

# Coexister avec nos artifices

## *Introduction à l'épistémologie du numérique*

Modern Times, Charlie Chaplin, 1936



Boris Beauce - STSLab - Université de Lausanne

Master en humanités et cultures numériques - UNIL - 2021

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Lee Sedol vs AlphaGo (DeepMind) - Mars 2016



Promesses des machines, machines à promesses - L'intelligence artificielle et l'avenir du travail

Université de Lausanne - 22 mars 2018

Boris Beaude - STSLab - Université de Lausanne

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James Bridle - Autonomous Trap 001 - Magic Salt Circle - 14 mars 2017

Promesses des machines, machines à promesses - L'intelligence artificielle et l'avenir du travail

Université de Lausanne - 22 mars 2018

## Quelle nouveauté ?

Problématique du changement

Expertise -> Expérience

Puissance de traitement

*Données*

*Algorithmes*

Modèles économiques



## Sous quel forme ?

Problématique de l'existence matérielle

Androïde / Humanoïde

Problématique de l'anthropomorphisme et vallée de l'étrange...

Cyborg

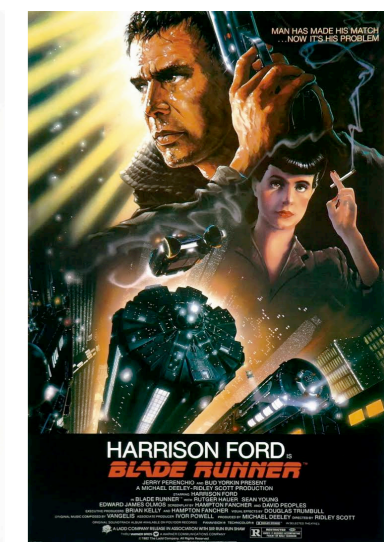
Problématique du transhumanisme...

Bot

Problématique de l'algorithme...

Hybride et distribuée

Problématique de la cybernétique...



## Intelligence artificielle ?

Intelligence produite par l'activité humaine

### Spécialisée

Intelligence artificielle faible

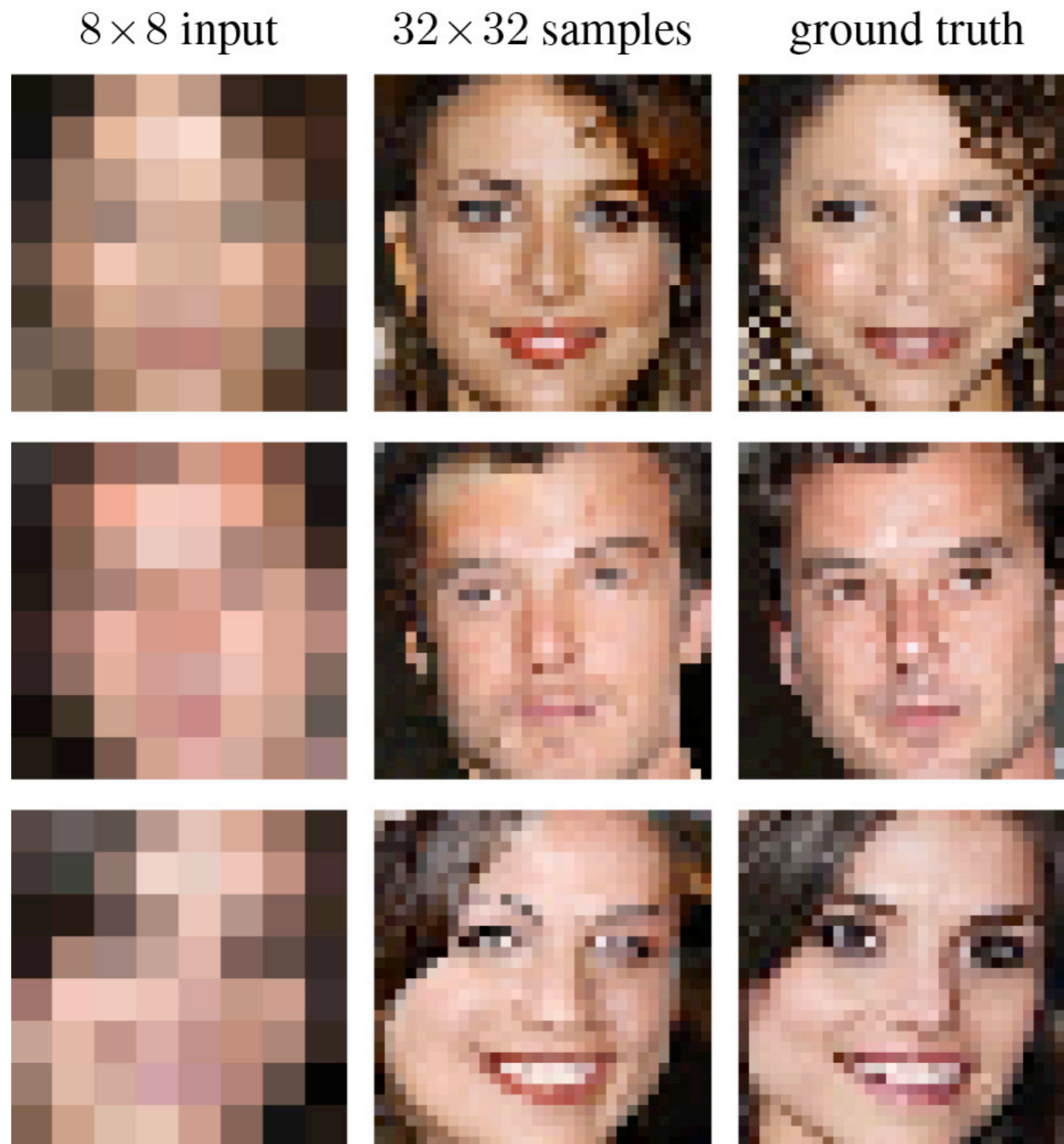
### Analogique

Intelligence artificielle forte

### Indépendante

Singularité





*Pixel Recursive Super Resolution* - Ryan Dahl & al. / Google Brain – Février 2017

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UK National Grid control room and DeepMind - Mars 2017

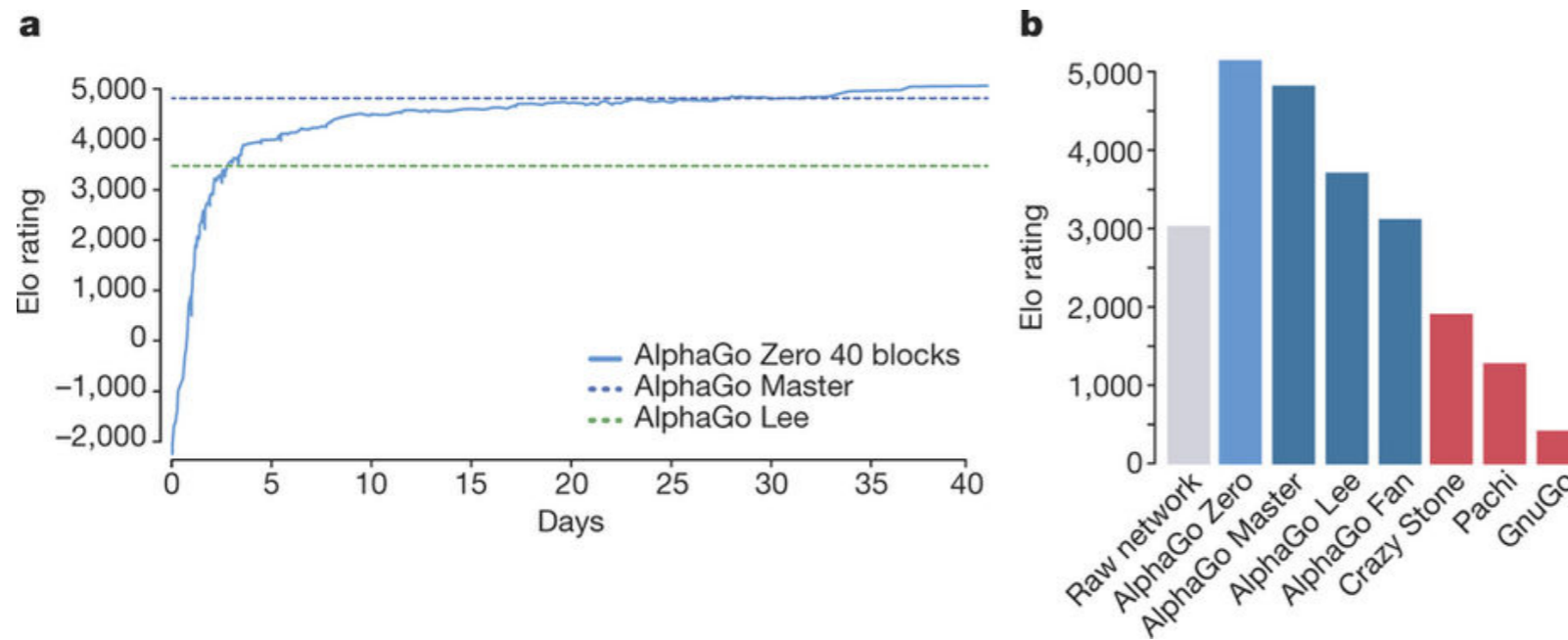






Wei Xiaoyong (Sichuan University) - Students being checked for boredom levels in class - West China Metropolis Daily - Septembre 2016

## Mastering the game of Go without human knowledge



- (1) **AlphaGo Fan** is the previously published program that played against Fan Hui in **October 2015**. This program was distributed over many machines using 176 GPUs.
- (2) **AlphaGo Lee** is the program that defeated Lee Sedol 4–1 in **March 2016**. It was previously unpublished, but is similar in most regards to AlphaGo Fan - 48 TPUs, rather than GPUs
- (3) **AlphaGo Master** is the program that defeated top human players by 60–0 in **January 2017** - initialized by supervised learning from human data + reinforcement
- (4) **AlphaGo Zero** learns from self-play reinforcement learning, with no human supervision in **April 2017**. It uses just a single machine in the Google Cloud with 4 TPUs
- (x) **AlphaZero** is a more generalized variant of the AlphaGo Zero (AGZ) algorithm, and is able to play **shogi** and **chess** as well as **Go**.
  - Defeated Stockfish 8 after **9 hours** of training.
  - Defeated AlphaGo Zero after **34 hours** of training.

## ALPHAGO ZERO CHEAT SHEET

The training pipeline for AlphaGo Zero consists of three stages, executed in parallel

### SELF PLAY

Create a 'training set'

The best current player plays 25,000 games against itself  
See MCTS section to understand how AlphaGo Zero selects each move

At each move, the following information is stored

The game state  
(see 'What is a Game State' section)

$\pi$ 

The search probabilities  
(from the MCTS)

The winner  
(+1 if this player won, -1 if this player lost - added once the game has finished)

### RETRAIN NETWORK

Optimise the network weights

A TRAINING LOOP

Sample a mini-batch of 2048 positions from the last 500,000 games

Retrain the current neural network on these positions  
- The game states are the input (see 'Deep Neural Network Architecture')

Loss Function

Compares predictions from the neural network with the search probabilities and actual winner

$P$   
PREDICTIONS  
 $V$

$\pi$   
Cross-entropy + Mean-squared error + Regularisation

$A$   
ACTUAL

After every 1,000 training loops, evaluate the network

### EVALUATE NETWORK

Test to see if the new network is stronger

Play 400 games between the latest neural network and the current best neural network

Both players use MCTS to select their moves, with their respective neural networks to evaluate leaf nodes

Latest player must win 55% of games to be declared the new best player

### WHAT IS A 'GAME STATE'

Current position of black's stones

19 x 19 x 17 stack

...and for the previous 7 time periods

Current position of white's stones

...and for the previous 7 time periods

All 1 if black to play  
All 0 if white to play

This stack is the input to the deep neural network

1	1	1
1	0	0
0	0	1

1 if black stone here  
0 if black stone not here

### THE DEEP NEURAL NETWORK ARCHITECTURE

How AlphaGo Zero assesses new positions

The network learns 'tabula rasa' (from a blank slate)  
At no point is the network trained using human knowledge or expert moves

#### The value head

game value for current player [-1, 1]

Input → 1 convolutional filter (3x3) → Batch normalisation → Rectifier non-linearity → Fully connected layer → Fully connected layer → Fully connected layer → tanh non-linearity → scalar

The network

140 residual layers

value head / policy head

#### The policy head

19 x 19 + 1 (for pass) move logit probabilities

Input → 2 convolutional filters (3x3) → Batch normalisation → Rectifier non-linearity → Fully connected layer

#### A residual layer

Input → 256 convolutional filters (3x3) → Batch normalisation → Rectifier non-linearity → Skip connection → Batch normalisation → Rectifier non-linearity → 256 convolutional filters (3x3)

### MONTE CARLO TREE SEARCH (MCTS)

How AlphaGo Zero chooses its next move

Each potential action from a game state stores four numbers:

- N: The number of times action a has been taken from state s
- W: The total value of the next state
- Q: The mean value of the next state
- P: The prior probability of selecting action a

1. Choose the action that maximises  $Q + U$

$Q + U$  is a function of P and N that increases if an action hasn't been explored much, relative to the other actions, or if the prior probability of the action is high.

2. Continue until a leaf node is reached

The game state of the leaf node is passed into the neural network, which outputs predictions about two things:

- $P$ : Move probabilities
- $V$ : Value of the state (for the current player)

The move probabilities p are attached to the new feasible actions from the leaf node

3. Backup previous edges

Each edge that was traversed to get to the leaf node is updated as follows:

$$N \rightarrow N + 1$$

$$W \rightarrow W + v$$

$$Q = W / N$$

...then select a move

After 1,600 simulations, the move can either be chosen:

- Deterministically (for competitive play): Choose the action from the current state with greatest N
- Stochastically (for exploratory play): Choose the action from the current state from the distribution  $\pi \sim N^{1/\tau}$  where  $\tau$  is a temperature parameter; controlling exploration

Other points:

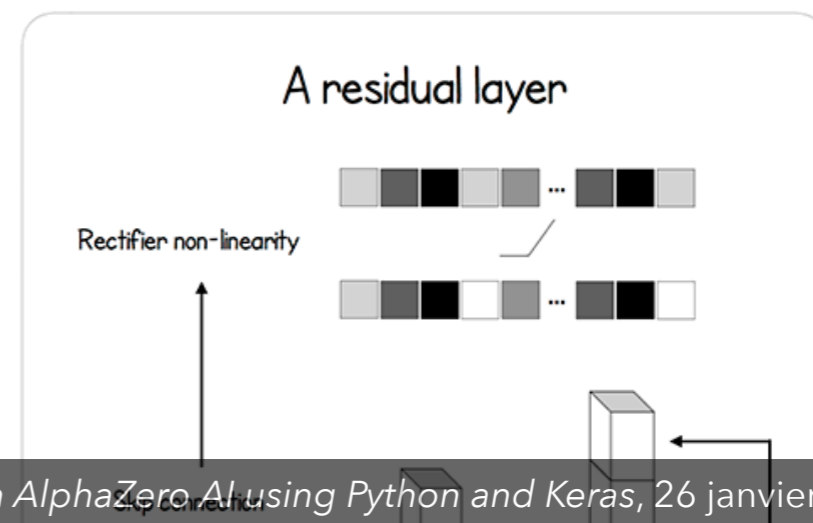
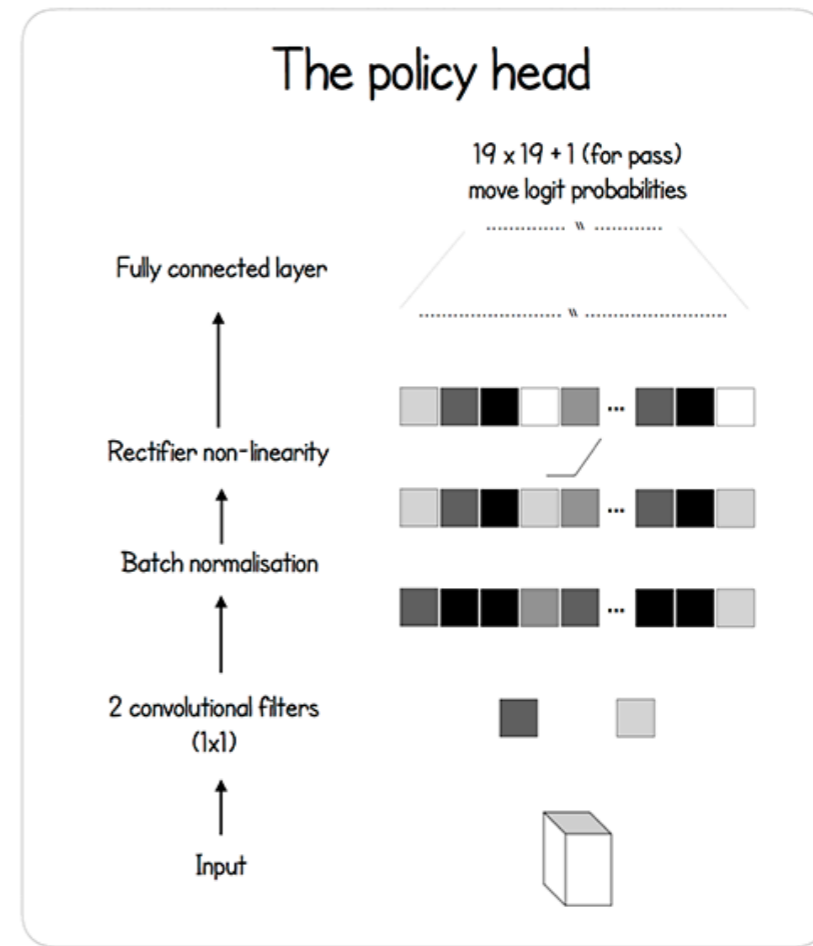
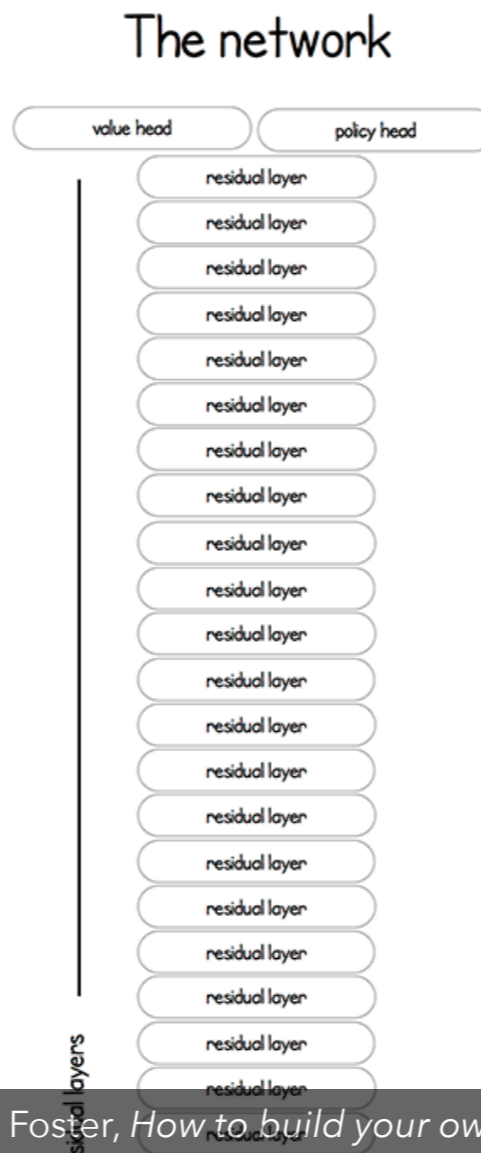
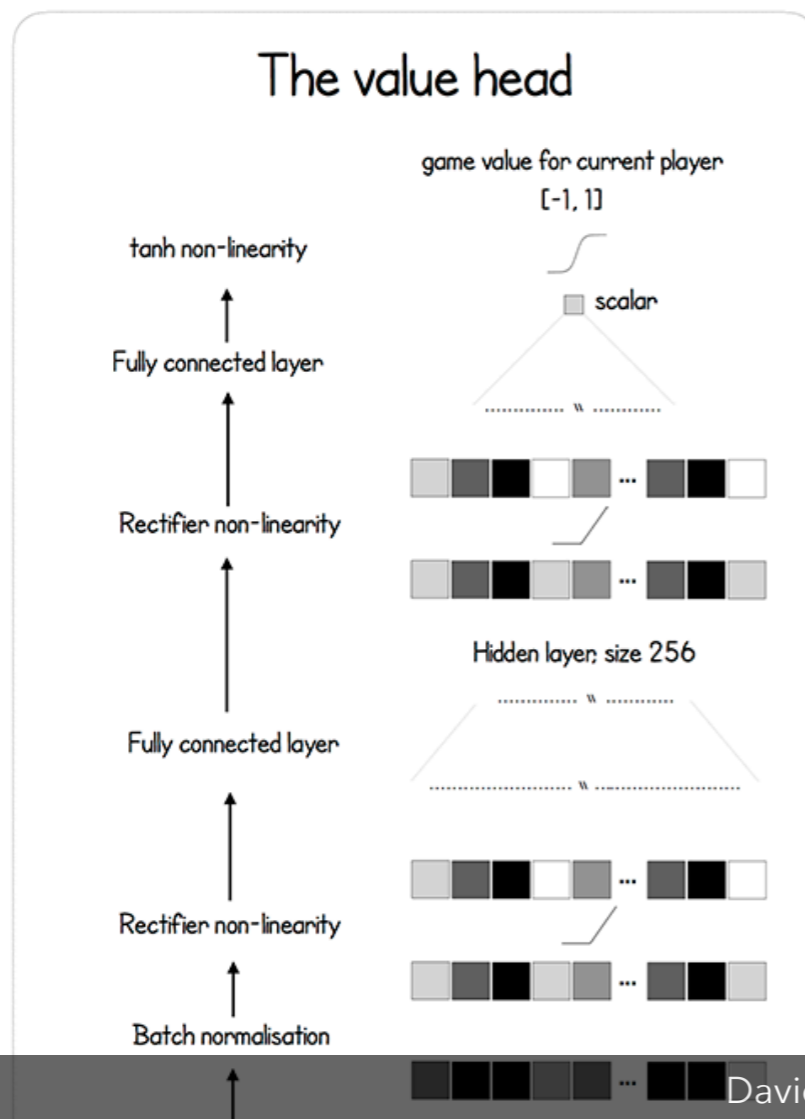
- The sub-tree from the chosen move is retained for calculating subsequent moves
- The rest of the tree is discarded

## THE DEEP NEURAL NETWORK ARCHITECTURE

### How AlphaGo Zero assesses new positions

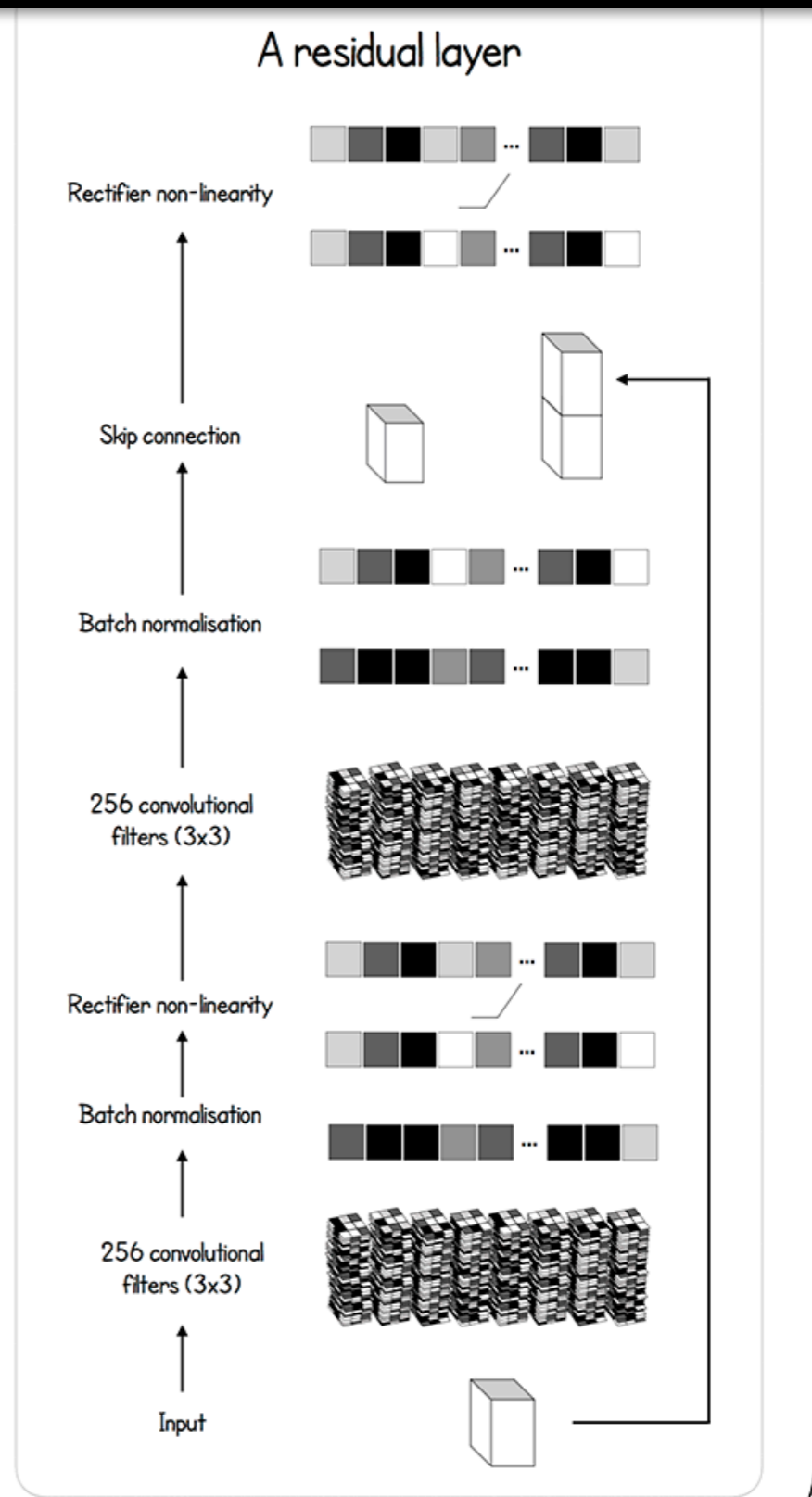
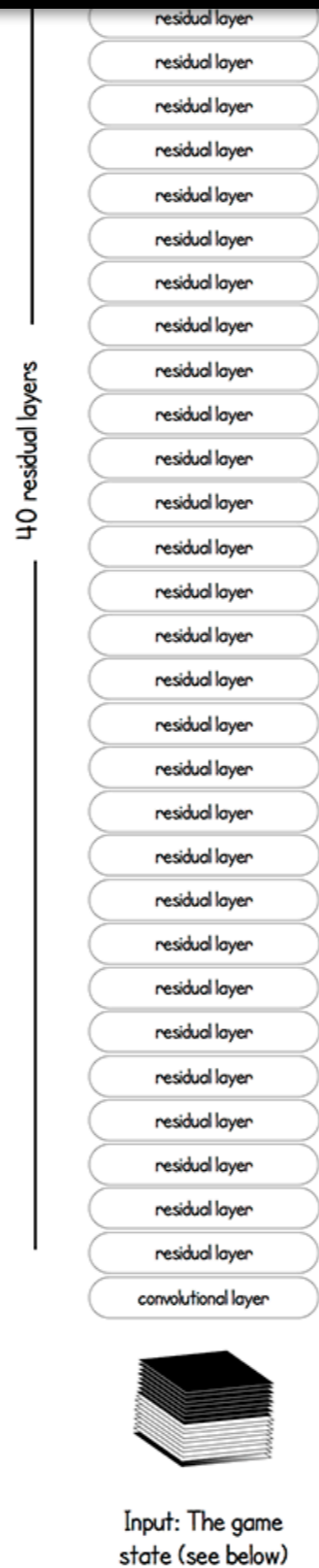
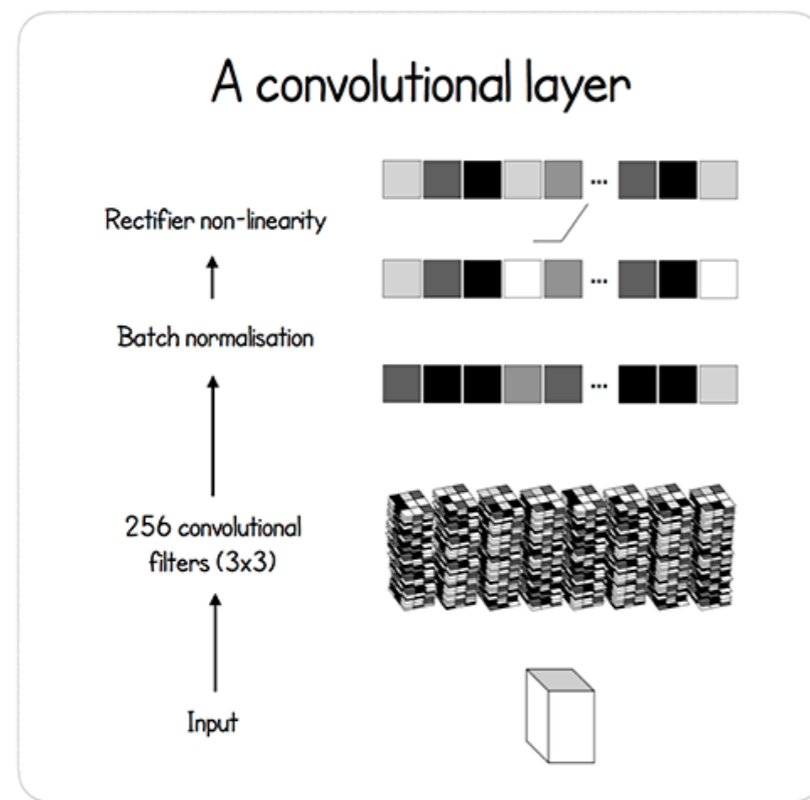
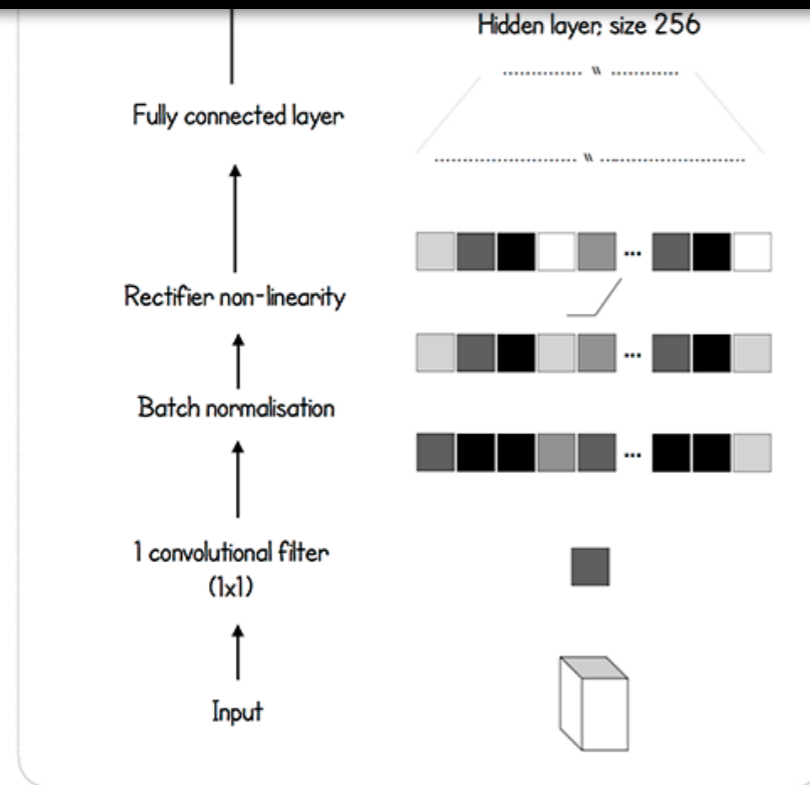
The network learns 'tabula rasa' (from a blank slate)

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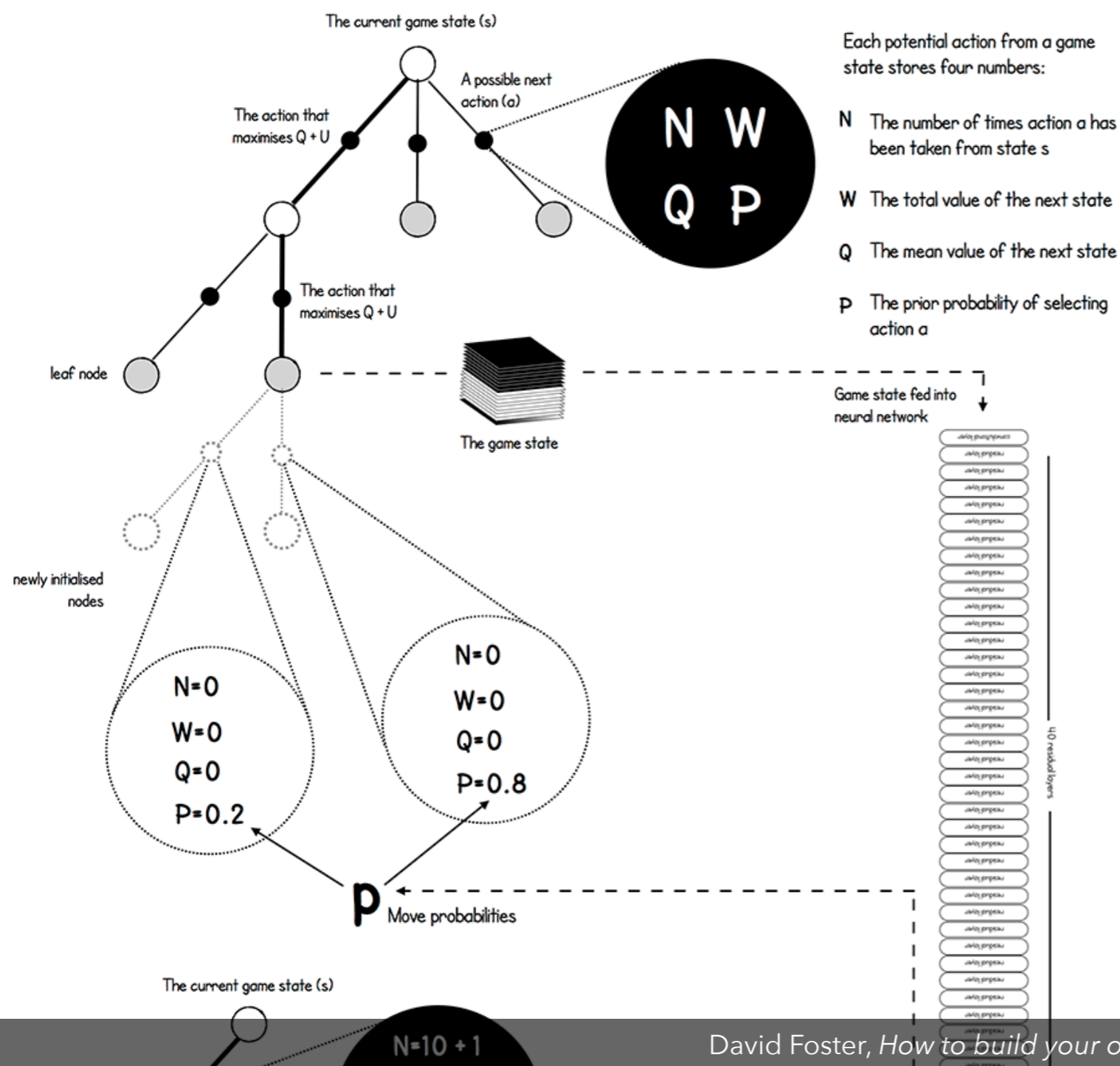
David Foster, How to build your own AlphaZero AI using Python and Keras, 26 janvier 2018, Medium

# Coexister avec nos artifices



## MONTE CARLO TREE SEARCH (MCTS)

How AlphaGo Zero chooses its next move



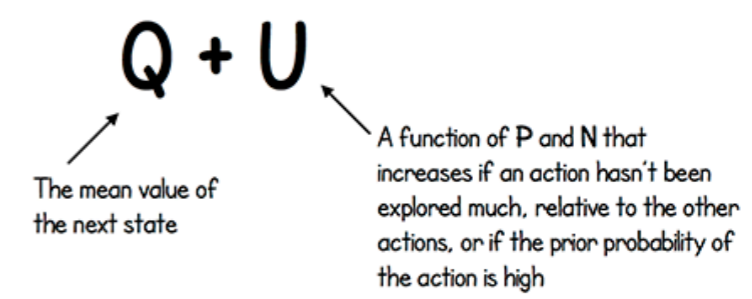
Each potential action from a game state stores four numbers:

- N The number of times action a has been taken from state s
- W The total value of the next state
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- P The prior probability of selecting action a

First, run the following simulation 1,600 times...

Start at the root node of the tree (the current game state)

1. Choose the action that maximises...



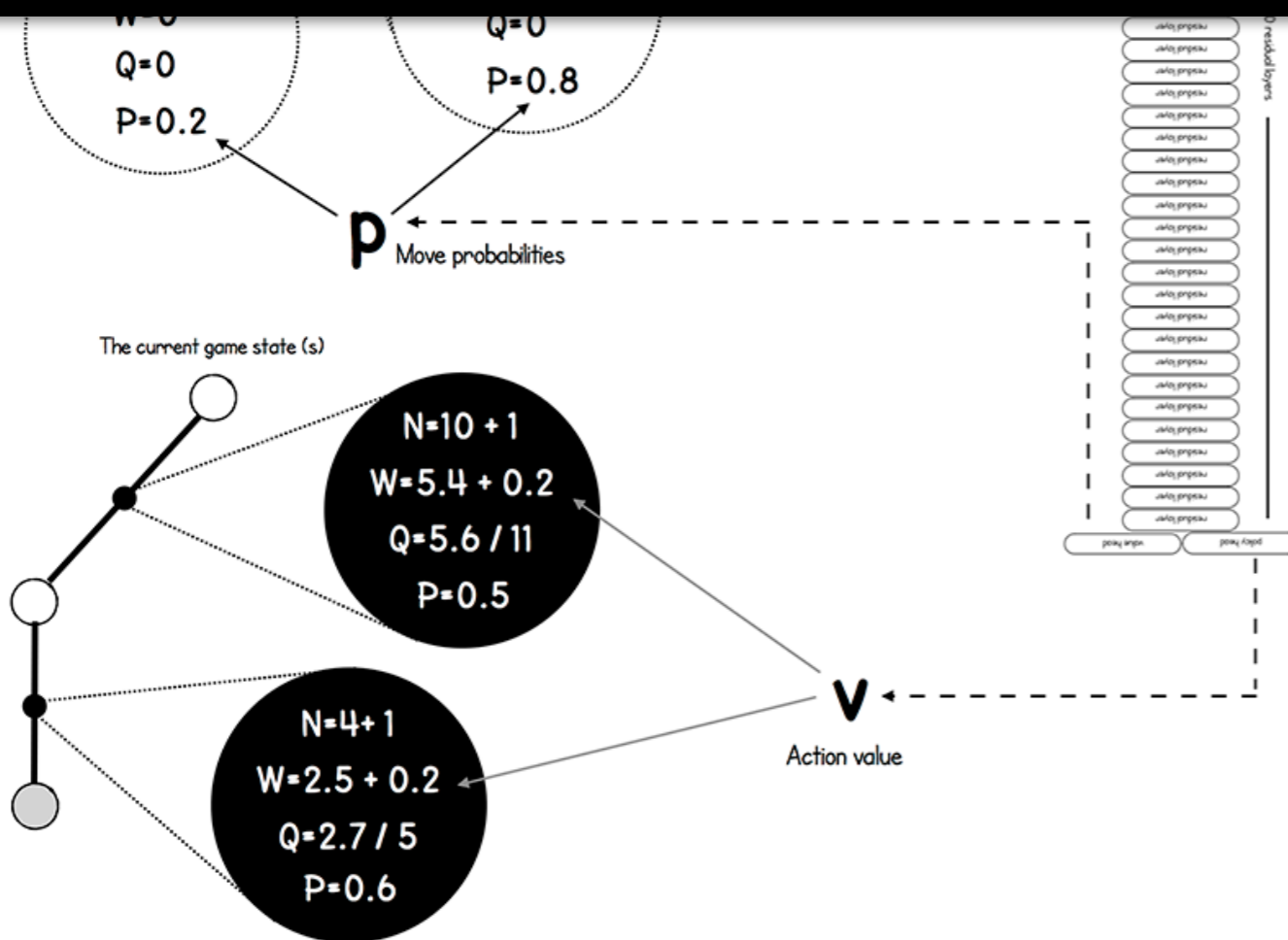
Early on in the simulation, U dominates (more exploration), but later, Q is more important (less exploration)

2. Continue until a leaf node is reached

The game state of the leaf node is passed into the neural network, which outputs predictions about two things:

- p** Move probabilities
- v** Value of the state (for the current player)

The move probabilities p are attached to the new feasible actions from the leaf node



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### 3. Backup previous edges

Each edge that was traversed to get to the leaf node is updated as follows:

$$N \rightarrow N + 1$$

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$$Q = W / N$$

## ...then select a move

After 1,600 simulations, the move can either be chosen:

### Deterministically (for competitive play)

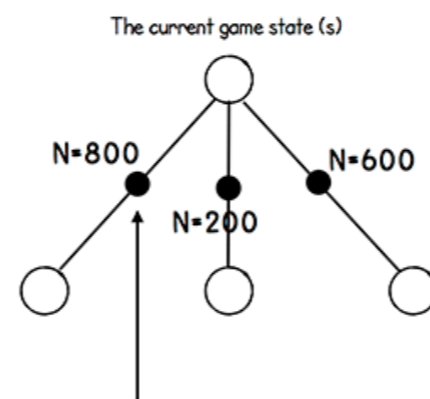
Choose the action from the current state with greatest N

### Stochastically (for exploratory play)

Choose the action from the current state from the distribution

$$\pi \sim N^{1/\tau}$$

where  $\tau$  is a temperature parameter, controlling exploration



Choose this move if deterministic  
 If stochastic, sample from categorical distribution  
 $\pi$  with probabilities (0.5, 0.125, 0.375)

## Other points

- The sub-tree from the chosen move is retained for calculating subsequent moves
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140 residual layers

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The mean value of the next state

A function of P and N that increases if an action hasn't been explored much, relative to the other actions, or if the prior probability of the action is high

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The current game state (s)

Choose this move if deterministic  
If stochastic, sample from categorical distribution  $\pi$  with probabilities (0.5, 0.125, 0.375)

## AI effect ?

Problématique de la qualification de l'intelligence

La reconnaissance de caractères (Lecun 1989)

Les échecs (IBM Deep Blue - mai 1997)

L'érudition - Jeopardy (IBM Watson - 16 février 2011)

Le Go (DeepMind AlphaGo Lee - mars 2016 & AlphaGo Master - janvier 2017)

La compréhension d'un texte (Alibaba 15 janvier 2018)

La traduction ? (DeepL, Google, Microsoft...)

Conduire ? (Waymo, Tesla, Volvo, BMW, GM, Apple...)





...

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'Uber's Self-Driving Car Just Killed Somebody. Now What?'

Arian Marshall, *Uber's Self-Driving Car Just Killed Somebody. Now What?*, 19 mars 2018, Wired

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Toyota **suspend** aussi ses tests de voitures autonomes - Le Blog Auto

Après l'accident d'Uber, Toyota aussi **suspend** ses essais de voitures autonomes - Sciences et Avenir

Comment l'Arizona est devenue « le **Far West** des voitures autonomes » - Les Échos

Accident mortel d'un Uber: Quels **obstacles** la voiture autonome doit-elle encore **surmonter**? - 20minutes.fr

Après l'accident mortel d'Uber, Toyota **suspend** ses tests de voitures autonomes - Numerama

Une voiture **dangereusement** autonome - Le Figaro

Transports. L'accident d'Uber, un **coup d'arrêt** pour les voitures autonomes ? - Courrier International

**Qui est responsable** en cas d'accident impliquant une voiture autonome ? - Le Monde

Voitures autonomes : l'accident qui **compromet** leur avenir ? - France Info

Uber : un accident mortel qui **remet en cause** l'avenir de la voiture autonome ? - Futura-Sciences

Uber : un accident mortel dans l'Arizona **pointe les limites** de la voiture autonome - Marianne

Une voiture autonome **tue un humain** - ICTjournal

Accident mortel d'un Uber autonome : **cauchemar** des constructeurs et **interrogations en série** - Europe1

Uber **suspend** ses voitures autonomes - Le Matin Online

Les voitures autonomes pourraient subir un '**revers important**' après la mort tragique d'une femme renversée par un véhicule autonome d'Uber - Business Insider

Google actualité - « Uber » - 21 mars 2018

Promesses des machines, machines à promesses : l'intelligence artificielle et l'avenir du travail - Boris Beaudé - STSLab - Université de Lausanne - 22 mars 2018

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Malgré l'accident d'Uber, **BMW accélère** vers la voiture autonome - LaPresse.ca

Malgré l'accident d'Uber, **BMW persiste** dans la voiture autonome - Le Soir

La **police**: 'Uber n'est **pas responsable** de l'accident mortel' - Le Vif

Accident mortel de voiture autonome : «Ça ne doit **pas remettre en cause** les projets», estime un **expert** - Le Parisien

Selon la **police**, « Uber n'est probablement pas en tort » dans l'accident mortel causé par une voiture autonome - Numerama

Uber **dédouané** par la chef de la **police** dans l'accident qui a causé la mort d'une femme - La Revue du digital

Accident mortel provoqué par un véhicule autonome : la **police blâme la victime** - Le Soir

Pourquoi la voiture autonome n'est **pas remise en cause** par l'accident mortel provoqué par Uber - BFMTV.COM

Tués par des humains ? « Près de 40 000 morts par an aux Etats-Unis, dont près de 6000 piétons - plus de 16 par jour ».

Google actualité - « Uber » - 21 mars 2018

Promesses des machines, machines à promesses : l'intelligence artificielle et l'avenir du travail - Boris Beaudé - STSLab - Université de Lausanne - 22 mars 2018

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Réflexions hors sol et sans contexte ?



Arian Marshall, *Uber's Self-Driving Car Just Killed Somebody. Now What?*, 19 mars 2018, Wired

Réflexions hors sol et sans contexte ?

Montées en généralité



Arian Marshall, *Uber's Self-Driving Car Just Killed Somebody. Now What?*, 19 mars 2018, Wired



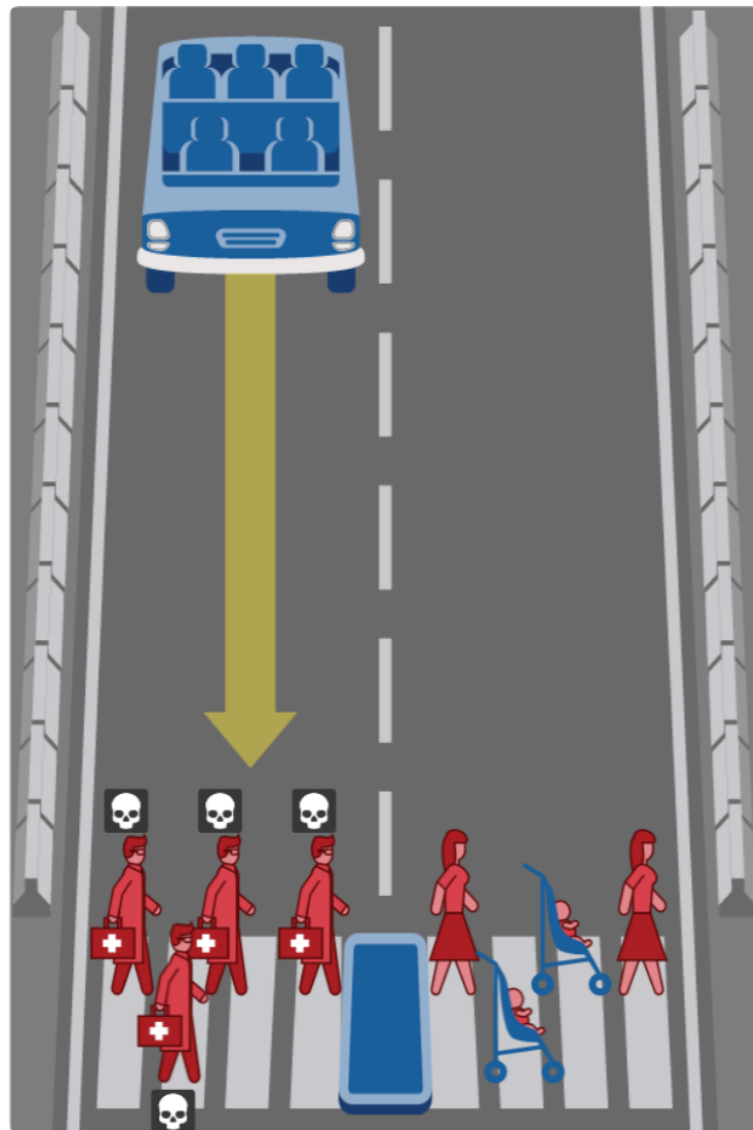
## Doctors vs Mothers and their children

Share

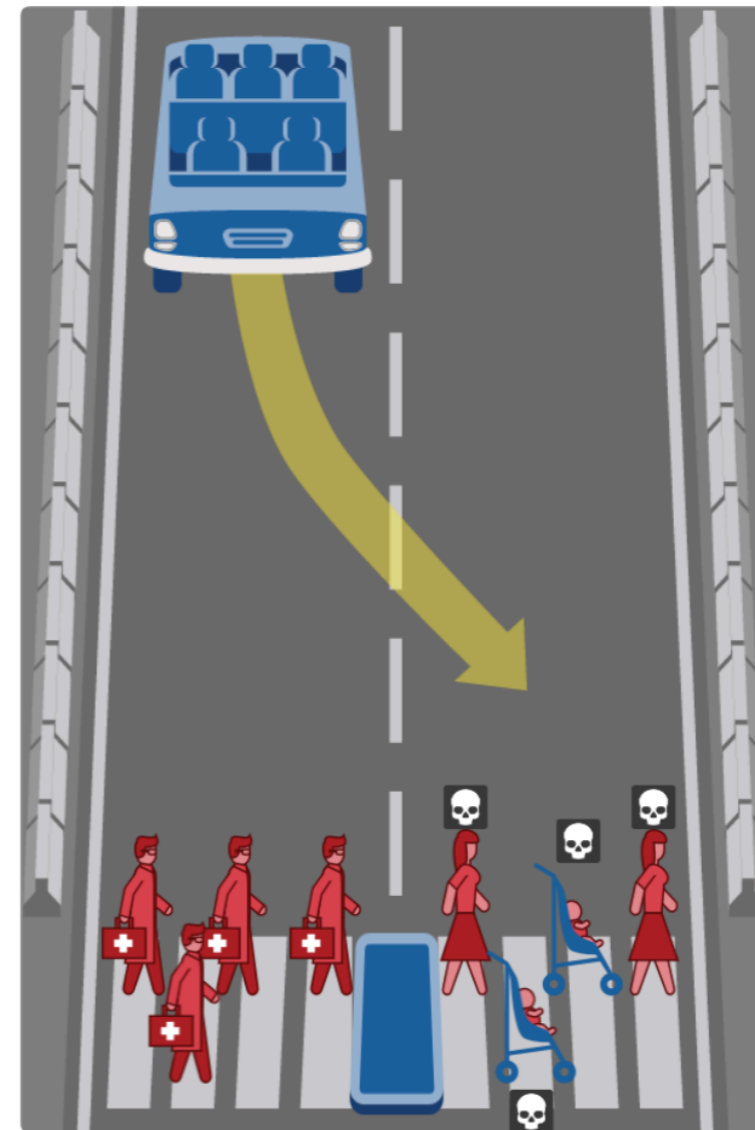
Link

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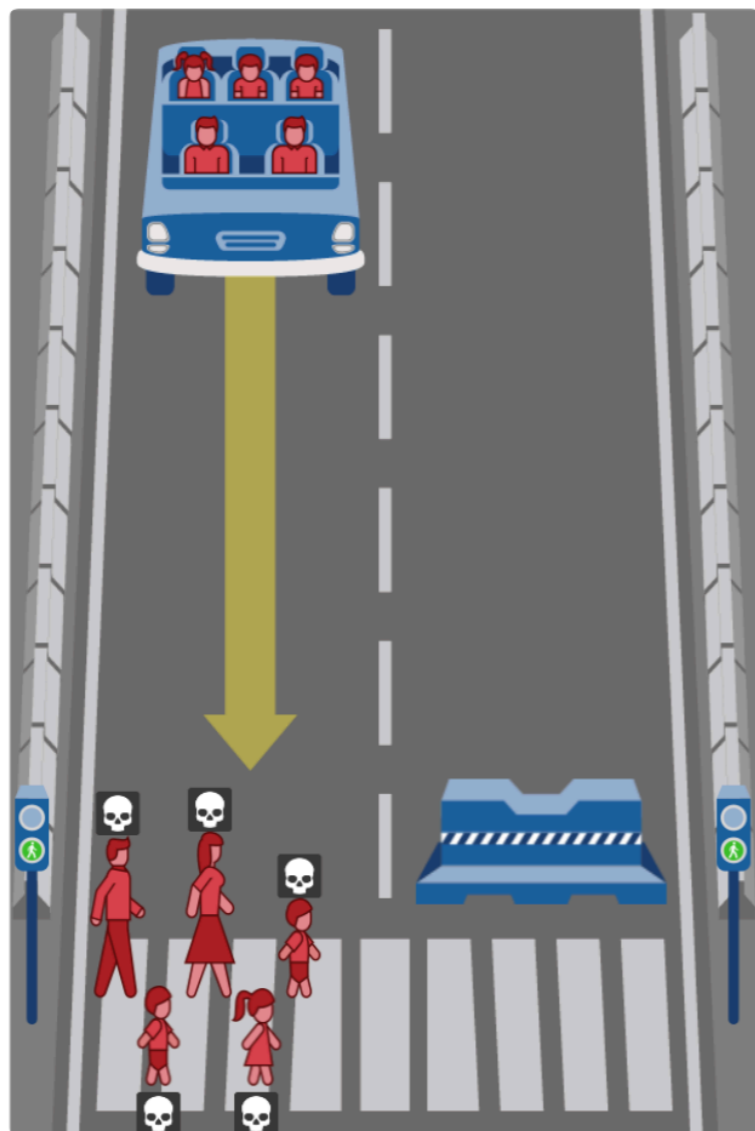


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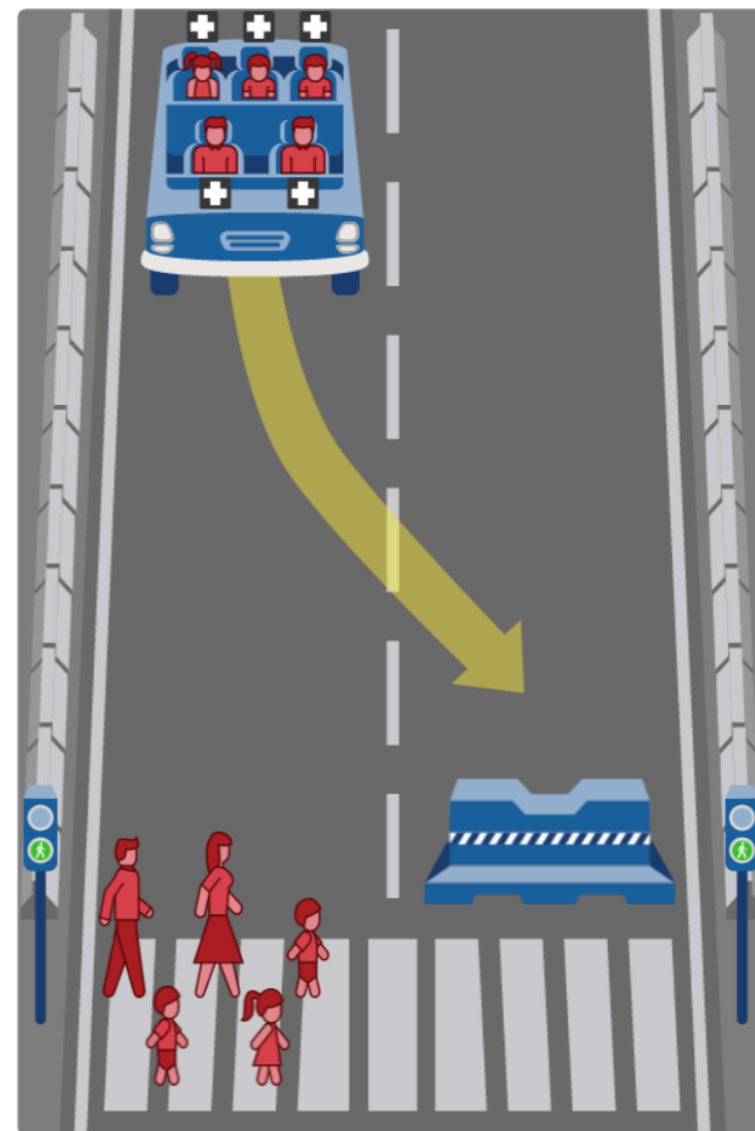


## Kill the LGBT family or Straight family

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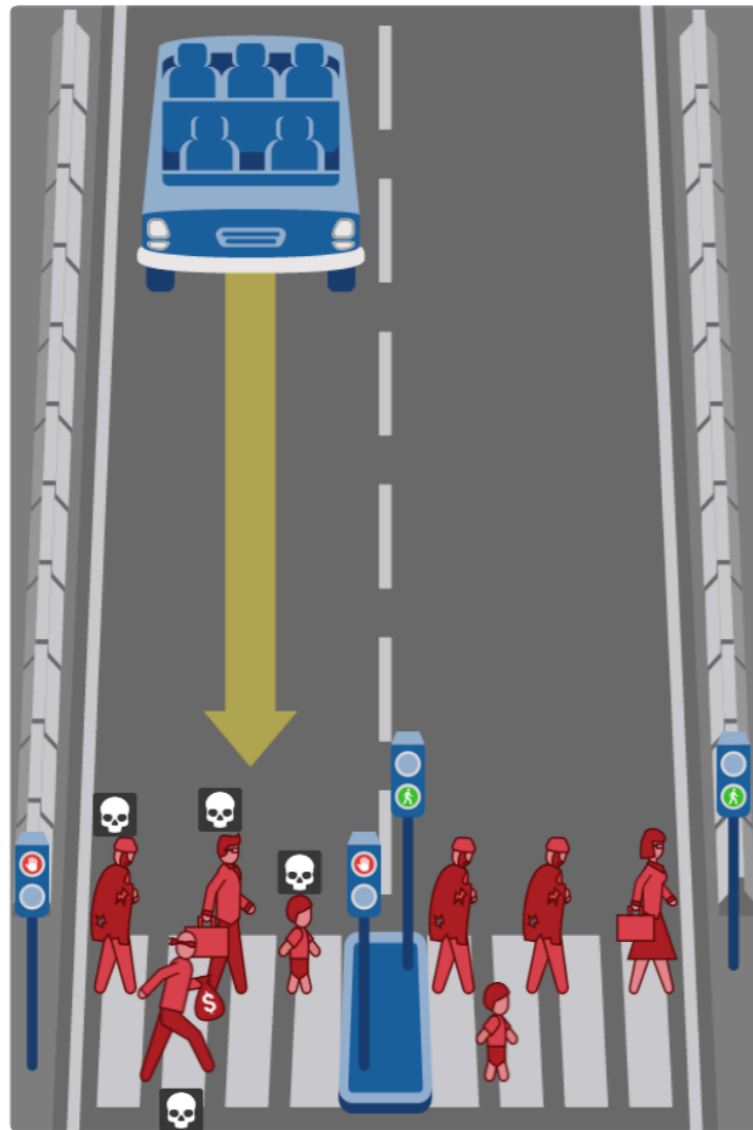


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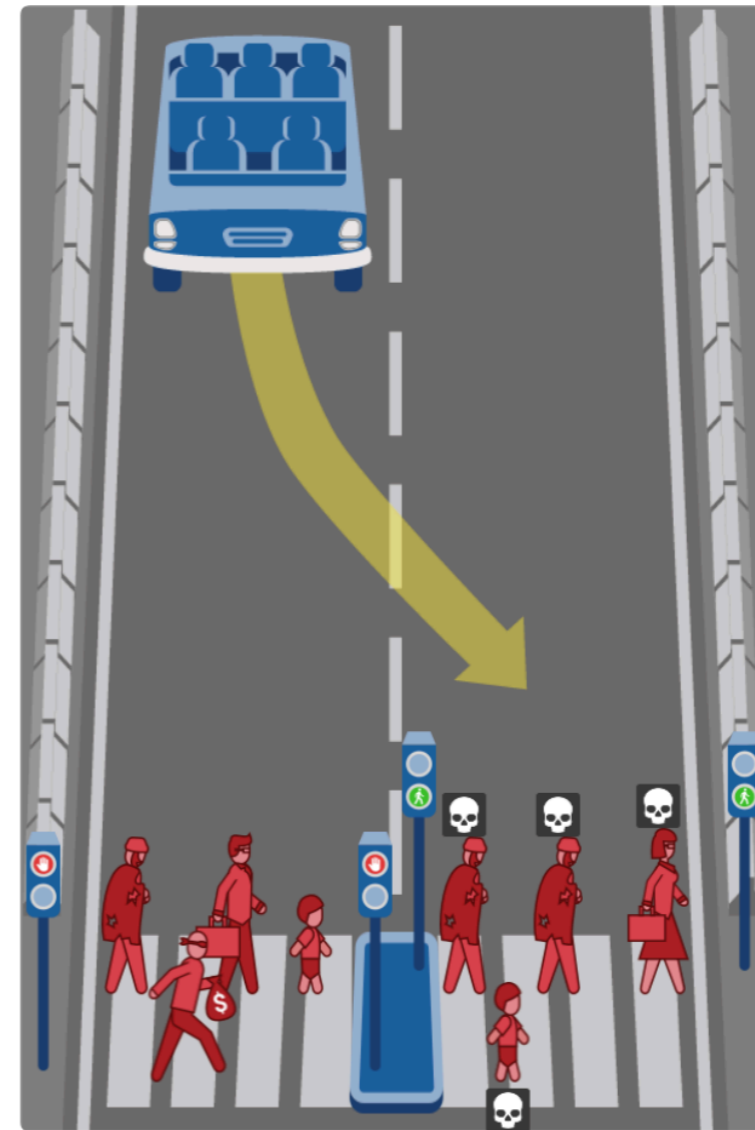


## No important people vs no important people

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## Baby Dilemma

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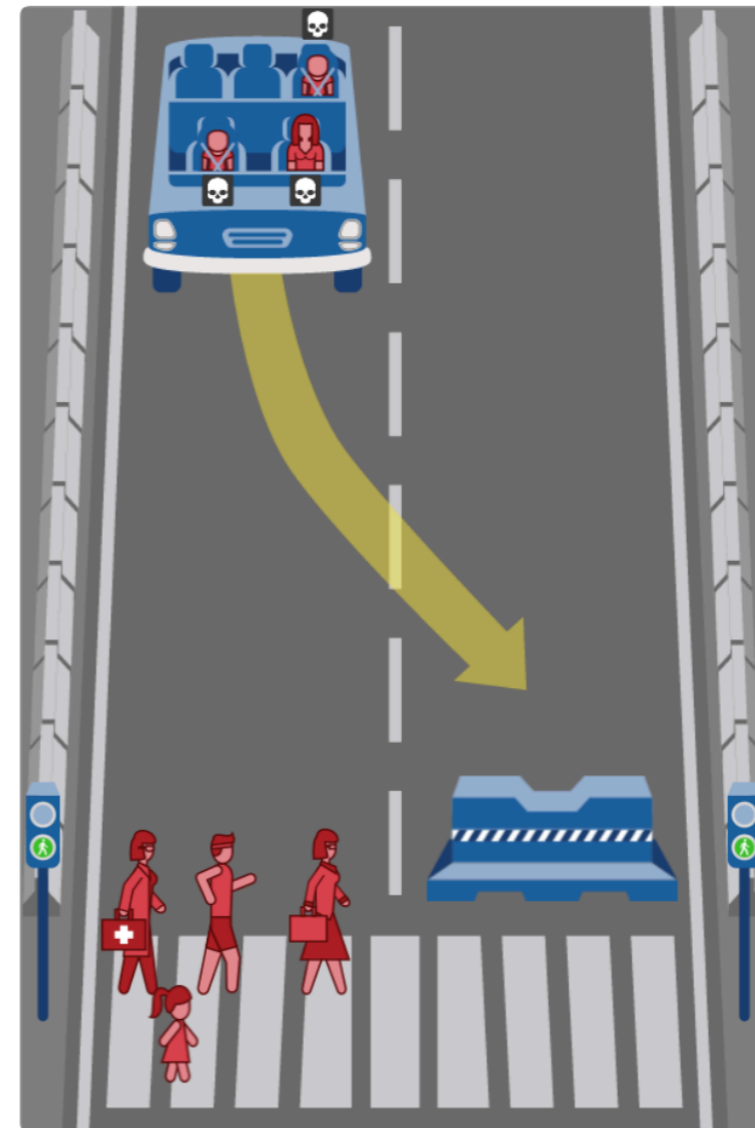
In this case, the self-driving car with sudden brake failure will continue ahead and drive through a pedestrian crossing ahead. This will result in ...

Dead:

- 1 female doctor
- 1 male athlete
- 1 female executive
- 1 girl

Note that the affected pedestrians are abiding by the law by crossing on the green signal.

Hide Description



Show Description



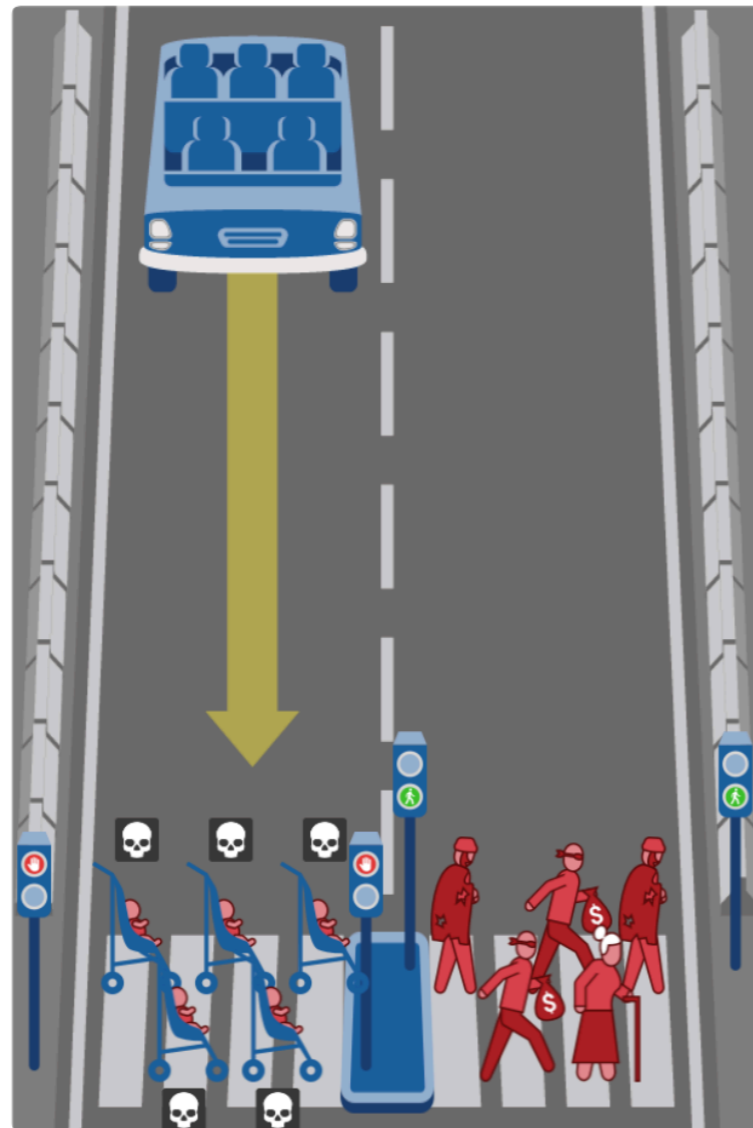
## Babies or People?

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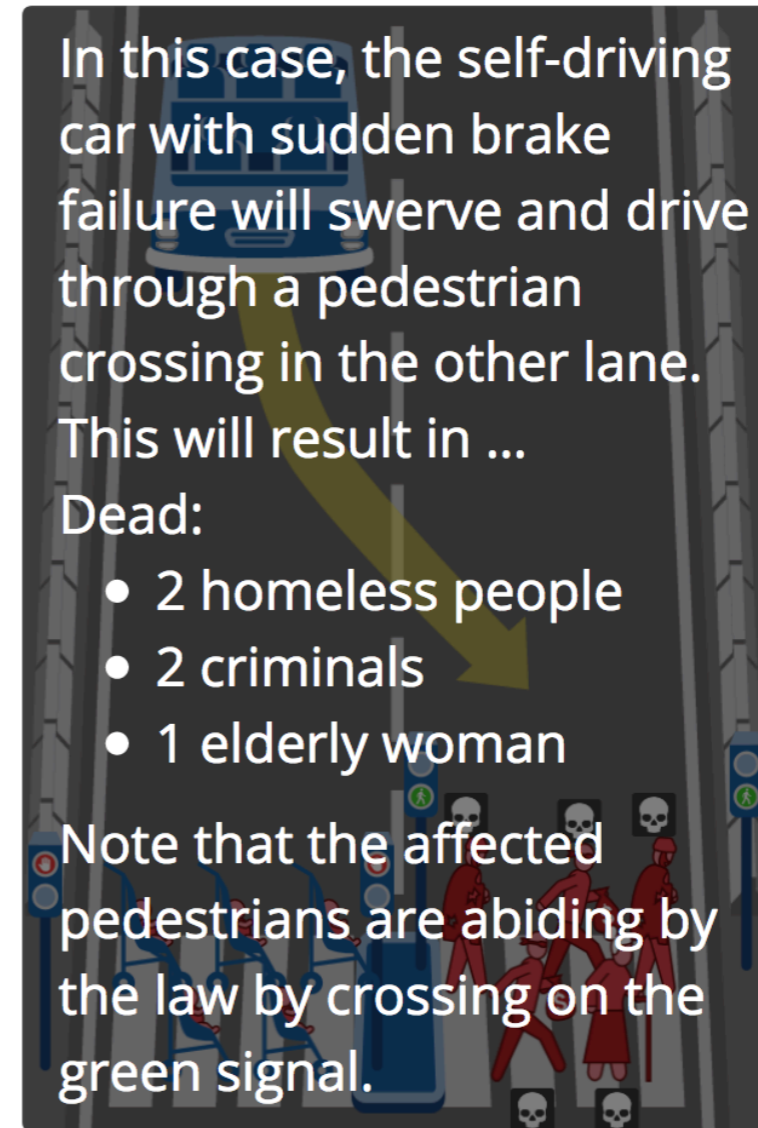
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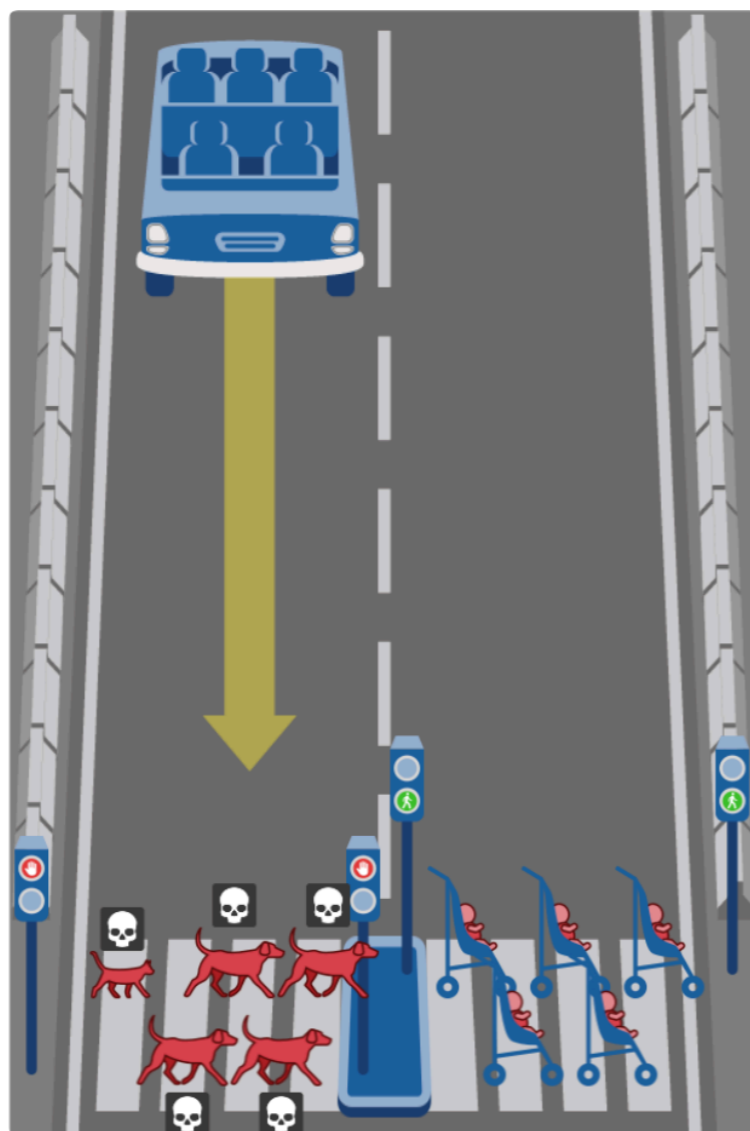


Hide Description

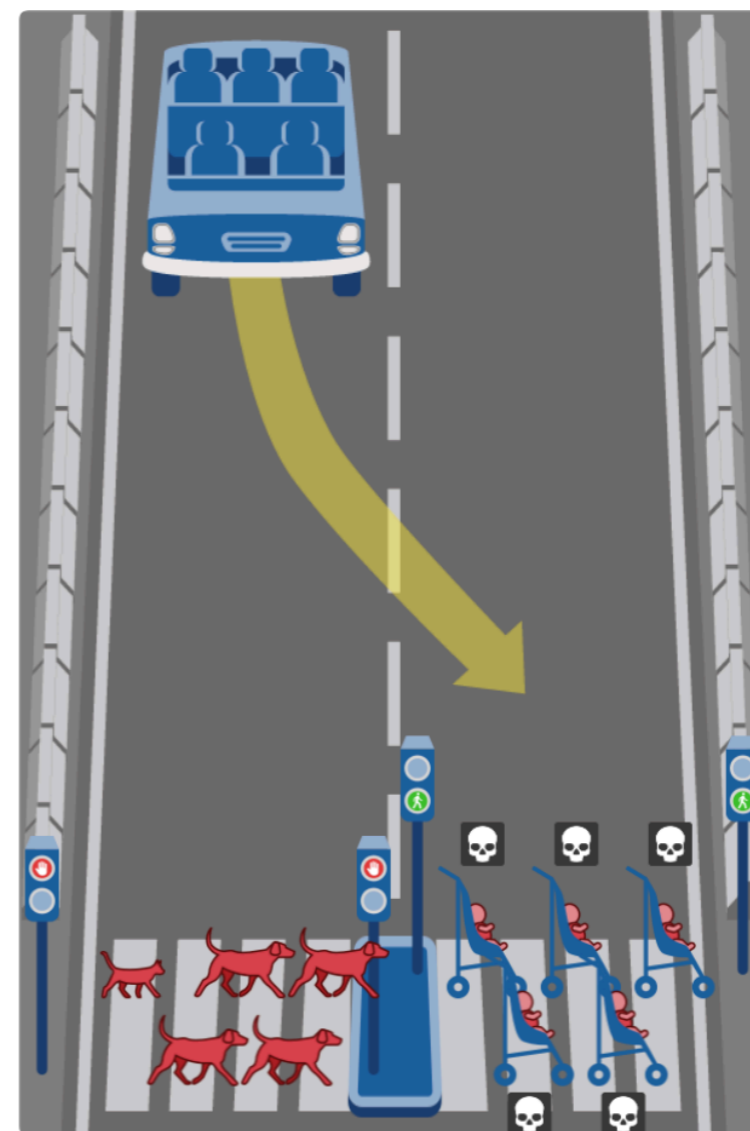


## Shrek

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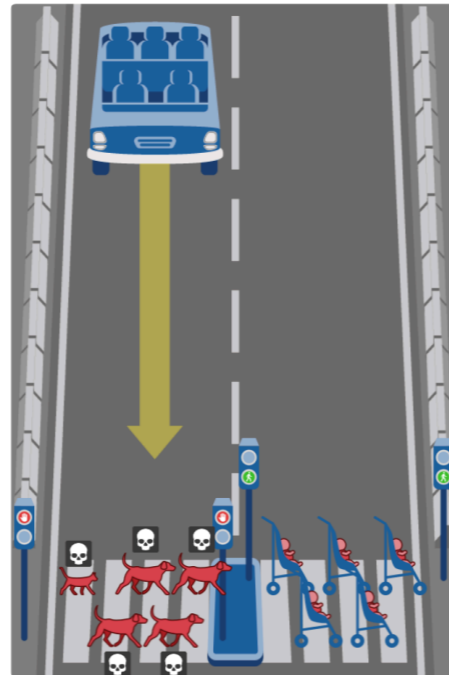


Show Description

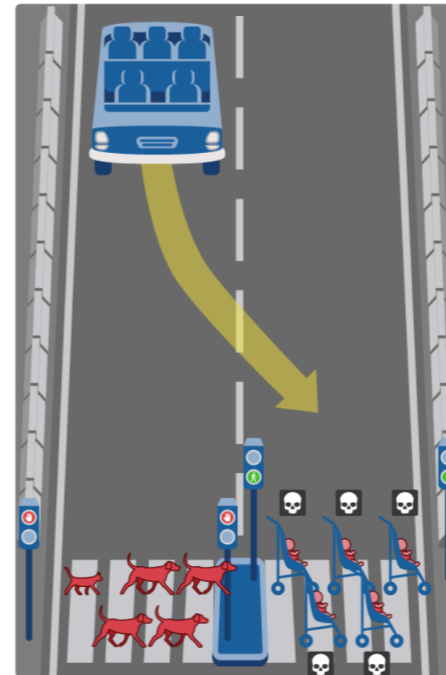


## Shrek

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## The social dilemma of autonomous vehicles

Jean-François Bonnefon<sup>1</sup>, Azim Shariff<sup>2,\*</sup>, Iyad Rahwan<sup>3,†</sup>

+ See all authors and affiliations

Science 24 Jun 2016:  
Vol. 352, Issue 6293, pp. 1573-1576  
DOI: 10.1126/science.aaf2654

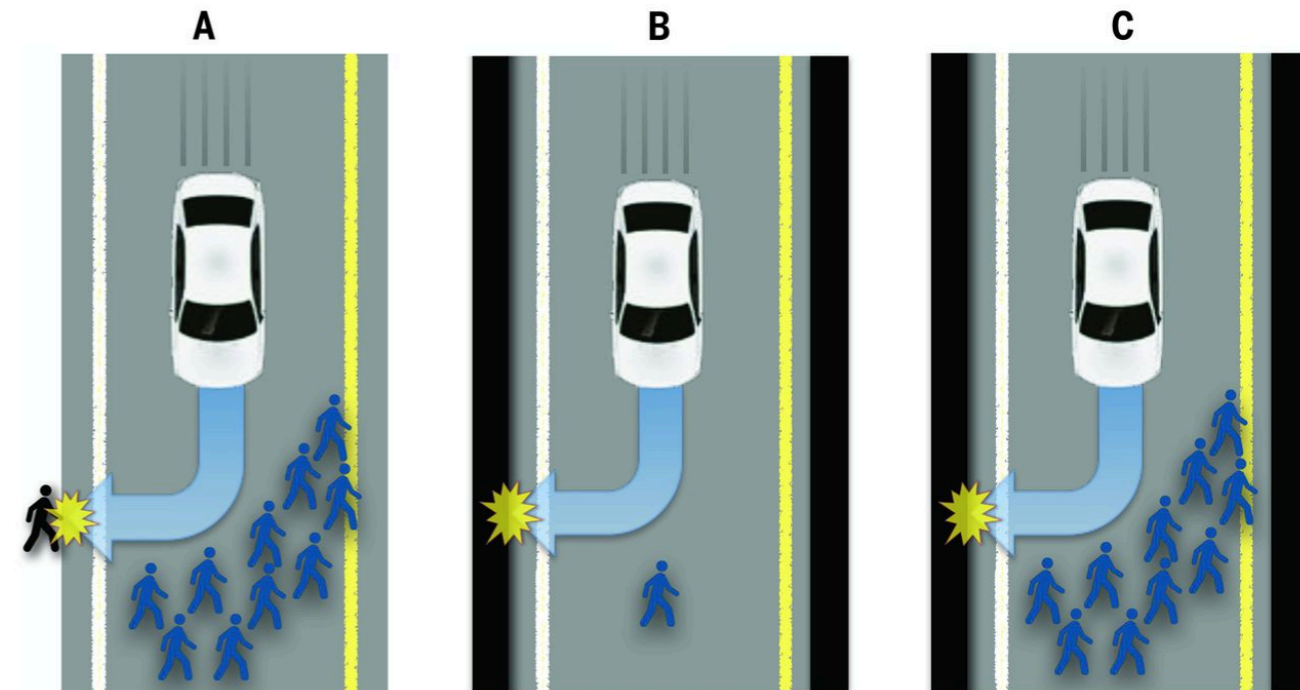
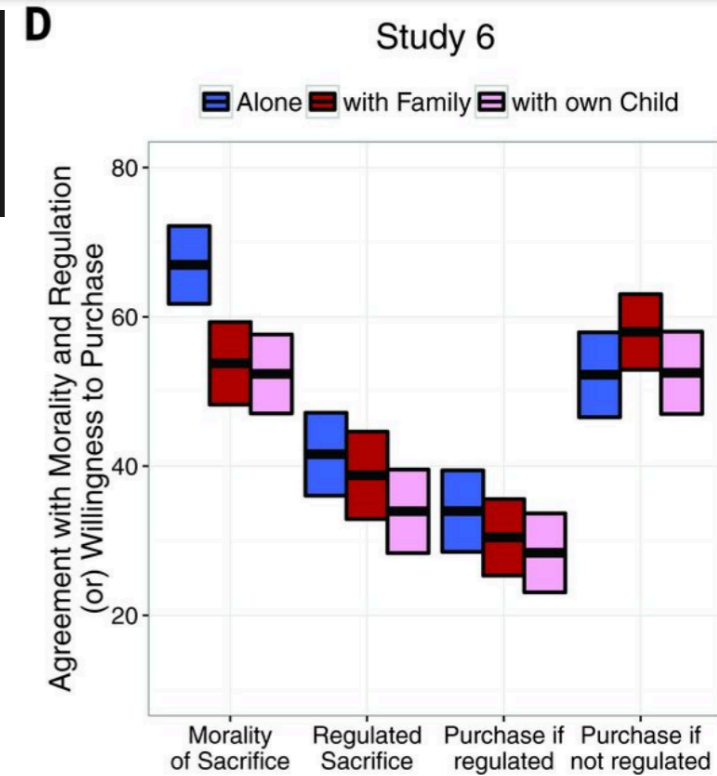
### The social dilemma of autonomous vehicles

Jean-François Bonnefon<sup>1</sup>, Azim Shariff<sup>2,\*</sup>, Iyad Rahwan<sup>3,†</sup>

+ See all authors and affiliations

Science 24 Jun 2016:  
Vol. 352, Issue 6293, pp. 1573-1576  
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- Our findings suggest that regulation for AVs may be necessary but also counterproductive.
- Although people tend to agree that everyone would be better off if AVs were utilitarian, these same people have a personal incentive to ride in AVs that will protect them at all costs.
- Figuring out how to build ethical autonomous machines is one of the thorniest challenges in artificial intelligence today.
- Our data-driven approach highlights how the field of experimental ethics can provide key insights into the moral, cultural, and legal standards that people expect from autonomous driving algorithms.
- Public opinion and social pressure may very well shift as this conversation progresses.





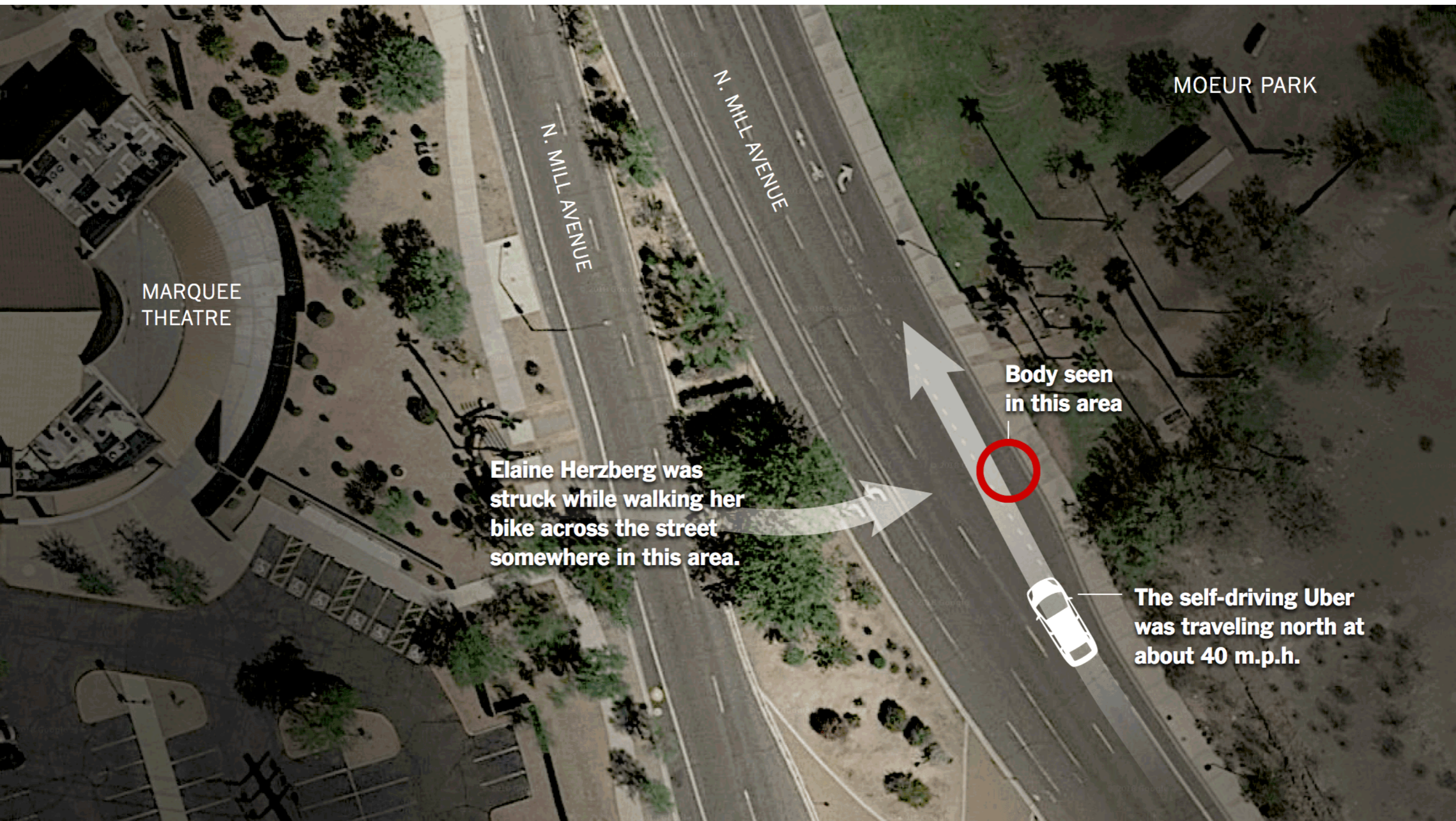


Arizona - Tempe - Dimanche 18 mars vers 22h

Elaine Herzberg, âgée de 49 ans- traversait la route de nuit - pas éclairé - en dehors des clous - avec un vélo, et beaucoup de sacs

VTC Uber - Volvo XC90 autonome - 61km/h (limité à 56.5km/h)

Troy Griggs and Daisuke Wakabayashi, *How a Self-Driving Uber Killed a Pedestrian in Arizona*, New York Times, 20 mars 2018



Troy Griggs and Daisuke Wakabayashi, *How a Self-Driving Uber Killed a Pedestrian in Arizona*, New York Times, 20 mars 2018

## How a Self-Driving Car Works

### LIDAR UNIT

Constantly spinning, it uses laser beams to generate a 360-degree image of the car's surroundings.

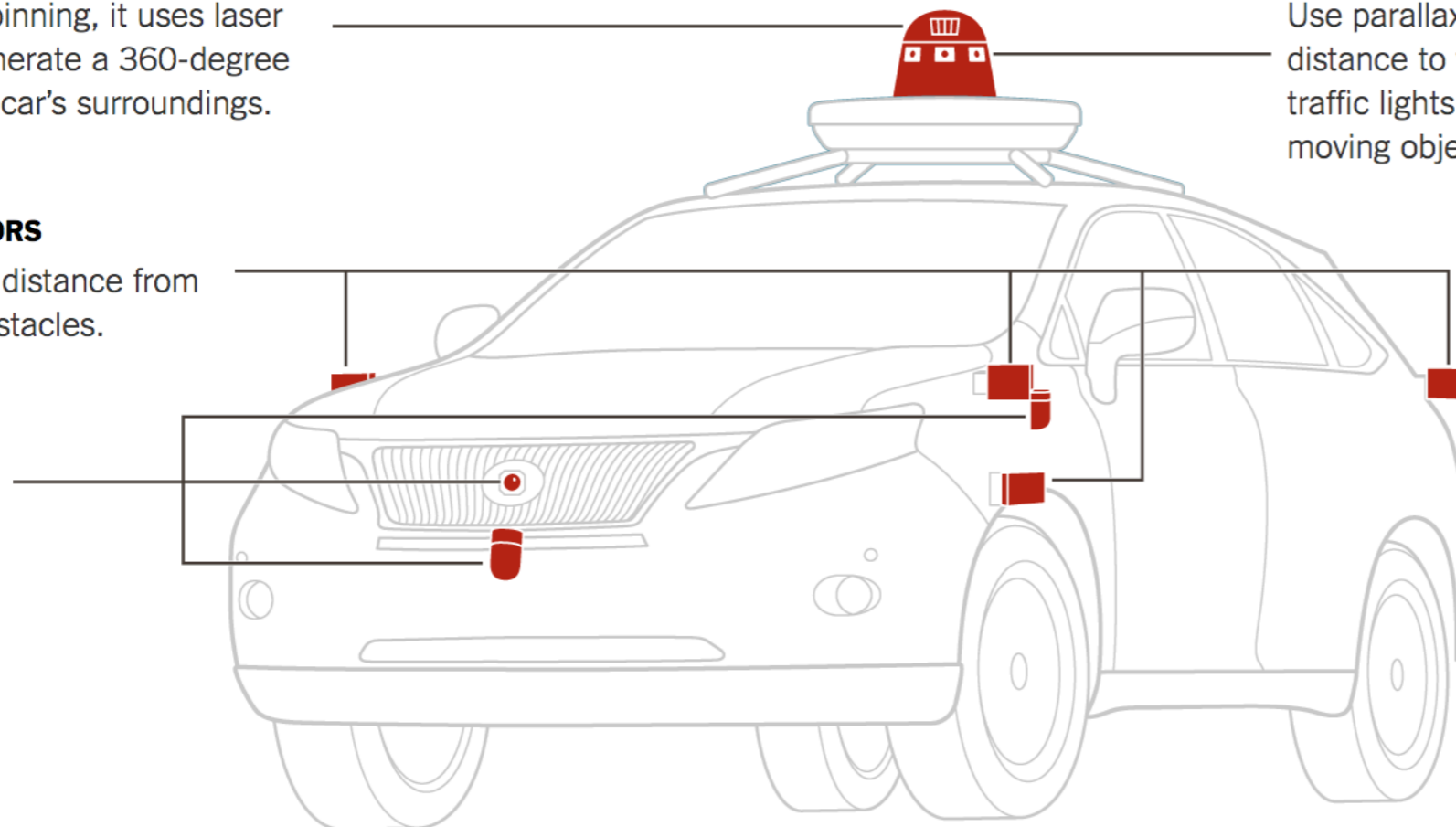
### RADAR SENSORS

Measure the distance from the car to obstacles.

### ADDITIONAL LIDAR UNITS

### CAMERAS

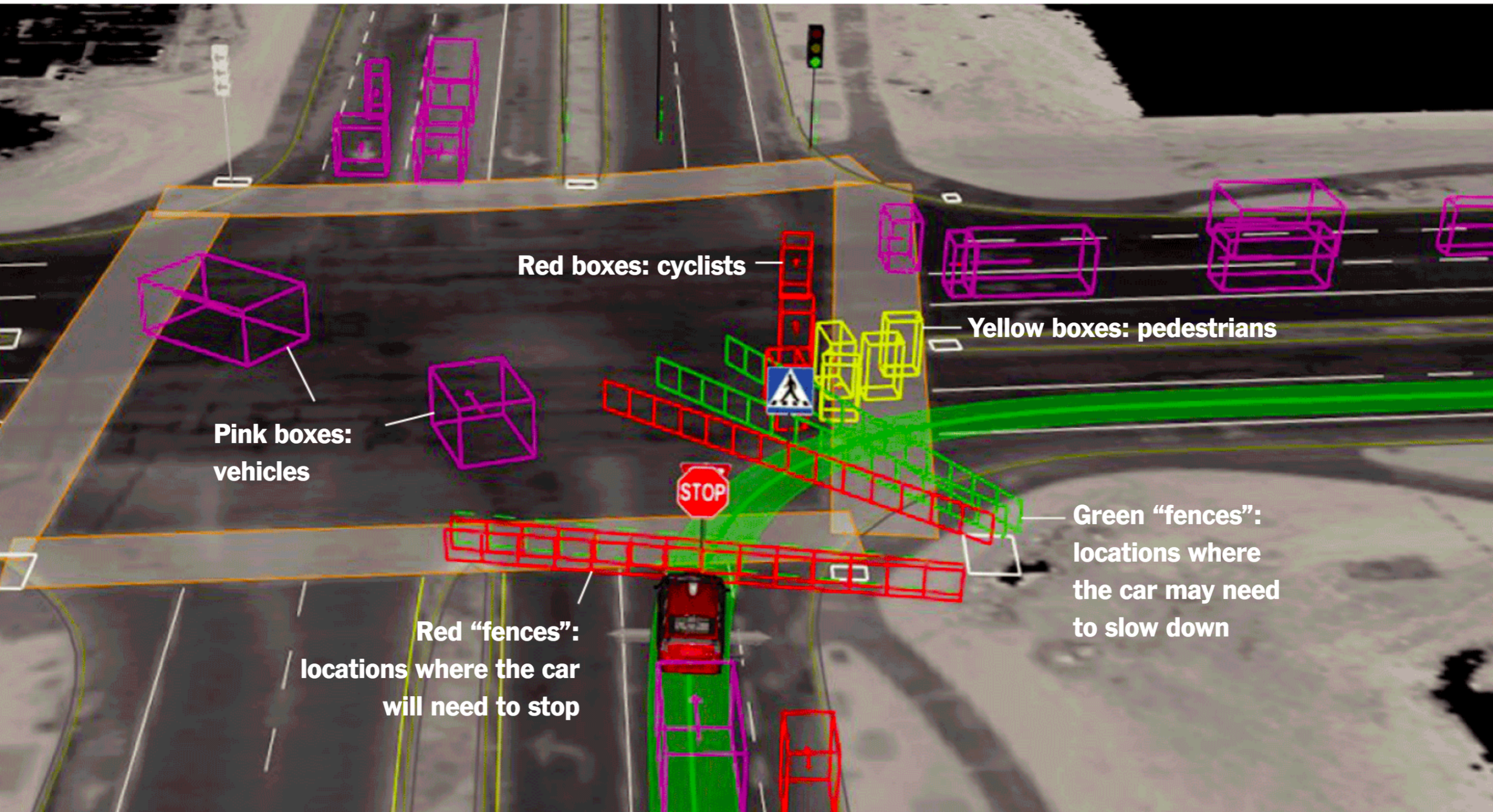
Use parallax from multiple images to find the distance to various objects. Cameras also detect traffic lights and signs, and help recognize moving objects like pedestrians and bicyclists.



### MAIN COMPUTER (LOCATED IN TRUNK)

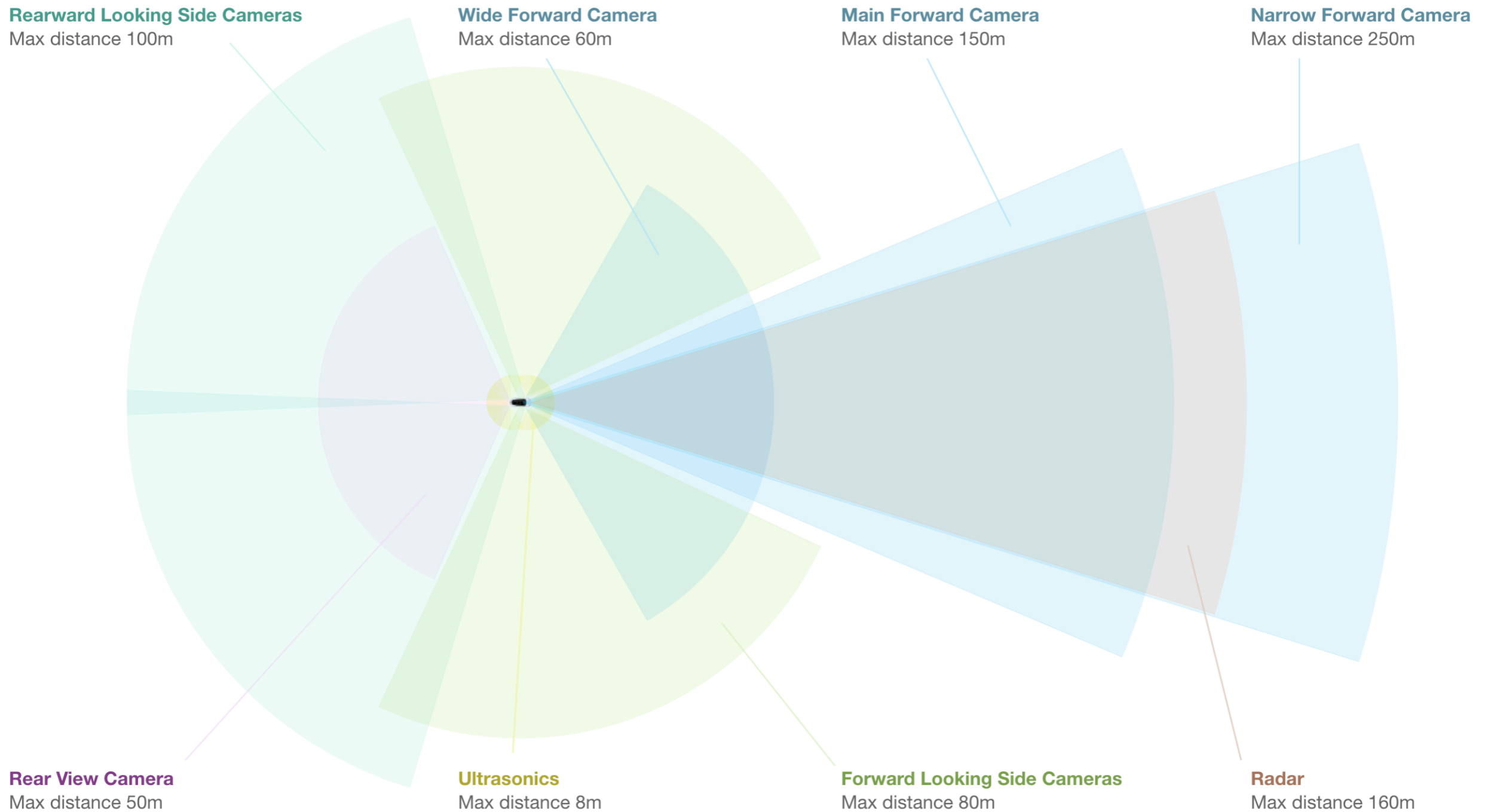
Analyzes data from the sensors, and compares its stored maps to assess current conditions.

By Guilbert Gates | Source: Google | Note: Car is a Lexus model modified by Google. Uber's sensing system uses similar technology.



Troy Griggs and Daisuke Wakabayashi, *How a Self-Driving Uber Killed a Pedestrian in Arizona*, New York Times, 20 mars 2018

# Coexister avec nos artifices



"All Tesla vehicles produced in our factory, including Model 3, have the hardware needed for full self-driving capability at a safety level substantially greater than that of a human driver".

THE PERSON IN THE DRIVER'S SEAT  
IS ONLY THERE FOR LEGAL REASONS.

HE IS NOT DOING ANYTHING.  
THE CAR IS DRIVING ITSELF.





**Tempe Police**  
@TempePolice



Tempe Police Vehicular Crimes Unit is actively investigating the details of this incident that occurred on March 18th. We will provide updated information regarding the investigation once it is available.

11:23 PM - Mar 21, 2018

753 1,109 people are talking about this

Tempe Police - Caméra intérieur et frontale - 21 mars 2018 à 11h23 - Twitter



Sony CMOS Image Sensor  
for Automotive Applications  
**IMX390**  
Simultaneous LED Flicker Mitigation & HDR



Arizona - Tempe - Dimanche 18 mars vers 22h

Elaine Herzberg, âgée de 49 ans- traversait la route de nuit - pas éclairé - en dehors des clous - avec un vélo, et beaucoup de sacs

VTC Uber - Volvo XC90 autonome - 61km/h (limité à 56.5km/h)

**Rafaela Vasquez, passager, regarde vers le bas, probablement un écran, pendant près de 5 secondes avant l'accident**

**Le changement soudain de luminosité questionne le fonctionnement du Lidar et des caméras**

Troy Griggs and Daisuke Wakabayashi, *How a Self-Driving Uber Killed a Pedestrian in Arizona*, New York Times, 20 mars 2018

# Coexister avec nos artifices

Unil



Waymo Team, *Same driver, different vehicle: Bringing Waymo self-driving technology to trucks*, 9 mars 2018, Medium

Promesses des machines, machines à promesses : l'intelligence artificielle et l'avenir du travail - Boris Beude - STSLab - Université de Lausanne - 22 mars 2018

# Coexister avec nos artifices

Unil



Waymo Team, *Same driver, different vehicle: Bringing Waymo self-driving technology to trucks*, 9 mars 2018, Medium



~8 millions de kilomètres

~ 8 milliards de kilomètres simulés

0 morts, ni passagers, ni autres passagers, ni piétons

Waymo Team, *Same driver, different vehicle: Bringing Waymo self-driving technology to trucks*, 9 mars 2018, Medium

## Intelligences artificielles distribuées

Problématique systémique

Apprentissages locaux

Compétences globales

Risques globaux



## Qu'est qu'une voiture autonome ?

Problématique du dispositif

Un voiture (mécanique)

Des capteurs (sens)

Des logiciels (apprentissage, pilotage...) locaux et distribués

Une infrastructure informatique locale et distribuée

De l'apprentissage

Des entreprises et des employés

Des investissements et des investisseurs

Des testeurs et des utilisateurs

Des représentations

Des réglementations

...



## Quels Biais ?

Problématique de l'expérience

Les biais de l'expertise

Les biais de l'apprentissage

Les biais de conservatisme



Exterior view - Uber Car - Tempe - 18 mars 2018



Joy Buolamwini, MIT Media Lab's Civic Media group 2017



## Quelles peurs ?

Problématique de l'inconnu

Que des personnes soient tuées ?

D'être tué ?

D'être remplaçable ?

Qu'il y ait des biais ?

Que cela soit discriminant ?

De ne plus avoir de travail ?

De ne plus avoir de revenus ?

Que cela ne profite qu'à certains ?

Que les inégalités s'accroissent ?

...



## Coexister avec nos artifices

Problématique de la coexistence

Qui les conçoit ?

Qui les implémente ?

Qui supervise l'apprentissage ?

Qui les vend ?

Qui les utilisent ?

Qui en tire un profit ?

Qui les régule ?

Qui travail, qui a un emploi, qu'est-ce qu'un individu ?

Quelle/s société/s ?

...



## Coexister avec nos artifices

Problématique du connu

La peur de nos artifices,

c'est finalement la peur de nous même

Mais quel nous ?





Illustration : Zak Bickel / The Atlantic / 2015

Boris Beaude

STSLab - Université de Lausanne

Courriel : [boris.beaude@unil.ch](mailto:boris.beaude@unil.ch)

Site : <http://www.beaude.net/boris/>

Site du cours : <http://www.beaude.net/ien/>

Blog : <http://www.beaude.net/no-flux/>

Twitter : [@nofluxin](https://twitter.com/nofluxin)

Facebook : [nofluxin](https://www.facebook.com/nofluxin)

*Les fins d'Internet*, Fyp, 2014

<http://www.beaude.net/ie/>

*Internet, changer l'espace, changer la société*, Fyp, 2012

<http://www.beaude.net/icecs/>



**David Auerbach**

23 février, 17:17 · 🌐

I wrote this article on Google Jigsaw's Conversation AI a few months back. Today, Google released an API for comment filtering, "Perspective," based on the same technology.

A few tests seem to bear out my criticisms:

- "trump sucks" = 96% toxic
- "I fucking love you man. Happy birthday." = 93% toxic
- "Donald Trump is a meretricious buffoon." = 85% toxic.
- "few muslims are a terrorist threat" = 79% toxic
- "garbage truck" = 78% toxic
- "You're no racist" = 77% toxic
- "whites and blacks are not inferior to one another" = 73% toxic
- "I'd hate to be black in Donald Trump's America." = 73% toxic
- "Jews are human" = 72% toxic
- "I think you're being racist" = 70% toxic
- "Hitler was an anti-semite" = 70% toxic
- "this comment is highly toxic" = 68% toxic
- "You are not being racist" = 65% toxic
- "Jews are not human" = 61% toxic
- "I'd hate to be you." = 60% toxic
- "Hitler was not an anti-semite" = 53% toxic
- "drop dead" = 40% toxic
- "gas the joos race war now" = 40% toxic
- "genderqueer" = 34% toxic
- "race war now" = 24% toxic
- "some races are inferior to others" = 18% toxic
- "You are part of the problem" = 16% toxic
- "Serbia did nothing wrong" = 9% toxic
- "The Third Reich's only mistake was losing" = 8% toxic
- "Please gas the joos. Thank you." = 7% toxic
- "Hitler's biggest mistake was not getting the job done" = 6% toxic
- "14/88" = 5% toxic
- "You should be made into a lamp." = 4% toxic
- "she was asking for it" = 3% toxic
- "The Protocols of the Elders of Zion is totally accurate." = 2% toxic

Original Phrase (Toxicity Score)	Modified Phrase (Toxicity Score)
Climate change is happening and it's not changing in our favor. If you think differently you're an <b>idiot</b> . (84%)	Climate change is happening and it's not changing in our favor. If you think differently you're an <b>idi</b> ot. (20%)
They're <b>stupid</b> , it's getting warmer, we should enjoy it while it lasts (86%)	They're <b>st.upid</b> , it's getting warmer, we should enjoy it while it lasts (2%)
They are liberal <b>idiots</b> who are <b>uneducated</b> (90%)	They are liberal <b>i.diots</b> who are <b>un.educated</b> (15%)
<b>idiots</b> . backward thinking people. <b>nationalists</b> . not accepting facts. susceptible to <b>lies</b> . (80%)	<b>idi</b> ots. backward thinking people. <b>nati</b> onalists. not accepting facts. susceptible to <b>l.ies</b> . (17%)
They are <b>stupid</b> and <b>ignorant</b> with no class (91%)	They are <b>st.upid</b> and <b>ig.norant</b> with no class (11%)
It's <b>stupid</b> and wrong (89%)	It's <b>stui</b> pd and wrong (17%)
If they voted for Hilary they are <b>idiots</b> (90%)	If they voted for Hilary they are <b>id.iots</b> (12%)
Anyone who voted for Trump is a <b>moron</b> (80%)	Anyone who voted for Trump is a <b>mo.ron</b> (13%)
<b>Screw</b> you trump supporters (79%)	<b>S c r e w</b> you trump supporters (17%)

*Deceiving Google's Perspective API Built for Detecting Toxic Comments, Hossein Hosseini et al. - arXiv:1702.08138 - 27 Février 2017*

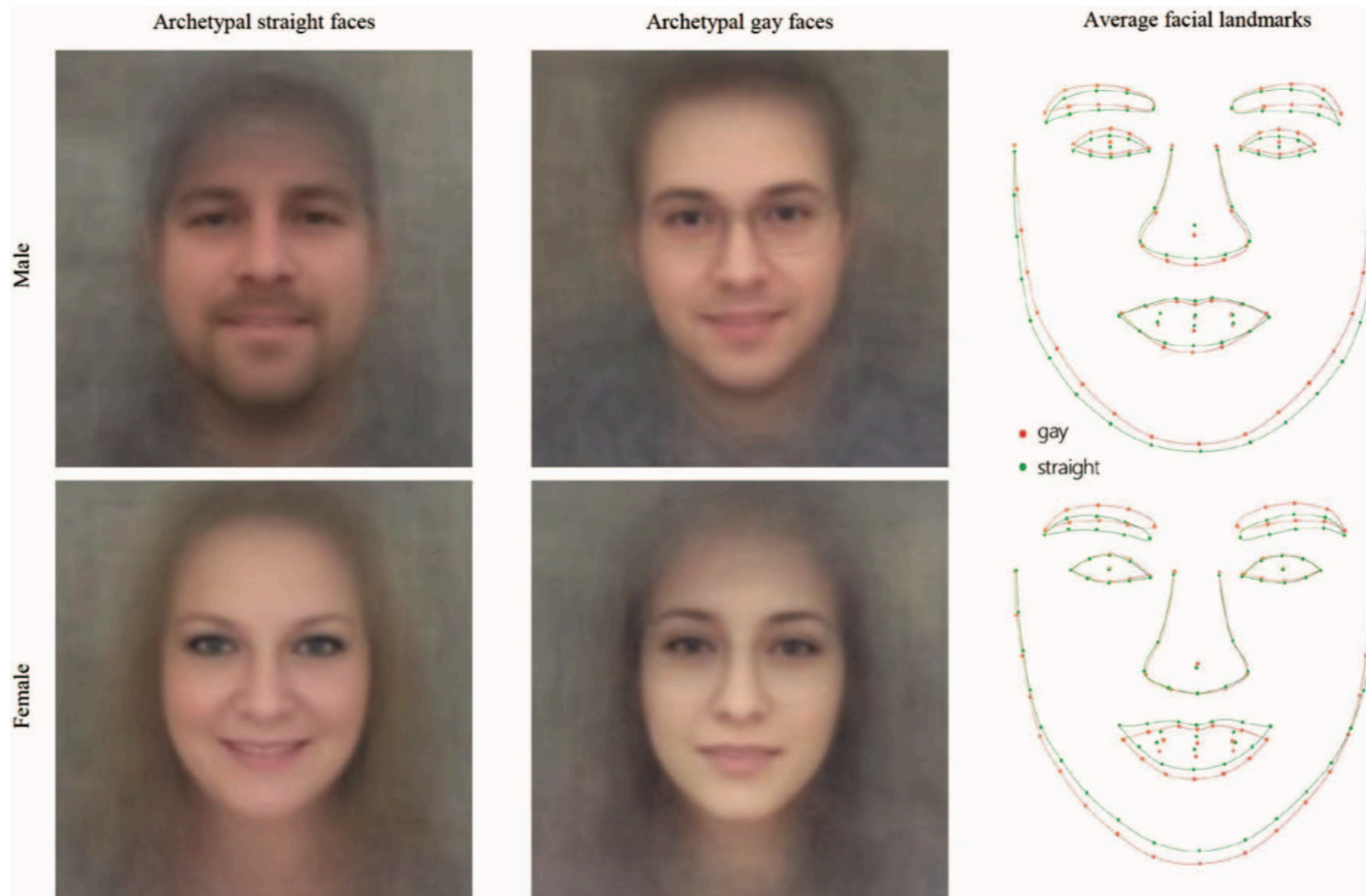


Figure 4. Composite faces and the average facial landmarks built by averaging faces classified as most and least likely to be gay.



Navigation: < > | English | Sign out

## Artificial Intelligence and Robotics

4th Industrial Revolution  
Co-curated with: Korea Advanced Institute of Science and Technology (KAIST)

Summary | Feed | Experts | Sessions | Projects

### Robots at Work

Robot surrogates are increasingly being used for dangerous work and extreme environments

Robots have long been used on factory floors for welding and painting. Now, they're also making custom-ordered hamburgers, navigating through crowded hotel lobbies, hopping on elevators and delivering room service. Amazon has been at the forefront of introducing robots to our daily lives, with its clerk-free markets that enable shoppers to simply select goods that are automatically paid for via credit card, Kiva automatic merchandise handling systems that eliminate the need for some human workers and drone delivery.

[... read more](#)

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Clinician-led.  
Patient-centred.