WeAreDevelopers
World Congress

NetApp

Confuse, Obfuscate, Disrupt

Using Adversarial Techniques for Better AI and True Anonymity

David vonThenen

@davidvonthenen

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

- What is Explainable AI
- Data Inconsistencies and How to Measure Them
- Adversarial Attacks for Good... & Bad
  - Demos, Demos, 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 Discriminator 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

Understanding How Our AI/ML Systems Produce The Answer!

Why Do We Care?

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

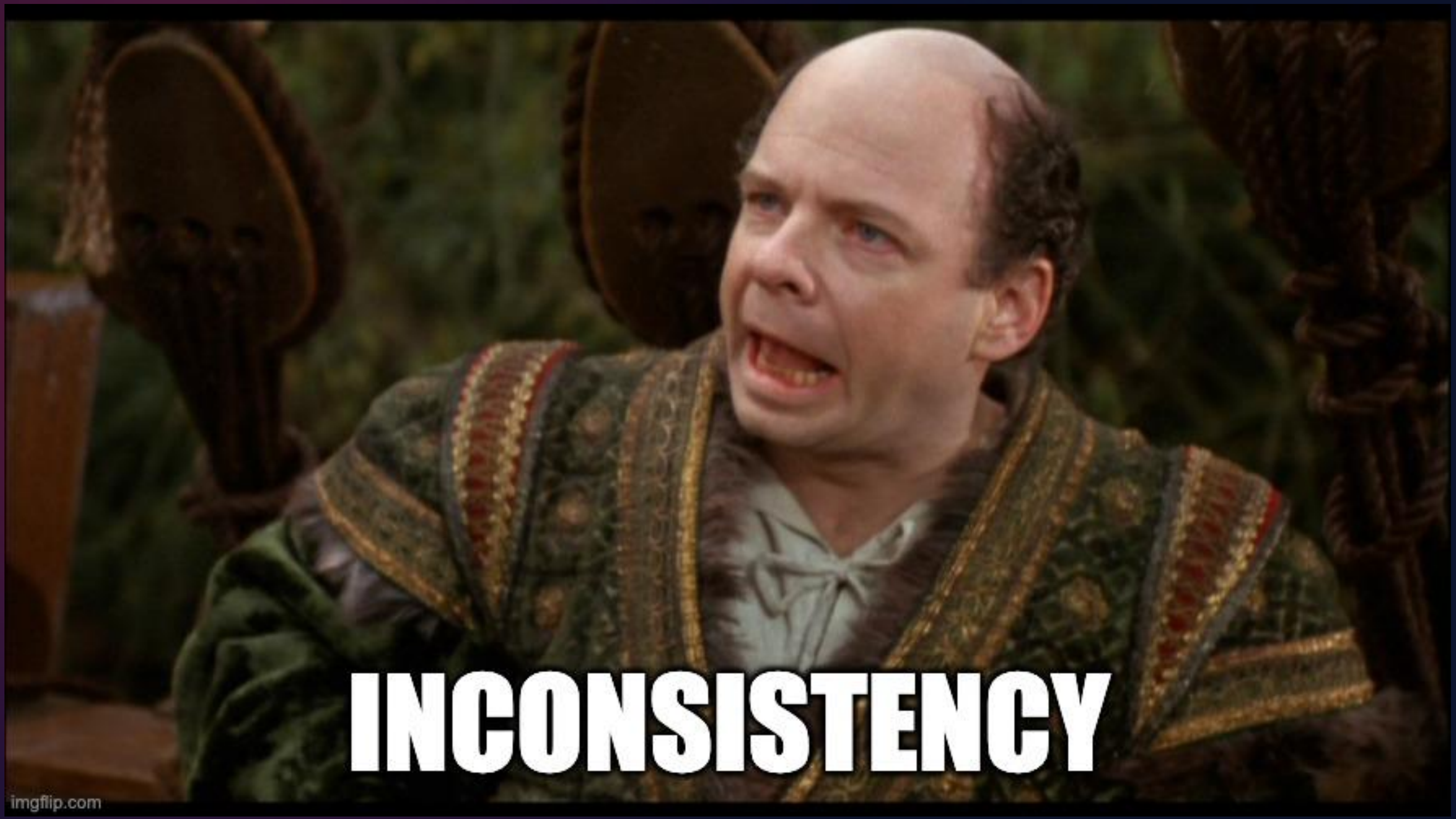
Key Goals:

- Interpretability
- Accountability
- Fairness + Bias Detection

Data Inconsistencies and How to Measure Them

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 Imbalance

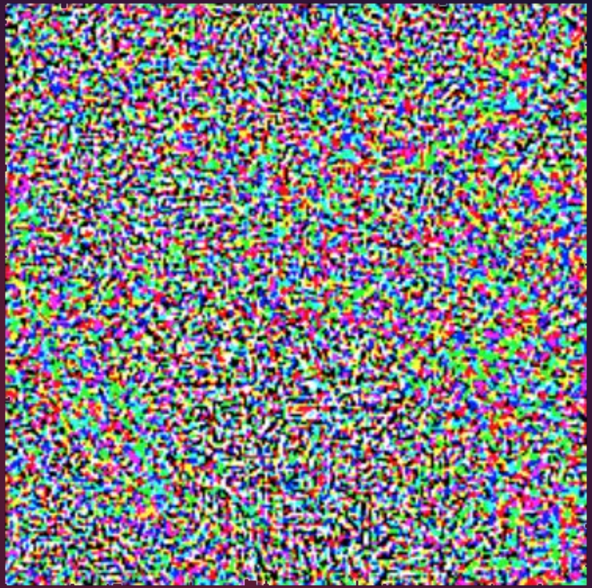
CATS

DOGS

Image Attribution
Introduction to Balanced and Imbalanced Datasets in Machine 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

Quantitatively Measure Results

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

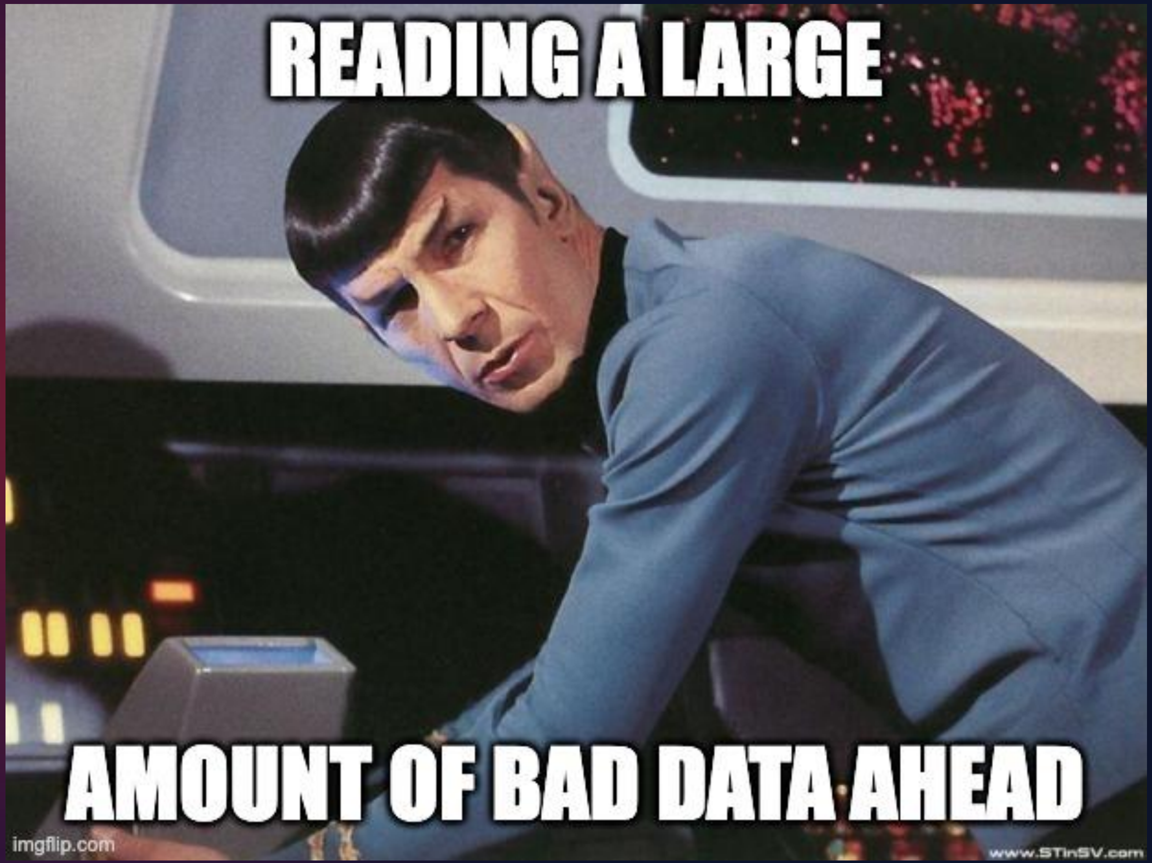
Captum

Adversarial Attacks: For Good… and Bad

Building Better Models via Intentional Disruption

Adversarial Inputs...

- For Good
  - Question Rigid Assumptions
  - Discover Data Flaws
  - Find Ethical Scenarios
  - Remove Biases
  - Promote Fairness
- For "Bad"
  - Protect Privacy
  - Obfuscation
  - Misdirection
  - Disrupt Surveillance



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: Captum + NLP Classifier

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

Demo: Captum + Vision Classifier

https://youtu.be/5J2sGIU0RV4

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

Adversarial Attack Defense

Protection Yourself From Bad Actors

Defending NLP Attacks

- Format Normalization
- Spelling/Grammar Checkers
- Word Recognition
  - Morphology (or Subwords Tokens)
- 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://hmmboutique.com - https://hmmboutique.com/products/bamboo-checkers-set

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
- Why Not Done? EXPENSIVE! -> More GPUs + Passes

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

Demo: Defending Adversarial NLP Attacks

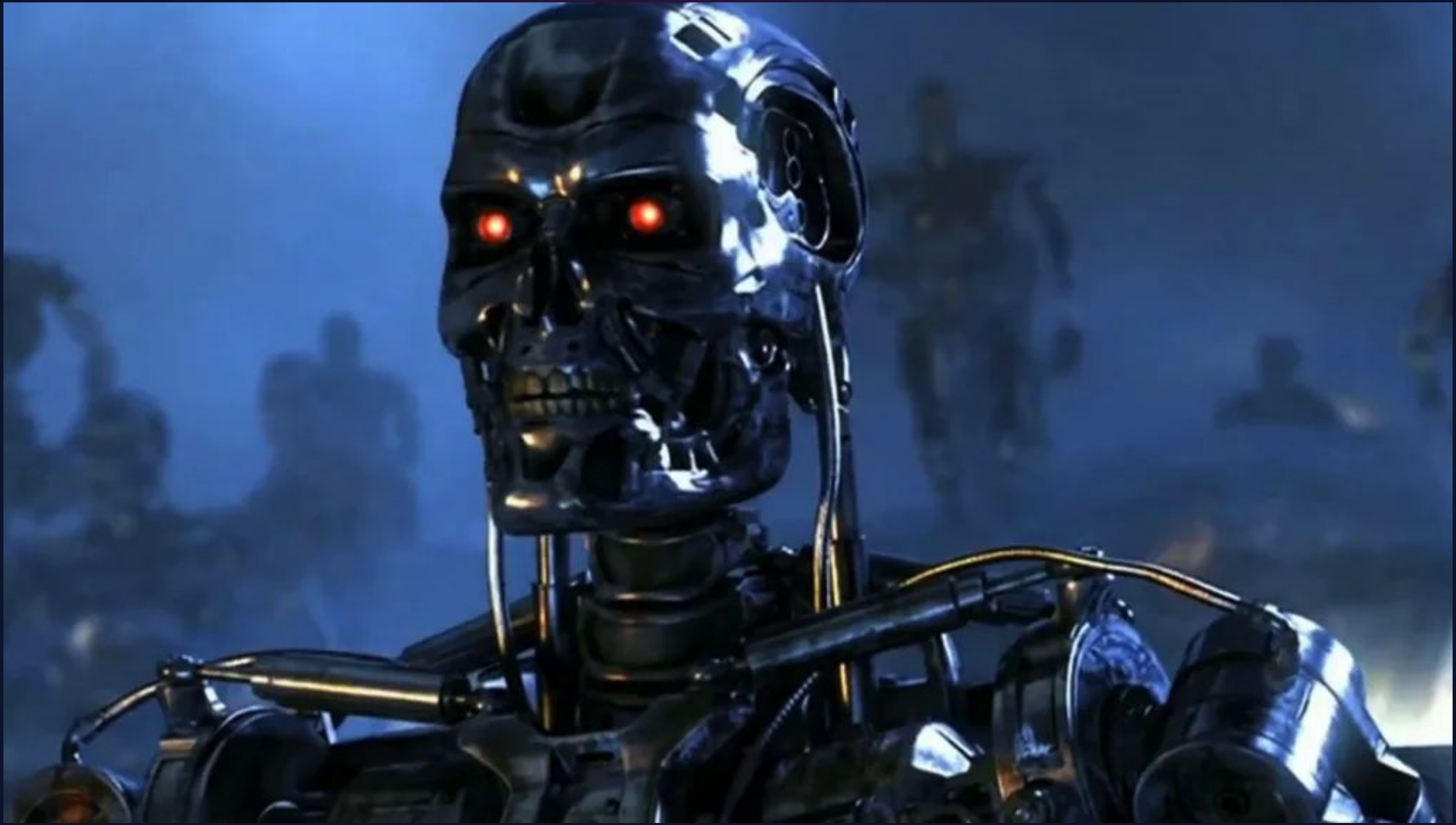
https://youtu.be/HB1RaL2OIQA

Demo: Defending Adversarial Vision Attacks

https://youtu.be/dLU5mBAt9qk

Why?

Just In Case...



Resources

All Materials/Code: github.com/davidvonthenen/2025-we-are-developers

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

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Thank You!

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