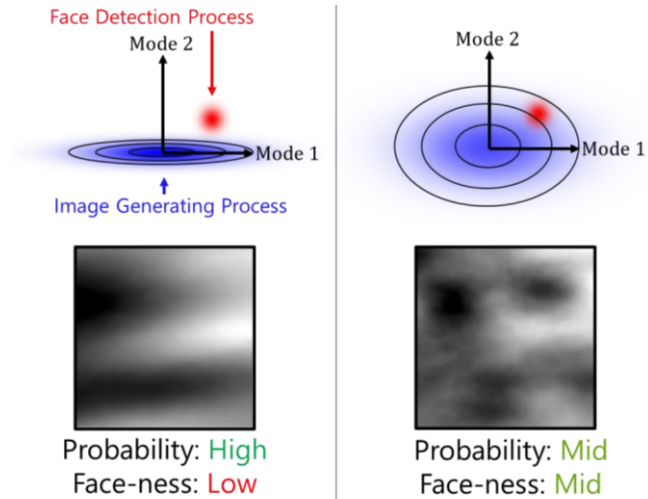
The Faces in Things Dataset



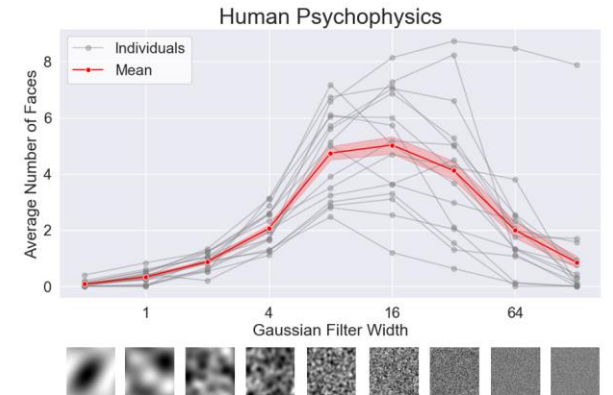
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Human and Machine Verification of theory



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aka.ms/faces-in-things