Confuse, Obfuscate, Disrupt

Using Adversarial Techniques for Better AI and True Anonymity

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David vonThenen

- Are you Human or an AI?
- I want 5 Kubernetes
- Virtual Machines are Real
- Cloudy, cloudy, cloudy…
- There is storage for that!

@davidvonthenen

Agenda

- Explainable AI
- How Data Inconsistencies Happen
  - Demos, Demos, Demos
- Adversarial Attacks for Good… & Bad
  - Demos, Demos, Demos
- Defending Adversarial Attacks
  - Demos, Demos, Demos
- Q&A

What is Explainable AI?

Flawed Data

- AI/ML Only As Good As the Data
  - Biased, Noise, Inaccuracies
- Real-World Examples:
  - Recruiter AI + Male Skewed
    - Not Representative Data
  - Offensive AI Chatbot
    - Using Racist Language
  - Court Case Hallucinations
    - ChatGPT fake cases
  - Many, Many, Many More

1. https://www.reuters.com/article/world/insight-amazon-scraps-secret-ai-recruiting-tool-that-showed-bias-against-women-idUSKCN1MK0AG/
2. https://storage.courtlistener.com/recap/gov.uscourts.nysd.575368/gov.uscourts.nysd.575368.31.0.pdf
3. https://en.wikipedia.org/wiki/Tay_(chatbot)

Explainable AI

Why Do We Care?

- Transparency Build Trust
- Debugging -> Improvement
- Compliance and Ethics

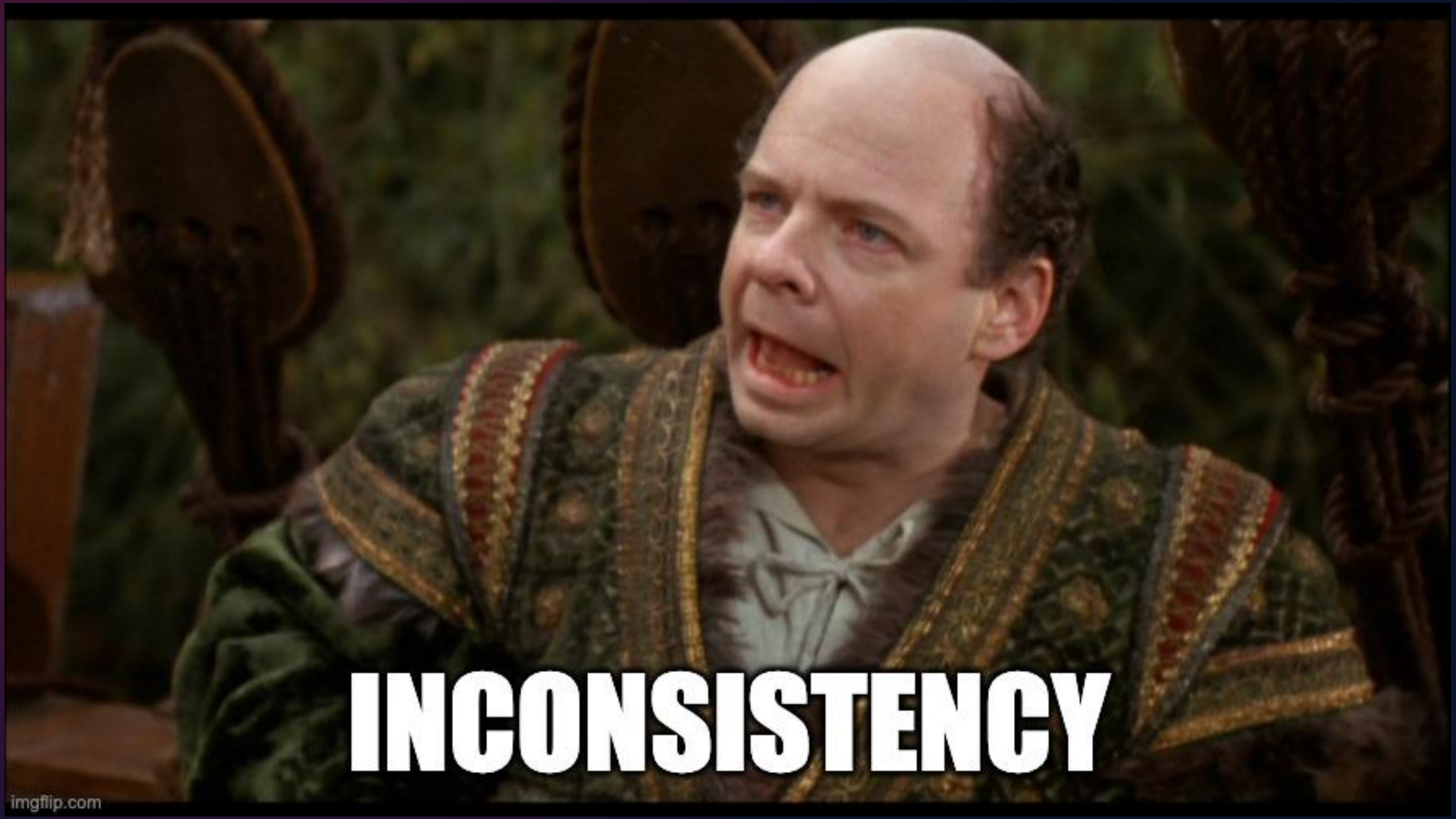
Key Goals:

- Interpretability
- Accountability
- Fairness + Bias Detection

How Data Inconsistencies Happen

Data Inconsistencies Matter

- AI "Decision Making" Directly Shaped By Data
    - Annotation Errors
    - Data Bias
    - Distribution Drift
    - Adversarial Data
    - Overfitting
    - Underfitting
    - Poor Feature Engineering
    - Noisy Data, etc…



Annotation Errors

RED

Data Bias

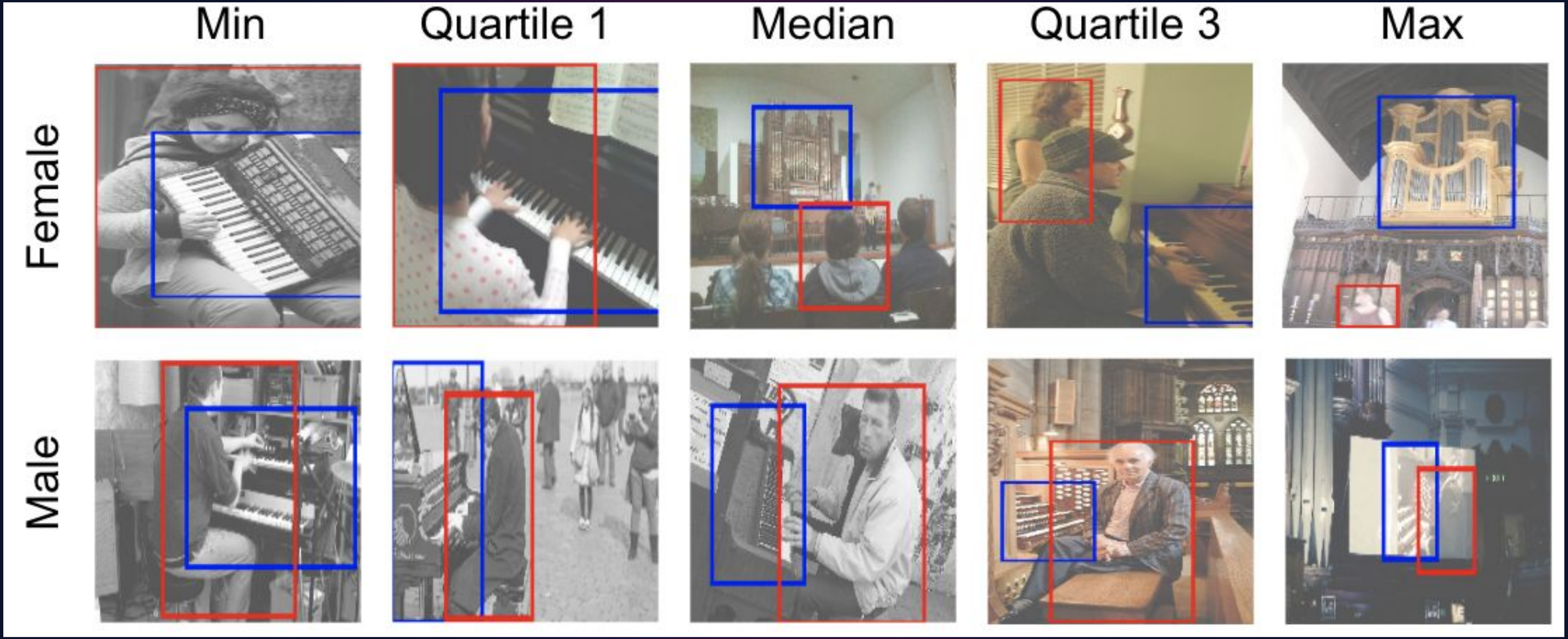


Image Attribution
Princeton University Researcher - [Tool helps clear biases from computer vision]
Molly Sharlach on October 1, 2020

Data Imbalance

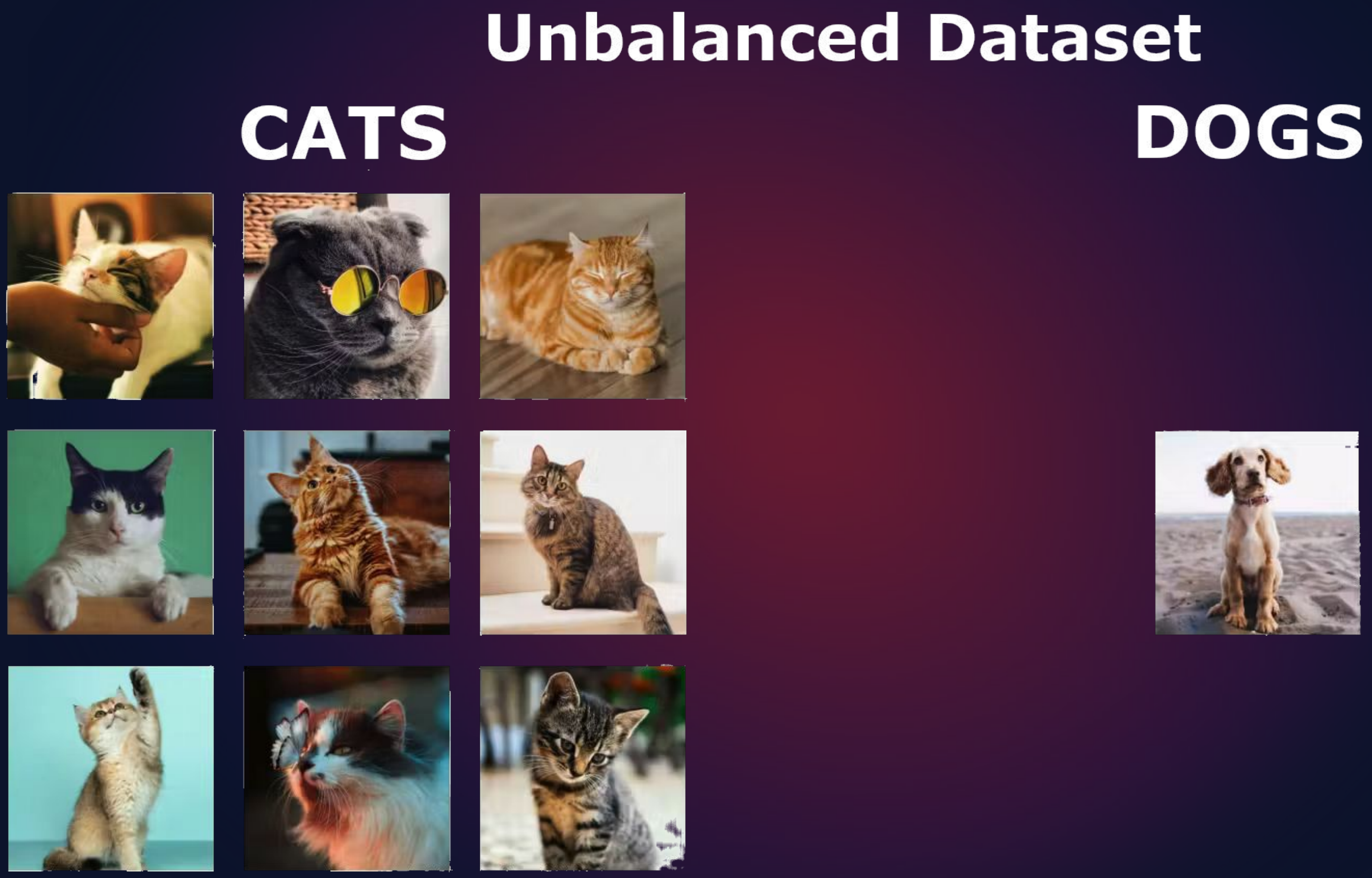


Image Attribution
[Introduction to Balanced and Imbalanced Datasets in Machine Learning]
Nikolaj Buhl on November 11, 2022

Distribution Shifts



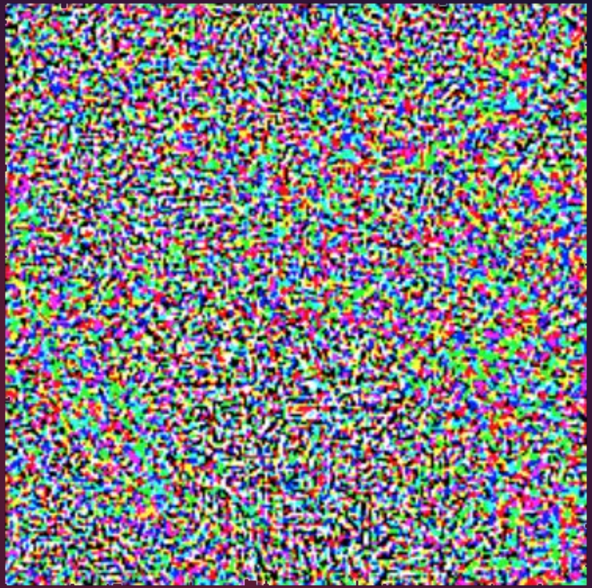

Let’s Input These




Image Attribution
Dive Into Deep Learning
Nikolaj Buhl on November 11, 2022

Adversarial Samples

$+ .007 \times$



$=$

$\boldsymbol{x}$
"panda"
57.7% confidence

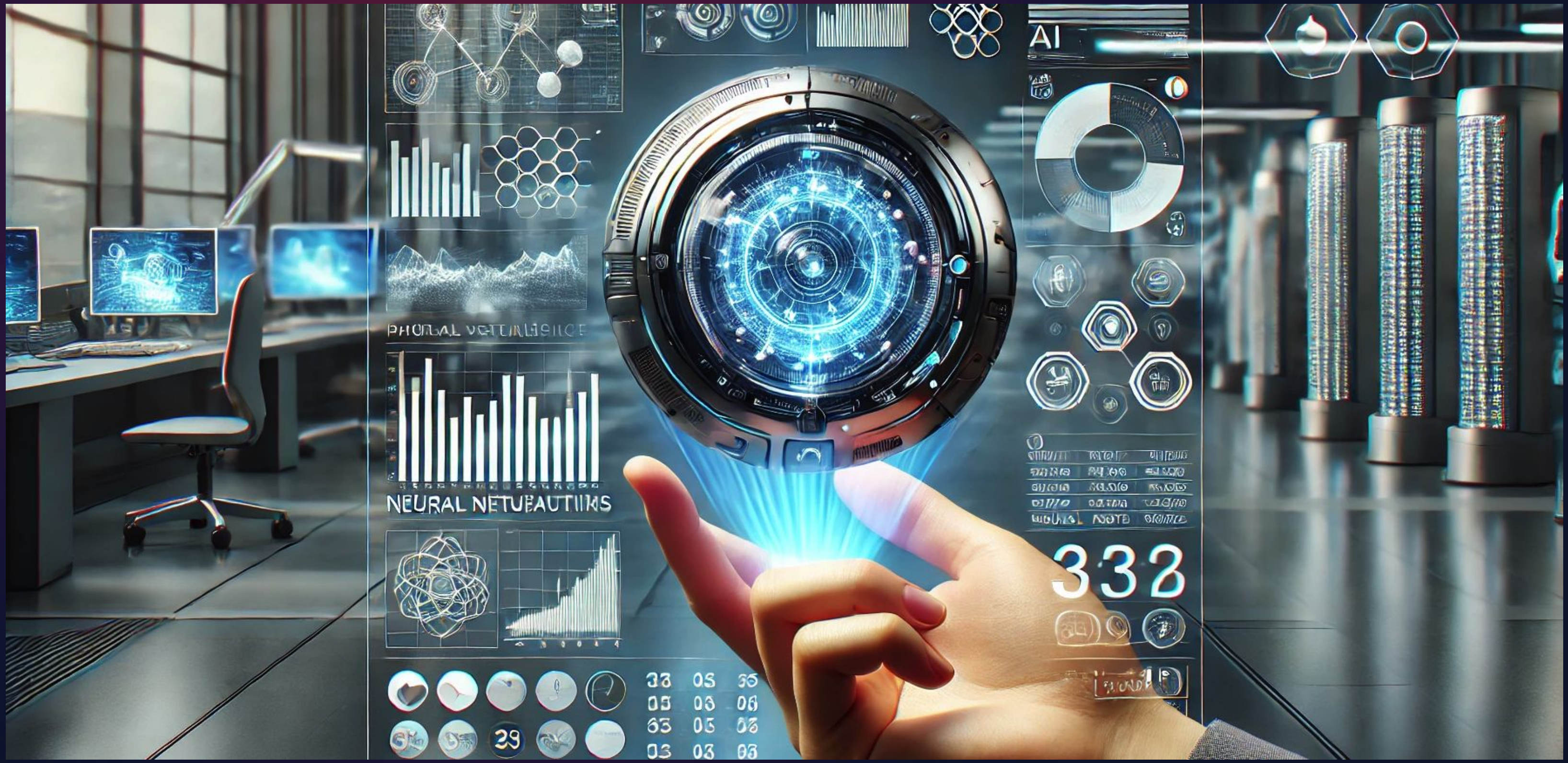
$\text{sign}(\nabla_{\boldsymbol{x}} J(\boldsymbol{\theta}, \boldsymbol{x}, y))$
"nematode"
8.2% confidence

$\boldsymbol{x} +$
$\epsilon\text{sign}(\nabla_{\boldsymbol{x}} J(\boldsymbol{\theta}, \boldsymbol{x}, y))$
"gibbon"
99.3 % confidence

Image Attribution:
PyTorch Documentation - Adversarial Example Generation

What Tools Can I Use?

- Captum - https://github.com/pytorch/captum
- SHAP - https://github.com/shap/shap
- LIME
- ELI5
- AIX360
- Many…
- Many…
- More



Let's Take a Look at Captum

- Open Source PyTorch Library
  - Gradients, Saliency Maps, SHAP
  - Layer/Neuron Contributions
  - NLP, Vision
- Detects:
  - Biases
  - Inconsistency
  - Hidden Patterns

Captum

Captum: Case Study

- Study: Urinary Incontinence
- Captum Revealed Findings:
  - Validated Contributions
  - Discovered 3 Features
- Future Application:
  - Update Surgical Protocols
  - Improved Techniques
  - Post-Op Therapy

An artificial intelligence method for predicting postoperative urinary incontinence based on multiple anatomic parameters of MRI

Jiakun Li [a,b], Xuemeng Fan [a,b,1], Tong Tang [b,c], Erman Wu [b], Dongyue Wang [d], Hui Zong [b], Xianghong Zhou
Li [a], Chichen Zhang [a], Yihang Zhang [a], Rongrong Wu [b], Cong Wu [b], Lu Yang [a,**], Bairong Shen [b,*]

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PMCID: PMC10520312 PMID: 37767466

Abstract

Background

Deep learning methods are increasingly applied in the medical field; however, their lack
interpretability remains a challenge. Captum is a tool that can be used to interpret neur
network models by computing feature importance weights. Although Captum is an
interpretable model, it is rarely used to study medical problems, and there is a scarcity

Case Study Paper
An artificial intelligence method for predicting postoperative urinary incontinence based on multiple anatomic parameters of MRI

Demo: Captum + NLP Classifier

https://youtu.be/geZNwLzoaT4
https://youtu.be/m0VxUAGhKcY

Demo: Captum + Vision Classifier

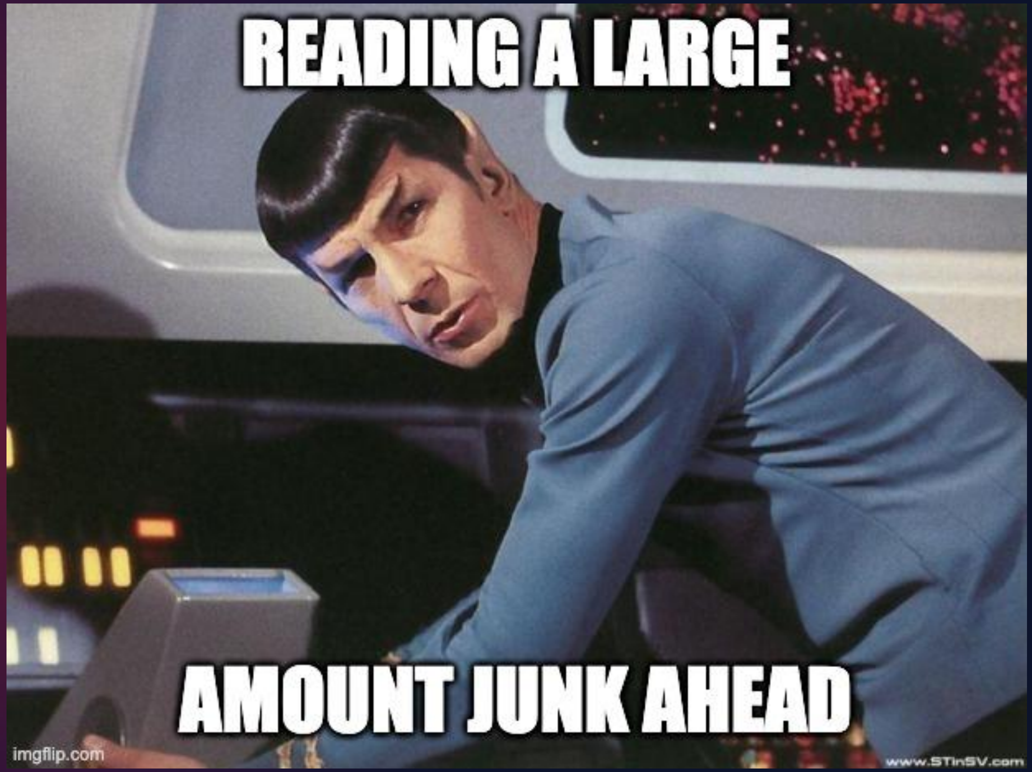
https://youtu.be/5J2sGIU0RV4

Adversarial Attacks: For Good… and Bad

Building Better Models via Intentional Disruption

Turning Insights Into Action

- Why Explainable AI and Use Adversarial Input?
  - Question Rigid Assumptions
  - Finding Data Flaws
  - Expose Ethical Scenarios
  - Adversarial Testing
- Result
  - Why Exclude Data
  - Fix Problematic Data
  - Under Representation
  - Fairness



What Else...

- Intentional Adversarial Attacks
  - Besides Finding Holes...
  - Disrupting Classification
    - Vision
    - NLP
- Why?
  - Unauthorized Surveillance
  - Protect Privacy
  - Obfuscation

Adversarial Strategies

Here Are Ideas/Concepts in NLP to Disrupt – Be Creative!!

- Encoding/Formatting
- Homophones and Phonetics
- Code Switching
- Low-Resource Languages
  - Navajo – "Code Talkers"
- Adversarial Spelling
- Polysemy/Multiple Meanings
- Speaking in Metaphors

Resources for Next Slide
Video Credit: Darmok, under 8 minutes (Star Trek Abridged)
Source: Star Trek: The Next Generator, Episode 102 - Darmok

Creative Communication

Demo: Read That Sentiment Wrong

https://youtu.be/CoLnvqHHN_M

Demo: One Pixel Attack

https://youtu.be/s8SHeXXAWjQ

Demo: Spoofing Real-Time Vision

https://youtu.be/b_T448UXaHw

Intentional Misspelling…

Do yuo fnid tihs smilpe to raed? Bceuase of the phaonmneal pweor of the hmuan mnid, msot plepoe do.

Creative Communication

Defending Adversarial Attacks

Protection Yourself From Bad Actors

Defending NLP Attacks

- Format Normalization
- Spell-Checker or Word Recognition
    - Morphology (or Subwords Tokens)
- Syntax/Grammar Checkers
- Semantic Similarity Checks
    - Synonym Encoding
- Phonetic Normalization
    - Text-to-Speech -> Speech-to-Text
- Adversarial Training:
    - Datasets w/ Noising and Typos, Synonyms, Phrase Diversity

Image Attribution
How Chess Works - https://entertainment.howstuffworks.com/leisure/brain-games/chess1.htm
Meredith Bower

Defending Vision Attacks

- Adversarial Training
  - Fast Gradient Sign Method (FGSM)
  - Projected Gradient Descent (PGD)
- Spatial Smoothing (Blurring)
  - Median Filtering (3x3 -> 1x1)
  - Gaussian Blur
  - Non-local Means, Bilateral Filters
- Feature Squeezing, Randomization
  - Bit-Depth Reduction
  - Random Resize/Pad, Add Noise

Image Attribution
https://www.gamesforyoungminds.com/blog/2018/3/23/othello-review

Non-Specific Defenses

- Adversarial Detection: Multiple Models
  - Use 2+ Different Models
- Voting Ensembles
  - Multi-Classifiers -> Majority Wins
- Reject On Low Confidence
  - Multi-Pass w/ Slight Variation
    - Drop Character
    - Swap Synonym
- EXPENSIVE and SLOW! -> More GPUs + Passes

Image Attribution
Princeton University Researcher - Tool helps clear biases from computer vision
Molly Sharlach on October 1, 2020

Demo: Defending Adversarial NLP Attacks

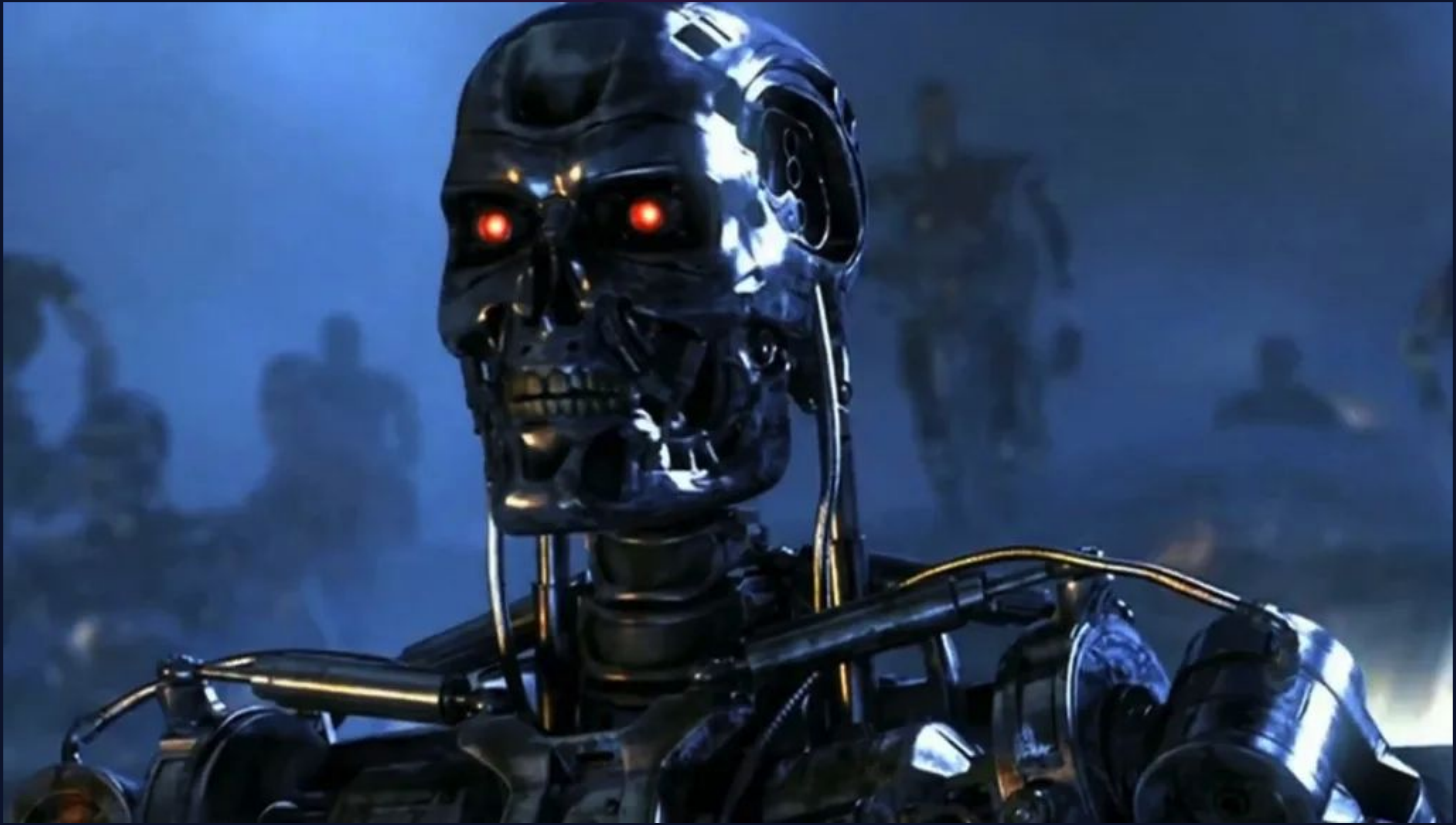
https://youtu.be/HB1RaL2OIQA

Demo: Defending Adversarial Vision Attacks

https://youtu.be/dLU5mBAt9qk

Why?

Just In Case...



Resources

Resources

All Materials/Code: github.com/davidvonthenen/2025-devbcn

Let's Chat on Discord: discord.gg/NetApp

NetApp ONTAP - Immutable Data Needs

- Captum:
  - GitHub – https://github.com/pytorch/captum
  - Tutorials – https://captum.ai/tutorials/
- PyTorch:
  - GitHub – https://github.com/pytorch/pytorch
  - Tutorials – https://pytorch.org/tutorials/index.html

DevBcn

NetApp

Thank You!

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