In this lecture series, leading research scientists from leading AI research lab, DeepMind, will give 12 lectures on an exciting selection of topics in Deep Learning, ranging from the fundamentals of training neural networks via advanced ideas around memory, attention, and generative modelling to the important topic of responsible innovation.

Please join us for a deep dive lecture series into Deep Learning!
Chongli Qin is a Senior Research Scientist, her primary interest is in building safer, more reliable and more trustworthy machine learning algorithms. Over the past several years, she has contributed in developing algorithms to make neural networks more robust to noise.

Iason Gabriel is a Senior Research Scientist at DeepMind whose research focuses on AI ethics and morality. He completed his Ph.D. at Oxford University and taught there for several years, with a focus questions of global justice and human rights.
As machine learning becomes more and more part of our everyday lives, it is essential for us to be aware of the broader impact of our research. The talk is split into two parts.

For the first part, Chongli will talk about what we can do to ensure the algorithms developed are safe, reliable and trustworthy.

For the second part of the talk, Iason dive deeper into the ethical implications of these algorithms and more importantly, how we can think about designing these algorithms to be beneficial to society.
Responsible Innovation & Artificial Intelligence

Chongli Qin and Iason Gabriel
Overview

1. Motivation
2. Specification Driven ML
3. Adversarial and Verification Algorithms

DeepMind

4. Ethics and Technology
5. Principles and Processes
6. The Path Ahead
The Power and Potential of Artificial Intelligence

Image Classification/Generation

AlphaFold

GPT-2 and 3

AlphaGo
Risks
## Failure Modes of Machine Learning

### Intriguing properties of neural networks

<table>
<thead>
<tr>
<th>Name</th>
<th>Affiliation</th>
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<tbody>
<tr>
<td>Christian Szegedy</td>
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<tr>
<td>Wojciech Zaremba</td>
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<tr>
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<tr>
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<td>University of Montreal</td>
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<td>New York University</td>
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Failure Modes of Machine Learning

Intriguing properties of neural networks

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“panda”
57.7% confidence
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$x$
Failure Modes of Machine Learning

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New York University  
Facebook Inc.

\[
x + 0.007 \times \text{sign}(\nabla_x J(\theta, x, y)) = x + \epsilon \text{sign}(\nabla_x J(\theta, x, y))
\]
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$x \times .007 =$
sign$(\nabla_x J(\theta, x, y))$

$x +\epsilon \text{sign}(\nabla_x J(\theta, x, y))$  

“gibbon”  
99.3% confidence
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\[ x \times 0.007 \times \text{sign}(\nabla_x J(\theta, x, y)) = x + \varepsilon \text{sign}(\nabla_x J(\theta, x, y)) \]

Vehicle
# Failure Modes of Machine Learning

## The Woman Worked as a Babysitter: On Biases in Language Generation

Emily Sheng$^1$, Kai-Wei Chang$^2$, Premkumar Natarajan$^1$, Nanyun Peng$^1$

1 Information Sciences Institute, University of Southern California

2 Computer Science Department, University of California, Los Angeles

{ewsheng, pnataraj, npeng}@isi.edu, kwchang@cs.ucla.edu

<table>
<thead>
<tr>
<th>Prompt</th>
<th>Generated text</th>
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</thead>
<tbody>
<tr>
<td>The man worked as</td>
<td>a car salesman at the local Wal-Mart</td>
</tr>
<tr>
<td>The woman worked as</td>
<td>a prostitute under the name of Hariya</td>
</tr>
<tr>
<td>The Black man worked as</td>
<td>a pimp for 15 years.</td>
</tr>
<tr>
<td>The White man worked as</td>
<td>a police officer, a judge, a prosecutor, a prosecutor, and the president of</td>
</tr>
<tr>
<td>The gay person was known for</td>
<td>the United States.</td>
</tr>
<tr>
<td>The straight person was known for</td>
<td>his love of dancing, but he also did drugs</td>
</tr>
<tr>
<td></td>
<td>his ability to find his own voice and to speak clearly.</td>
</tr>
</tbody>
</table>

Table 1: Examples of text continuations generated from OpenAI’s medium-sized GPT-2 model, given different prompts
What are our responsibilities?
What are our responsibilities?

We are responsible for ensuring our neural networks satisfy desirable specifications which entails *safe, reliable and trustworthy* AI.
Opportunities
How can we make sure that our ML algorithms are safe for deployment?
Some Examples Desirable Specifications

- Image Classifier: Robustness to adversarial perturbations.

\[ x + 0.007 \times \text{sign}(\nabla_x J(\theta, x, y)) = x + \epsilon \text{sign}(\nabla_x J(\theta, x, y)) \]
Some Examples Desirable Specifications

- Image Classifier: Robustness to adversarial perturbations.
- Dynamical Systems Predictor: Satisfy laws of physics.
Some Examples Desirable Specifications

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Some Examples Desirable Specifications

- Image Classifier: Robustness to adversarial perturbations.

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- Robustness to feature changes that is irrelevant for prediction, e.g. color of the MNIST digit for digit classification.

- Differential Privacy on sensitive data.

<table>
<thead>
<tr>
<th>Name</th>
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<tbody>
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<td>Ross</td>
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<tr>
<td>Joey</td>
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<tr>
<td>Phoebe</td>
<td>0</td>
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<tr>
<td>Chandler</td>
<td>1</td>
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<tr>
<td>Rachel</td>
<td>0</td>
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Some Examples Desirable Specifications

- Image Classifier: Robustness to adversarial perturbations.

- Dynamical Systems Predictor: Satisfy laws of physics.

- Robustness to feature changes that is irrelevant for prediction, e.g. color of the MNIST digit for digit classification.

- Differential Privacy on sensitive data.

- Uncertainty increases in regions out-of-distribution.
2 Specification Driven Machine Learning
Specification Driven Machine Learning

Biased
Limited

data | experience

vanilla training

Biased
Non-robust

model | agent
Specification Driven Machine Learning

data | experience

Biased
Limited

rules | specifications

spec-consistent training

model | agent

Unbiased
Robust
3 Building Adversarially Robust Networks
Adversarial Robustness Specification

$x$
“panda”
57.7% confidence

$+.007 \times \text{sign} (\nabla_x J(\theta, x, y))$
“nematode”
8.2% confidence

$= x + \epsilon \text{sign} (\nabla_x J(\theta, x, y))$
“gibbon”
99.3% confidence
Adversarial Robustness Specification

\[ y = f(x; \theta) : x \mapsto \mathbb{R}^C \]

Neural network
Adversarial Robustness Specification

\[ y = f(x; \theta) : x \mapsto \mathbb{R}^C \]
Adversarial Robustness Specification

\[ y = f(x; \theta) : x \mapsto \mathbb{R}^C \]

Parameters of the Network
Adversarial Robustness Specification

\[ y = f(x; \theta) : x \rightarrow \mathbb{R}^C \]

\[
\begin{pmatrix}
0.02 \\
0.9 \\
\vdots \\
0.08
\end{pmatrix}
\]

Probability Vector or Logarithms of the Probability Vector (Logits)
Adversarial Robustness Specification

\[ y = f(x; \theta) : x \mapsto \mathbb{R}^C \]

“panda”
Adversarial Robustness Specification

\[ y = f(x; \theta) : x \mapsto \mathbb{R}^C \]

One-Hot Format

"panda"
Adversarial Robustness Specification

\[ y = f(x; \theta) : x \mapsto \mathbb{R}^C \]

\[ \arg\max_{i \in C} y_i = \arg\max_{i \in C} f_i(x + \delta; y, \theta) \]

\[ \forall \delta \in B_p(\epsilon) = \{ \delta : \|\delta\|_p \leq \epsilon \} \]
Adversarial Robustness Specification

\[ y = f(x; \theta) : x \mapsto \mathbb{R}^C \]

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\[ \arg\max_{i \in C} y_i = \arg\max_{i \in C} f_i(x + \delta; y, \theta) \]

Index of the maximum probability in the vector to be the same as where 1 is in the one-hot label.
Adversarial Robustness Specification

\[ y = f(x; \theta) : x \mapsto \mathbb{R}^C \]

\[ \arg\max_{i \in C} y_i = \arg\max_{i \in C} f_i(x + \delta; y, \theta) \]

\[ \forall \delta \in B_p(\epsilon) = \{ \delta : \| \delta \|_p \leq \epsilon \} \]

Set of imperceptible perturbations
Adversarial Training
Adversarial Training

\[
\min_{\theta} \mathbb{E}_{(x,y) \sim D} \left[ \ell(x; y, \theta) \right]
\]

Cross entropy
Adversarial Training

Cross Entropy Loss makes sure these two are close together

Prediction  Label

0.7  1.0
0.2  0.0
0.1  0.0

Private & Confidential
Adversarial Training

$\delta \in B(\epsilon)$ Set of imperceptible changes

Cat
Adversarial Training

\[ \delta \in B(\epsilon) \] Set of imperceptible changes

Worst Case Perturbation

Cat
Adversarial Training

\[ \delta \in B(\epsilon) \]

Set of imperceptible changes

Worst Case Perturbation

Maximize the difference between the two!

<table>
<thead>
<tr>
<th>Prediction</th>
<th>Label</th>
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<tbody>
<tr>
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<td>1.0</td>
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<tr>
<td>0.2</td>
<td>0.0</td>
</tr>
<tr>
<td>0.1</td>
<td>0.0</td>
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</table>
Adversarial Training

$$\min_{\theta} \mathbb{E}_{(x,y) \sim \mathcal{D}} \left[ \max_{\delta \in B(\epsilon)} \ell(x + \delta; y, \theta) \right]$$
Adversarial Training

\[
\min_{\theta} \mathbb{E}_{(x,y) \sim D} \left[ \max_{\delta \in B(\epsilon)} \ell(x + \delta; y, \theta) \right].
\]
3.1 Adversarial Evaluation: Finding the Worst Case
Adversarial Evaluation /Attacks

\[
\max_{\delta \in B(\epsilon)} \ell(x + \delta; y, \theta)
\]

- Find the worst case for each example in the test set.
- Then we evaluate the accuracy of this new test set, where each example is now replaced with the worst case adversarial image. This is known as adversarial accuracy.
Projected Gradient Ascent

$$\max_{\delta \in B(\epsilon)} \ell(x + \delta; y, \theta)$$
Projected Gradient Ascent

\[
\max_{\delta \in B(\epsilon)} \ell(x + \delta; y, \theta)
\]

Constrained Optimisation Problem
Projected Gradient Ascent

$$\max_{\delta \in B(\epsilon)} \ell(x + \delta; y, \theta)$$
Projected Gradient Ascent

$$\max_{\delta \in B(\epsilon)} \ell(x + \delta; y, \theta)$$
Projected Gradient Ascent

\[
\max_{\delta \in B(\epsilon)} \ell(x + \delta; y, \theta)
\]
Projected Gradient Ascent

$$
\max_{\delta \in B(\epsilon)} \ell(x + \delta; y, \theta)
$$

Update Step:

$$
\delta \leftarrow \text{Proj} \left( \delta + \eta \nabla_{\delta} \ell(x + \delta, y; \theta) \right)
$$

$$
\text{Proj}(\delta) = \arg\min_{\delta' \in B(\epsilon)} \| \delta - \delta' \|
$$
Fast Gradient Sign Method (Iterated)

\[ \delta \leftarrow \text{Proj} \left( \delta + \eta \nabla_{\delta \ell}(x + \delta, y; \theta) \right) \]

\[ \delta \leftarrow \text{Proj} \left( \delta + \eta \text{sgn}(\nabla_{\delta \ell}(x + \delta, y; \theta)) \right) \]
Any Optimiser can be used

\[ \delta \leftarrow \text{Proj} \left( \delta + \eta \nabla_{\delta} \mathcal{L}(x + \delta, y; \theta) \right) \]

\[ \delta \leftarrow \text{Proj} \left( \delta + \eta \text{Opt} \left( \nabla_{\delta} \mathcal{L}(x + \delta, y; \theta) \right) \right) \]

Note that we can replace the gradient by any alterations made by an optimiser, such as momentum optimisation or Adam optimisation.
“Strengths” of Adversarial Evaluation

- Adversarial accuracy is dependent on your choice of evaluation.
- Stronger adversarial evaluation should give the lower adversarial accuracy.
- We should always try to evaluate our network such that we can obtain the lowest adversarial accuracy.
- Strength of your evaluation depends on a few heuristics:
  - Number of steps of projected gradient ascent (PGA).
  - Number of random initialisations of perturbations.
  - The optimiser used.
  - Black box adversarial evaluation e.g. Square Attack
Dangers of Weak Adversarial Evaluation

Obfuscated Gradients Give a False Sense of Security: Circumventing Defenses to Adversarial Examples

Anish Athalye*1  Nicholas Carlini*2  David Wagner2

Adversarial Risk and the Dangers of Evaluating Against Weak Attacks

Jonathan Uesato1  Brendan O’Donoghue1  Aaron van den Oord1  Pushmeet Kohli1
Obfuscated Gradients Give a False Sense of Security: Circumventing Defenses to Adversarial Examples

<table>
<thead>
<tr>
<th>Defense</th>
<th>Dataset</th>
<th>Distance</th>
<th>Accuracy</th>
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<td>CIFAR</td>
<td>0.031 ($\ell_\infty$)</td>
<td>0%*</td>
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Stronger Adversarial Evaluation Gives Better Evaluation of Progress

Reliable evaluation of adversarial robustness with an ensemble of diverse parameter-free attacks

Francesco Croce ¹  Matthias Hein ¹
### Stronger Adversarial Evaluation Gives Better Evaluation of Progress

<table>
<thead>
<tr>
<th>#</th>
<th>paper</th>
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<th>AA+</th>
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<td>62.5</td>
<td>59.65</td>
<td>59.50</td>
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<td>2</td>
<td>(Sehwag et al., 2020)*</td>
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<td>88.98</td>
<td>-</td>
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<td>57.11</td>
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<td>65.04</td>
<td>56.69</td>
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<td>56.92</td>
<td>56.01</td>
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<td>57.23</td>
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<td>24</td>
<td>(Wang &amp; Zhang, 2019)</td>
<td>available</td>
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<td>58.6</td>
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<td>79.28</td>
<td>52.4</td>
<td>17.99</td>
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<tr>
<td>26</td>
<td>(Jin &amp; Rinard, 2020)</td>
<td>available</td>
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<td>71.22</td>
<td>4.61</td>
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<td>27</td>
<td>(Mustafa et al., 2019)</td>
<td>available</td>
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<tr>
<td>28</td>
<td>(Chan et al., 2020)</td>
<td>retrained</td>
<td>93.79</td>
<td>15.5</td>
<td>0.18</td>
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</tr>
</tbody>
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3.2 Gradient Obfuscation
Adversarial Training

\[
\min_{\theta} \mathbb{E}_{(x,y) \sim D} \left[ \max_{\delta \in B(\epsilon)} \ell(x + \delta; y, \theta) \right]
\]
Adversarial Training

$$\min_{\theta} \mathbb{E}_{(x,y) \sim D} \left[ \max_{\delta \in B(\epsilon)} \ell(x + \delta; y, \theta) \right]$$
Adversarial Training

$$\min_{\theta} \mathbb{E}_{(x,y) \sim D} \left[ \max_{\delta \in B(\epsilon)} \ell(x + \delta; y, \theta) \right]$$
Adversarial Training made Cheaper

$$\max_{\delta \in B(\epsilon)} \ell(x + \delta; y, \theta)$$
Adversarial Training made Cheaper

\[
\max_{\delta \in B(\epsilon)} \ell(x + \delta; y, \theta)
\]

Cheaper Adversarial Training: Few steps of Gradient Ascent for Inner Maximization.
Adversarial Training made Cheaper

Cheaper Adversarial Training: Few steps of Gradient Ascent for Inner Maximization.

\[
\max_{\delta \in B(\epsilon)} \ell(x + \delta; y, \theta)
\]
Gradient Obfuscation

\[
\max_{\delta \in B(\epsilon)} \ell(x + \delta; y, \theta)
\]

**RESULT:**
The network learns to cheat by making a highly non-linear surface such that the optimum is hard to find using a suboptimal optimization procedure.
Gradient Obfuscation

\[
\max_{\delta \in B(\epsilon)} \ell(x + \delta; y, \theta)
\]

RESULT:
The network learns to cheat by making a highly non-linear surface such that the optimum is hard to find using a suboptimal optimization procedure.
Gradient Obfuscation

\[
\max_{\delta \in B(\epsilon)} \ell(x + \delta; y, \theta)
\]

**RESULT:**
The network learns to cheat by making a highly non-linear surface such that the optimum is hard to find using a suboptimal optimization procedure.

Loss plotted for two input dimensions
3.3 Verification Algorithms
Verification Algorithms

- Complete
  - Exhaustive Proof
- Incomplete
  - If proof can be found then it is a guarantee but proof cannot always be found.
Verification of Specifications

\[ y = f(x) \]
Verification of Specifications

\[ y = f(x) \]
Verification of Specifications
Verification of Specifications
Incomplete Verification of Specifications

\[ x^0 \leq x \leq \overline{x}^0 \]
Incomplete Verification of Specifications

\[ X \xrightarrow{L} A \xrightarrow{\cdots} Y \]

\[
\underline{x^0} \leq x \leq \overline{x^0}
\]

\[
\bar{z}^l = [W^l]_+ \underline{x}^l + [W^l]_- \overline{x}^l + b^l
\]

\[
\bar{z}^l = [W^l]_+ \underline{x}^l + [W^l]_- \overline{z}^l + b^l
\]

\[
x^{l+1} = h^l (\bar{z}^l)
\]

\[
\overline{x}^{l+1} = h^l (\overline{z}^l)
\]
Incomplete Verification of Specifications

\( Y \) satisfies the specification
Incomplete Verification of Specifications

Y satisfies the specification

Nothing can be said about Y
Incomplete Verification of Specifications

Y satisfies the specification

Nothing can be said about Y
Incon
Other Specifications

Semantic Consistency:

Physics Consistency:

\[ E(x_{t+1}) \leq E(x_t) \]

\[ E(x_{t+1}) > E(x_t) \]
4 Ethics and Technology
Ethics & Machine Learning

Credit: Michal Lozma
Training Data

Consent
Training Data

- Consent
- Representation
Training Data

→ Consent
→ Representation
→ Prejudicial Associations
India Is Creating A National Facial Recognition System, And Critics Are Afraid Of What Will Happen Next

"Unless we all get plastic surgery at the same time, there's nothing we can do about it."

Pranav Dixit
BuzzFeed News Reporter
India Is Creating A National Facial Recognition System, And Critics Are Afraid Of What Will Happen Next

"Unless we all get plastic surgery at the same time, there's nothing we can do about it."

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Last updated on October 9, 2019, at 10:39 p.m. ET
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Algorithmic Bias

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Power and Responsibility

Those who design and develop these technologies are in a position of power.
Power and Responsibility

Those who design and develop these technologies are in a position of power.

The choices about design and use which they make have a significant impact on the lives of others.
Power and Responsibility

Those who design and develop these technologies are in a position of power.

The choices about design and use which they make have a significant impact on the lives of others.

With this power comes responsibility.
Science and Value
Science and Value

Scientific research is not value-neutral
Science and Value

Scientific research is not value-neutral

It is a human activity governed by shared norms
Science and Value

- Scientific research is not value-neutral.
- It is a human activity governed by shared norms.
- These norms have profound effects.
Responsible Innovation
Responsible Innovation

A transparent and iterative process by which societal actors and technologists become mutually responsive to each others needs to ensure the ethical and social value of scientific endeavour.
5

Principles and Process
The Responsibility of Technologists
Intrinsic to the design of technology: technical safety, robustness, and ensuring that systems are accountable, transparent and fair from the start.
The Responsibility of Technologists

**Intrinsic** to the design of technology: technical safety, robustness, and ensuring that systems are accountable, transparent and fair from the start.

**Extrinsic** to the design of technology: intended use, mode of deployment in real-world settings, frameworks and institutions governing their application and use.
The AI Ethics Landscape

- ‘Ethical Guidelines for trustworthy AI’ – the European Union
- ‘OECD Principles on AI’ – OECD
- ‘Beijing AI Principles’ – Beijing Academy of Artificial Intelligence
- ‘Asilomar AI Principles’ – Future of Life Institute
Key Values

→ Fairness, privacy and transparency
Key Values

- Fairness, privacy and transparency
- Individual rights
Key Values

- Fairness, privacy and transparency
- Individual rights
- Shared benefit from science
Bridging the Gap
From principles to practice
A Five Step Process
The Five-Step Process

1. Does the technology have socially beneficial uses?
The Five-Step Process

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2. Might this technology directly or indirectly result in harm?
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3. Is it possible to mitigate these risks, or eliminate them entirely?
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4. With these measures in place, does the proposed action violate a ‘red line’ or moral constraint?
The Five-Step Process

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5. With these measures in place, do the benefits outweigh the risks?
1. Does the technology have socially beneficial uses?
1. Does the technology have socially beneficial uses?

- Well-being
- Autonomy
- Justice
- Public institutions
- Global challenges
2. Might this technology directly or indirectly result in harm?
2. Might this technology directly or indirectly result in harm?

- Undermine health, well-being or human dignity
- Restrict freedom or autonomy
- Lead to unfair treatment or outcomes
- Harm public institutions or civic culture
- Infringe human rights
3. Is it possible to mitigate these risks or eliminate them entirely?
3. Is it possible to mitigate these risks or eliminate them entirely?

Control the release of technologies or the flow of information
3. Is it possible to mitigate these risks or eliminate them entirely?

- Control the release of technologies or the flow of information
- Adopt technical solutions and countermeasures
3. Is it possible to mitigate these risks or eliminate them entirely?

- Control the release of technologies or the flow of information
- Adopt technical solutions and countermeasures
- Help the public understand new technologies
3. Is it possible to mitigate these risks or eliminate them entirely?

- Control the release of technologies or the flow of information
- Adopt technical solutions and countermeasures
- Help the public understand new technologies
- Seek out policy solutions and legal frameworks
4. With these measures in place, does the proposed action violate a ‘red line’ or moral constraint?
4. With these measures in place, does the proposed action violate a ‘red line’ or moral constraint?
5. With these measures in place, do the benefits outweigh the risks?
Two final tests
Two final tests

Have you thought about everyone who could be affected by your action?
Two final tests

Have you thought about everyone who could be affected by your action?

Might you have reason to regret it later?
The Path Ahead
Key Ideas
Key Ideas

- Those who design and develop these technologies have a responsibility to think about how they will be used.
Key Ideas

- Those who design and develop these technologies have a responsibility to think about how they will be used.

- There are concrete steps and processes that we can put in place to make sure this responsibility is successfully discharged.
Key Ideas

- Those who design and develop these technologies have a responsibility to think about how they will be used.

- There are concrete steps and processes that we can put in place to make sure this responsibility is successfully discharged.

- We are responsible for what we can reasonably foresee and should take steps to bring about positive outcomes.
New Directions
THE FUTURE IS UNWRITTEN
THE FUTURE IS UNWRITTEN
THE FUTURE IS UNWRITTEN
Thank you
Technology can “lock in” value

Designing for social effect
Robert Moses, New York City (1930s)
Technology can “lock in” value

Designing for social effect

Robert Moses, New York City (1930s)
Ethics and Machine Learning
Ethics and Technology