



## Confuse, Obfuscate, Disrupt

Using Adversarial Techniques for Better AI and True Anonymity

David vonThenen







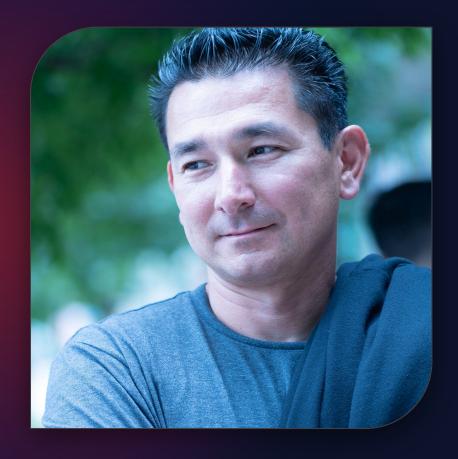


in C and avidvonthenen

## David vonThenen

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







## Agenda

- How Data Inconsistencies Happen
  - Demos, Demos, Demos
- Adversarial Attacks for Good... & Bad
  - Demos, Demos, Demos
- Adversarial Attack Defense
  - Demos, Demos, Demos
- Q&A



## How Data Inconsistencies Happen



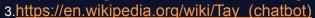
#### Flawed Data

- AI/ML Only As Good As the Data
  - Biased, Noise, Inaccuracies
- Real-World Examples:
  - Recruiter AI + Male Skewed
    - Not Representative Data
  - Offensive Al Chatbot
    - Using Racist Language
  - Court Case Hallucinations
    - ChatGPT fake cases
- Common Ways Of Flawed Data Getting Into Our Datasets...





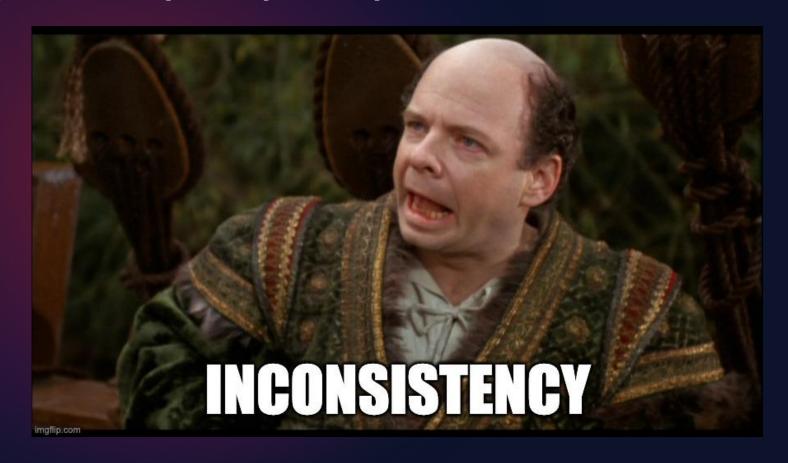
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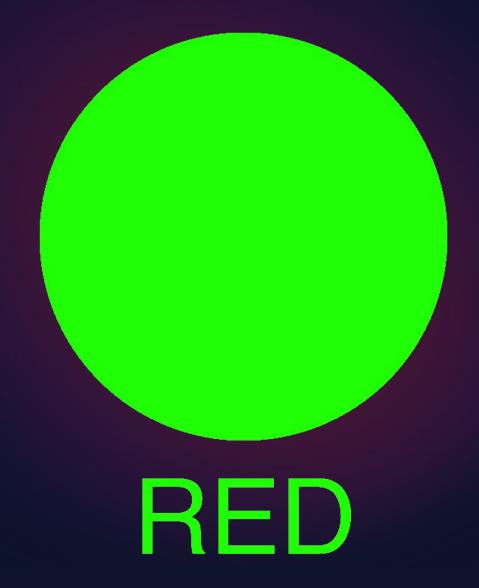
#### Data Inconsistencies Matter

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





### **Annotation Errors**





#### Data Imbalance

#### **Unbalanced Dataset**

**CATS DOGS** 



















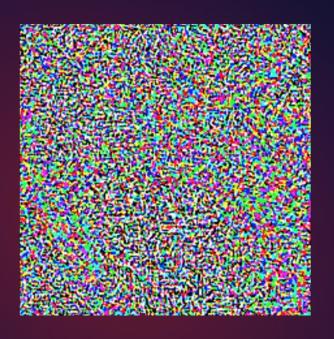




## **Adversarial Samples**

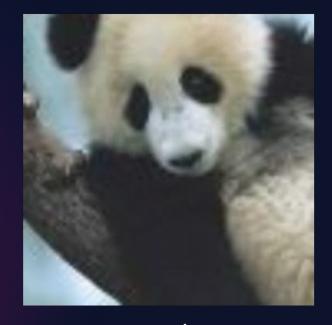


 $+.007 \times$ 



 $\operatorname{sign}(\nabla_{\boldsymbol{x}}J(\boldsymbol{\theta},\boldsymbol{x},y))$ 

"nematode" 8.2% confidence



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

 $\boldsymbol{x}$ 

"panda" 57.7% confidence



#### What Tools Can I Use?

- Captum <a href="https://github.com/pytorch/captum">https://github.com/pytorch/captum</a>
- SHAP <a href="https://github.com/shap/shap">https://github.com/shap/shap</a>
- LIME
- ELI5
- AIX360
- Many...
- Many...
- More





#### Demo: Captum + NLP Classifier

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

#### Demo: Captum + Vision Classifier

https://youtu.be/5J2sGIU0RV4



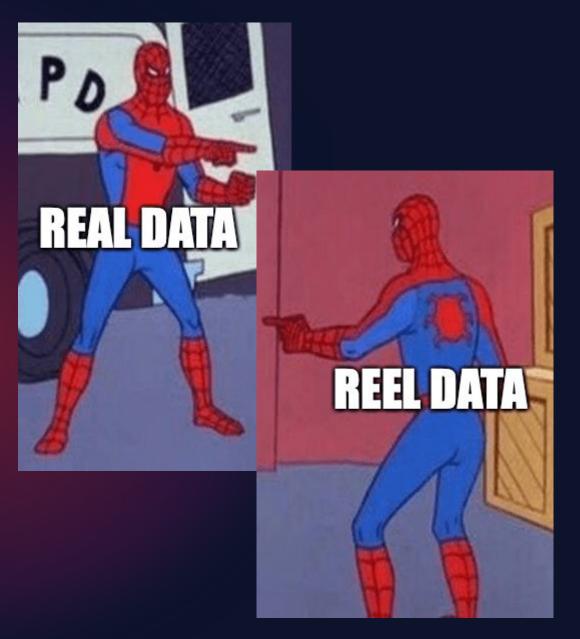
#### Adversarial Attacks: For Good... and Bad

**Building Better Models via Intentional Disruption** 



## Adversarial Attacks

- TODO
- 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





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



## Creative Communication



#### **Adversarial Attack Defense**

**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







## **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





## 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





#### 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: <a href="mailto:github.com/davidvonthenen/2025-we-are-developers">github.com/davidvonthenen/2025-we-are-developers</a>

#### Let's Chat on Discord: <a href="mailto:discord.gg/NetApp">discord.gg/NetApp</a>

- Captum:
  - GitHub <a href="https://github.com/pytorch/captum">https://github.com/pytorch/captum</a>
  - Tutorials <a href="https://captum.ai/tutorials/">https://captum.ai/tutorials/</a>
- PyTorch:
  - GitHub <a href="https://github.com/pytorch/pytorch">https://github.com/pytorch/pytorch</a>
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## ThankYou



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