Final Project Presentations

MIT 6.S191
February 1, 2019

6.S191 Project Group 1

Varnika Sinha
Julia Wang
Emily Zhang

Problem

Current security systems are not robust enough to adequately protect user data.

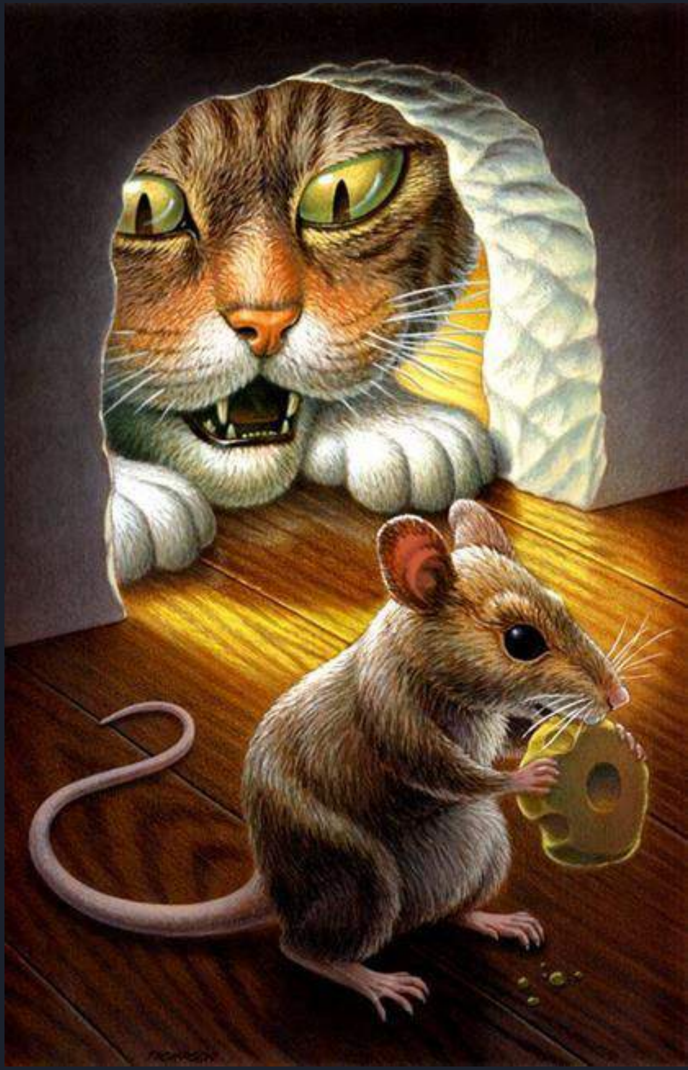
Cybersecurity Challenges:

- Unprecedented attacks
- Cyber espionage
- Data theft

Solution & Algorithms

cat:mouse::attacker:defense

- Reinforcement Learning
- Reward system
- Policy gradient



Applications & Impact

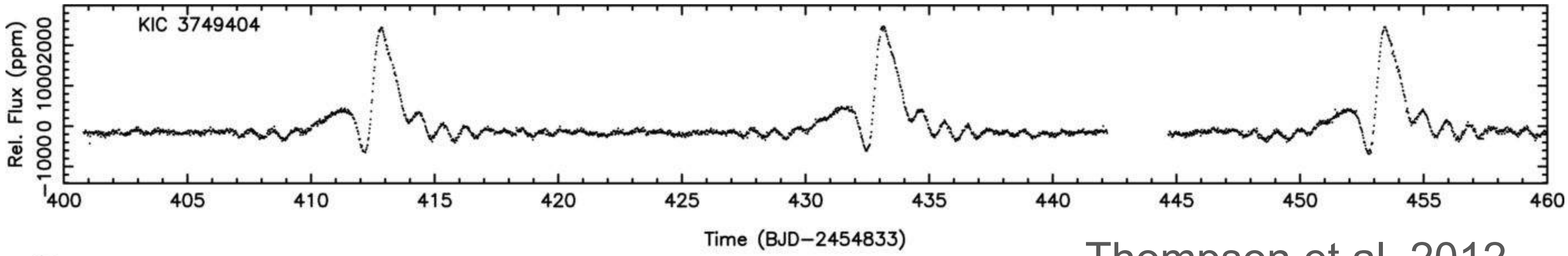
- Password protection
- Cloud security
- Protection against malware & viruses
- Voting systems security
- Internet of things security

Identification of Heartbeat Systems in Photometric Surveys

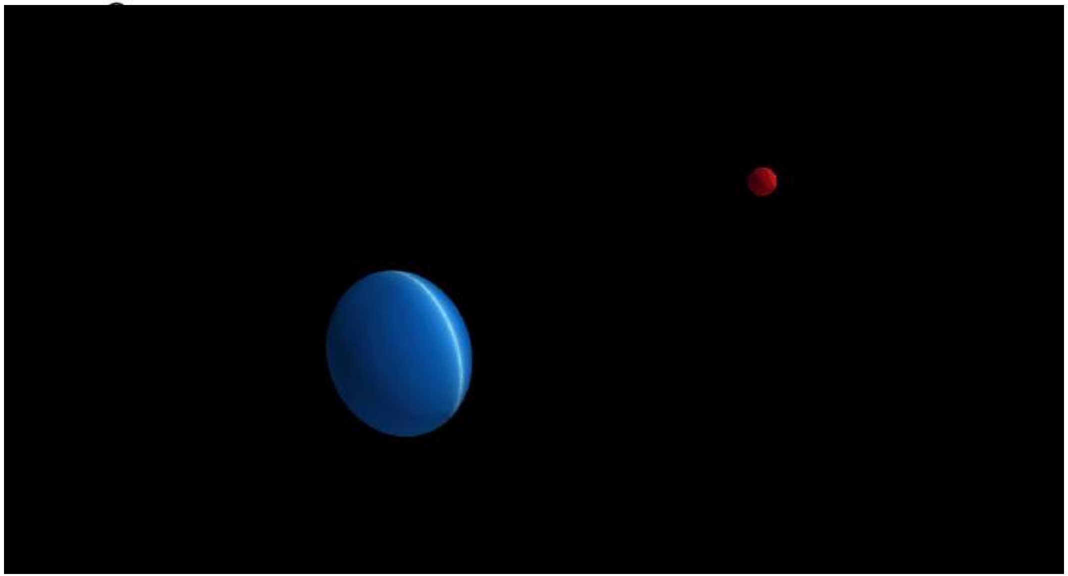
Baichuan Mo, Erik Tamre,
Prajwal Niraula, Yunpo Li

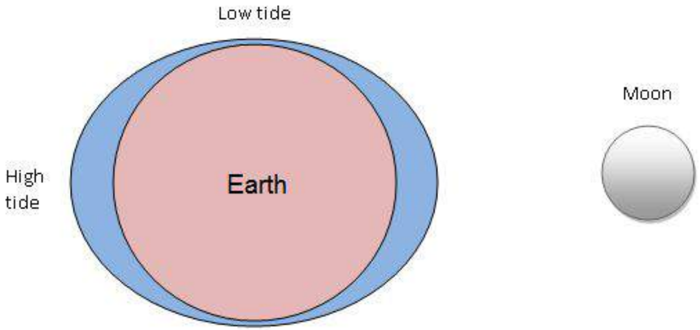
6.S191
Feb 1, 2019

Heartbeat Systems

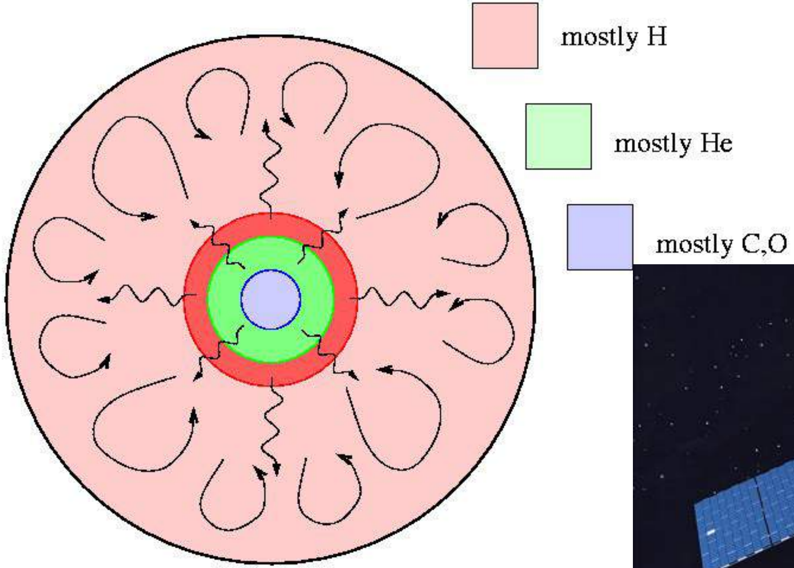


Thompson et al. 2012



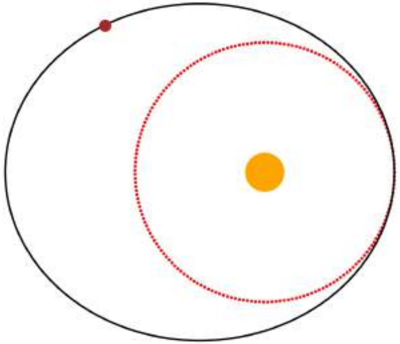


Scientific Motivations



Probing the Internal Stellar Structure

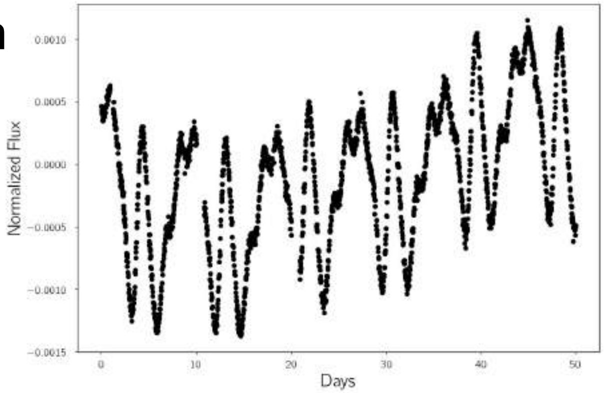
As method of finding exoplanet

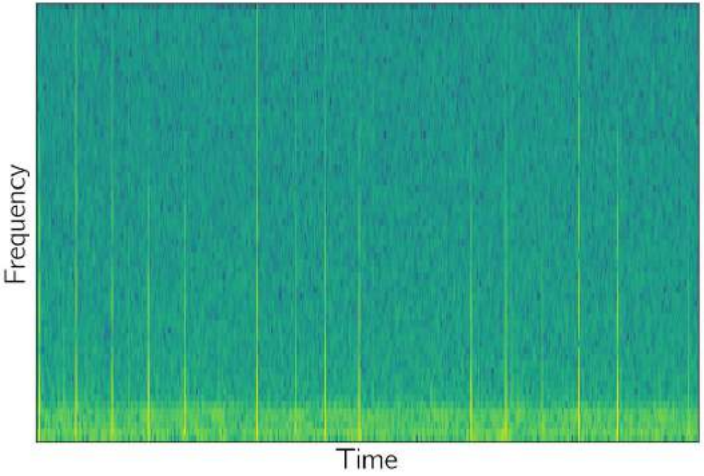


Tidal Circularization

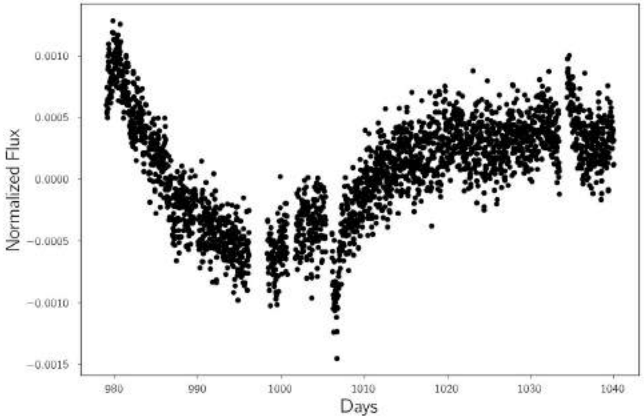
Distinguishing the HeartBeat Systems

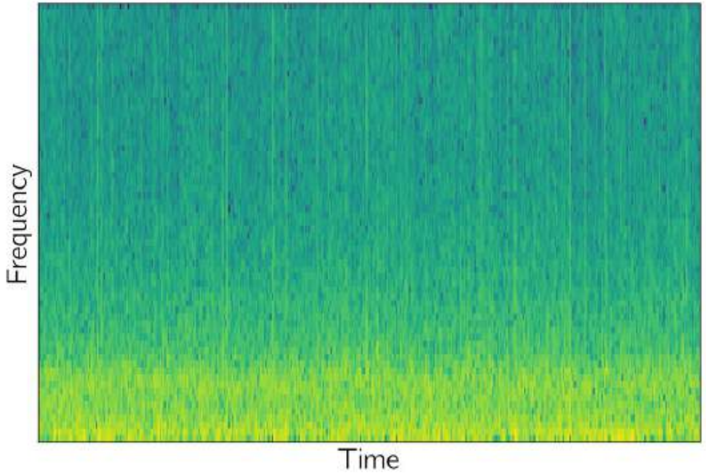
HB System





Non - HB



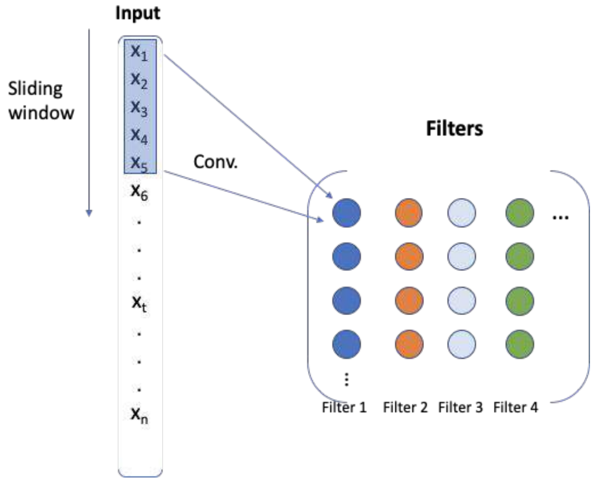


Proposed method

Deep Learning! But why?

Method one: 1-D Convolutional Neural Network

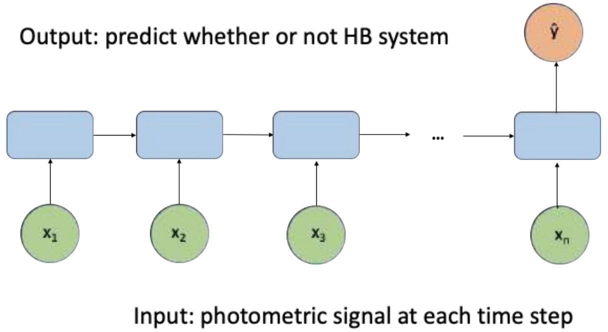
Motivation: Extract local features in the time domain (e.g., peaks, valleys, etc.)



Method Two: Recurrent Neural Network (LSTM)

Motivation:

1. Time series input data
2. Different duration of each photometric survey : Handle variable length input



We will try to run the models on both time domain and frequency domain

Challenges and path forward

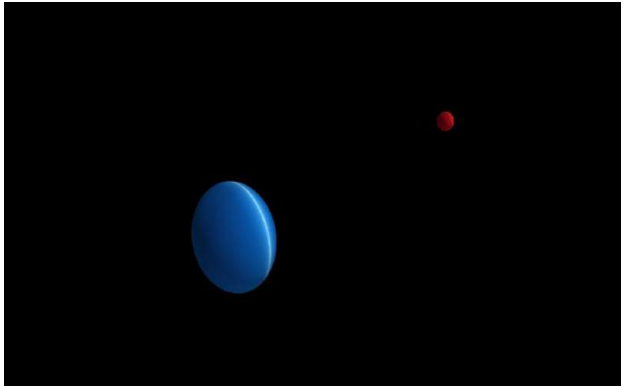
Challenges at current stage

More than 100,000 unlabeled observed data, small amount of labeled data

To push forward this work

Manual labeling vs. model labeling

Introduce data other than photometric survey



Advanced Scoliosis Detection with Deep Neural Nets

Group 3
Sandra Liu
Eric Magliarditi
Nathan Rebello

Scoliosis is an abnormal lateral spinal curvature

- Starts before 15 yrs. old
- 600,000 patient visits/year
- 30,000 children fitted w/brace
- 40,000 undergo spinal fusion surgery

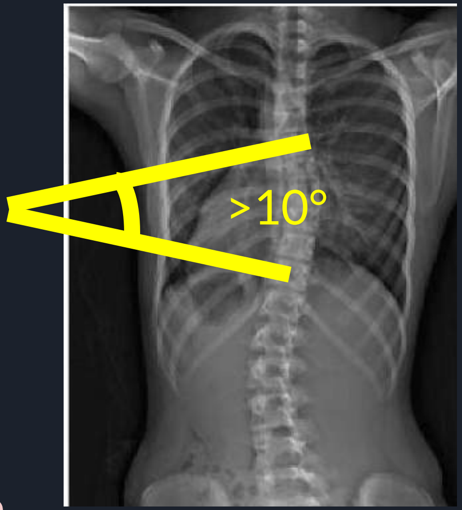
Brace
May 2014-July 2015

https://www.aans.org/Patients/Neurosurgical-Conditions-and-Treatments/Scoliosis

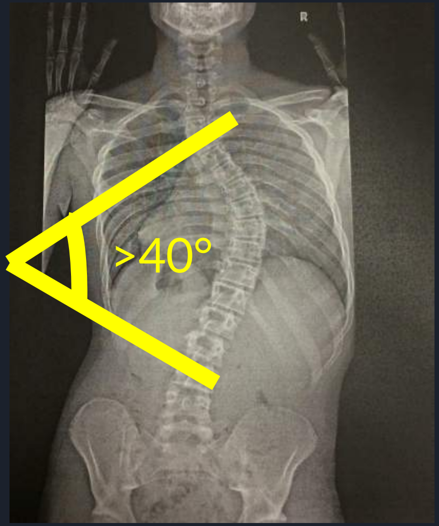
How do we map early signs to advanced scoliosis?

- No predictive methods
- Costs:
  - $5K on bracing
  - $100K/surgery
  - $1K/year on checkups
- If detected, preventative measures can improve posture

Mild



Severe



https://health.costhelper.com/scoliosis.html

Use Convolutional Neural Nets & Supervised Learning to predict severe scoliosis

Input Data:

X-Ray of patient with early signs of Scoliosis: Curvature ~10-20°

Labels:
Future Scoliosis Severity
(Mild, Moderate, Severe)

Convolution Neural Net

1. Learns features present in patients who had mild scoliosis but became severe after a time, T
3. Assigns weights to features
4. Outputs classification

Classification

Class 1:
Mild Scoliosis after time T

Class 2:
Moderate Scoliosis after time T

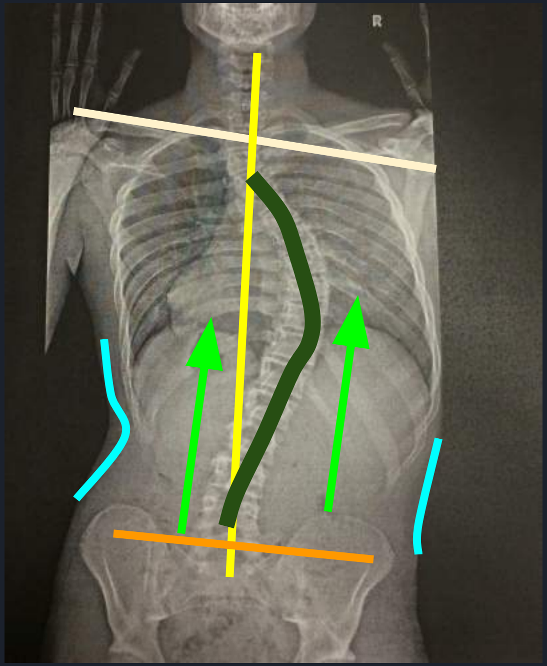
Class 3:
Severe Scoliosis after time T

*Classification Subject to Change

Goal: CNN Detect Subtle Features that Trigger Advanced Scoliosis

- Severe:
  - Spinal curving
- Subtle:
  - Uneven Shoulders
  - Ribs at different heights
  - Head not centered above pelvis
  - Uneven waist
  - Hips raised high

Severe



What are the challenges?

- Validation
- Data Acquisition
    - 600,000 patient visits/year
    - Potential privacy issues with hospitals

Further Applications

- Individual-specific physical therapy treatments
- Potential using physician/therapist data with the deep neural net to develop effective therapy treatments
- Detecting features in X-ray images that might lead to severe scoliosis

https://www.webmd.com/back-pain/what-are-the-symptoms-of-scoliosis#1

Thank you!

Dementia

One case every **3 seconds**.

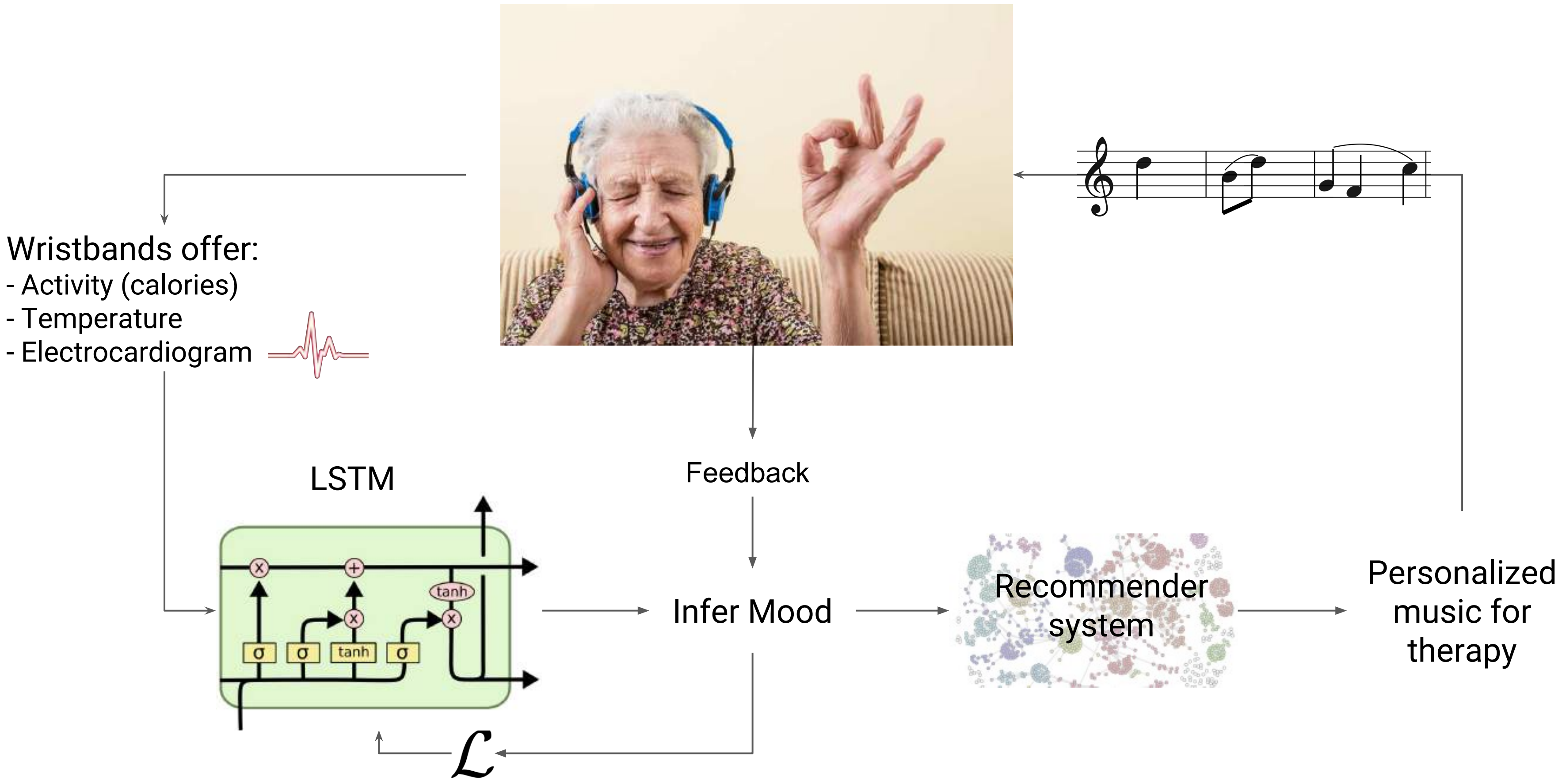
131.5 million by 2050.

Costs above a **$1 trillion** in 2018.

Music can help…

…but which music works best?

TheraTune. Personalized music therapy

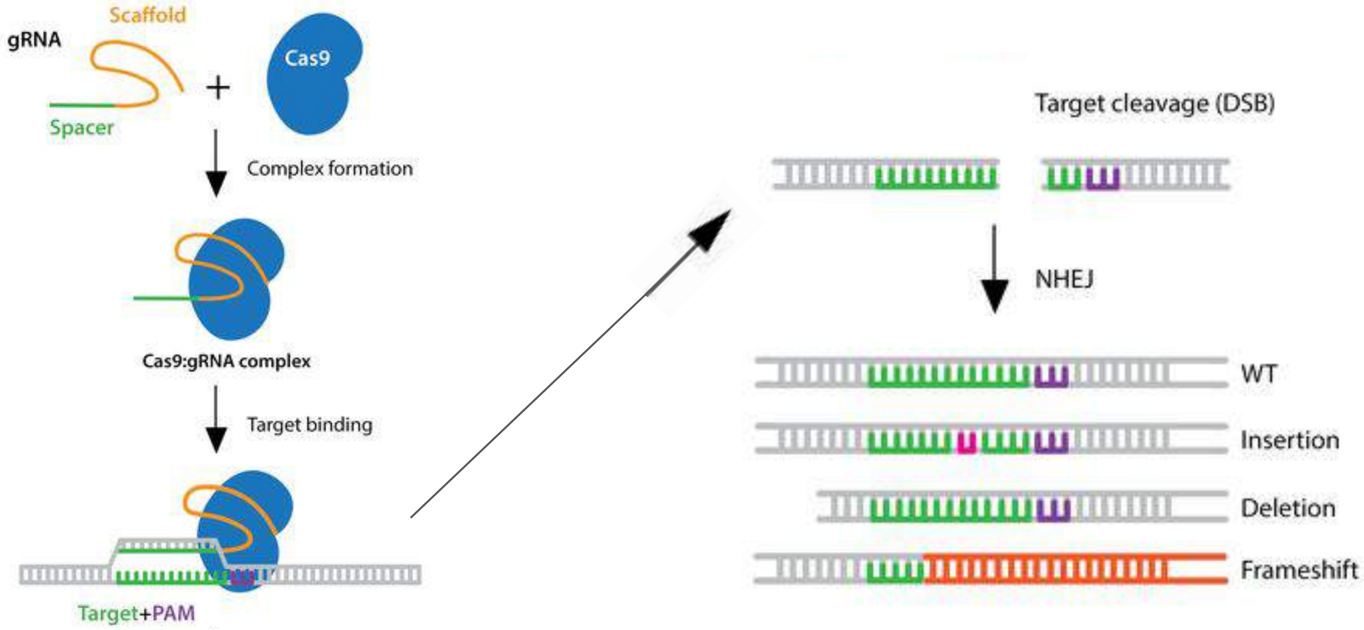


Pred1ct: Predicting Useful CRISPR-Cas9 Outcomes

David Li, Joshua Park, Akshaj Kadaveru
6.S191 Group 5

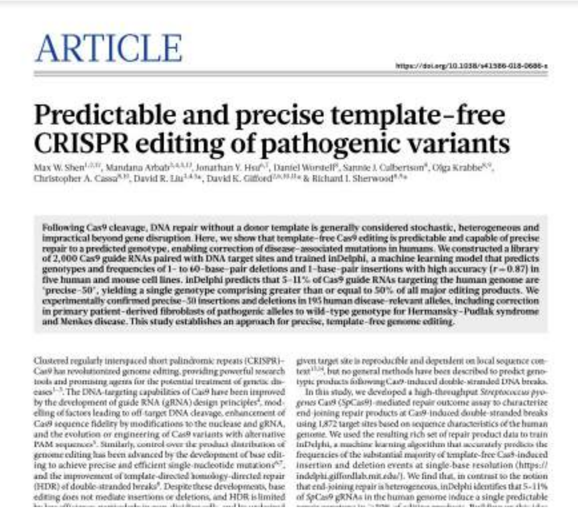
CRISPR/Cas9 allows for targeted gene editing

- CRISPR/Cas9 cuts at specific locations given a guide RNA
- Cells have own mechanisms to repair cuts in DNA



Existing Approaches

- Library of guide RNAs (target different areas)
- Treated cells containing target sequences with Cas9
- Sequence and compare



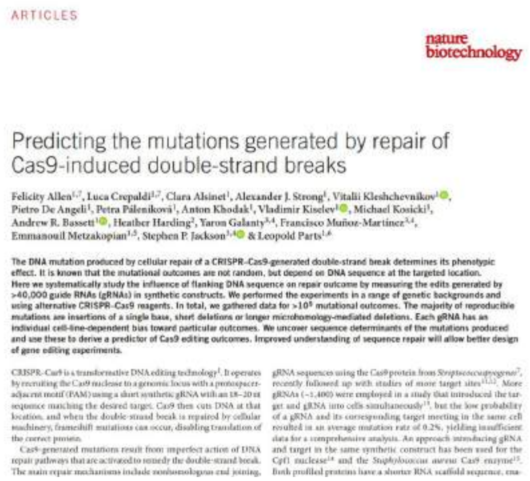
ARTICLE

https://doi.org/10.1038/s41586-018-0686-x

Predictable and precise template-free CRISPR editing of pathogenic variants

Max W. Shen, Mandana Arbab, Jonathan Y. Hsu, Daniel Worstell, Sannie J. Culbertson, Olga Krabbe, Christopher A. Cassa, David R. Liu, David K. Gifford & Richard I. Sherwood

Following Cas9 cleavage, DNA repair without a donor template is generally considered stochastic, heterogeneous and impractical beyond gene disruption. Here, we show that template-free Cas9 editing is predictable and capable of precise repair to a predicted genotype, enabling correction of disease-associated mutations in humans. We constructed a library of 2,000 Cas9 guide RNAs paired with DNA target sites and trained inDelphi, a machine learning model that predicts genotypes and frequencies of 1- to 60-base-pair deletions and 1-base-pair insertions with high accuracy ($r = 0.87$) in five human and mouse cell lines. inDelphi predicts that 5–11% of Cas9 guide RNAs targeting the human genome are 'precise-50', yielding a single genotype comprising greater than or equal to 50% of all major editing products. We experimentally confirmed precise-50 insertions and deletions in 195 human disease-relevant alleles, including correction in primary patient-derived fibroblasts of pathogenic alleles to wild-type genotype for Hermansky–Pudlak syndrome and Menkes disease. This study establishes an approach for precise, template-free genome editing.



ARTICLES

nature biotechnology

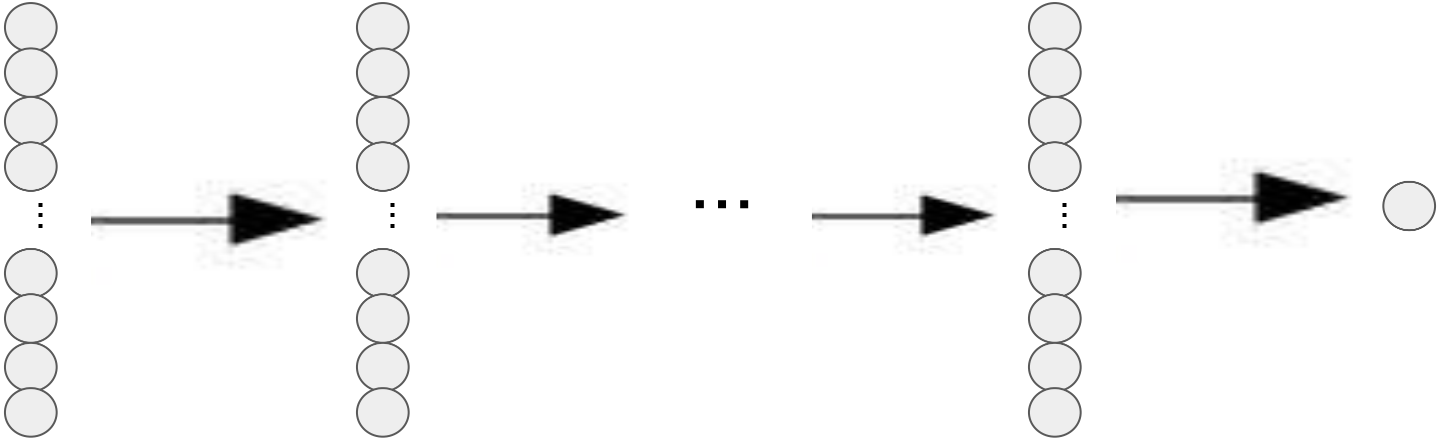
Predicting the mutations generated by repair of Cas9-induced double-strand breaks

Felicity Allen, Luca Crepaldi, Clara Alsinet, Alexander J. Strong, Vitalii Kleshchevnikov, Pietro De Angeli, Petra Páleníková, Anton Khodak, Vladimir Kiselev, Michael Kosicki, Andrew R. Bassett, Heather Harding, Yaron Galanty, Francisco Muñoz-Martinez, Emmanouil Metzakopian, Stephen P. Jackson & Leopold Parts

The DNA mutation produced by cellular repair of a CRISPR–Cas9-generated double-strand break determines its phenotypic effect. It is known that the mutational outcomes are not random, but depend on DNA sequence at the targeted location. Here we systematically study the influence of flanking DNA sequence on repair outcome by measuring the edits generated by >40,000 guide RNAs (gRNAs) in synthetic constructs. We performed the experiments in a range of genetic backgrounds and using alternative CRISPR–Cas9 reagents. In total, we gathered data for $>10^9$ mutational outcomes. The majority of reproducible mutations are insertions of a single base, short deletions or longer microhomology-mediated deletions. Each gRNA has an individual cell-line-dependent bias toward particular outcomes. We uncover sequence determinants of the mutations produced and use these to derive a predictor of Cas9 editing outcomes. Improved understanding of sequence repair will allow better design of gene editing experiments.

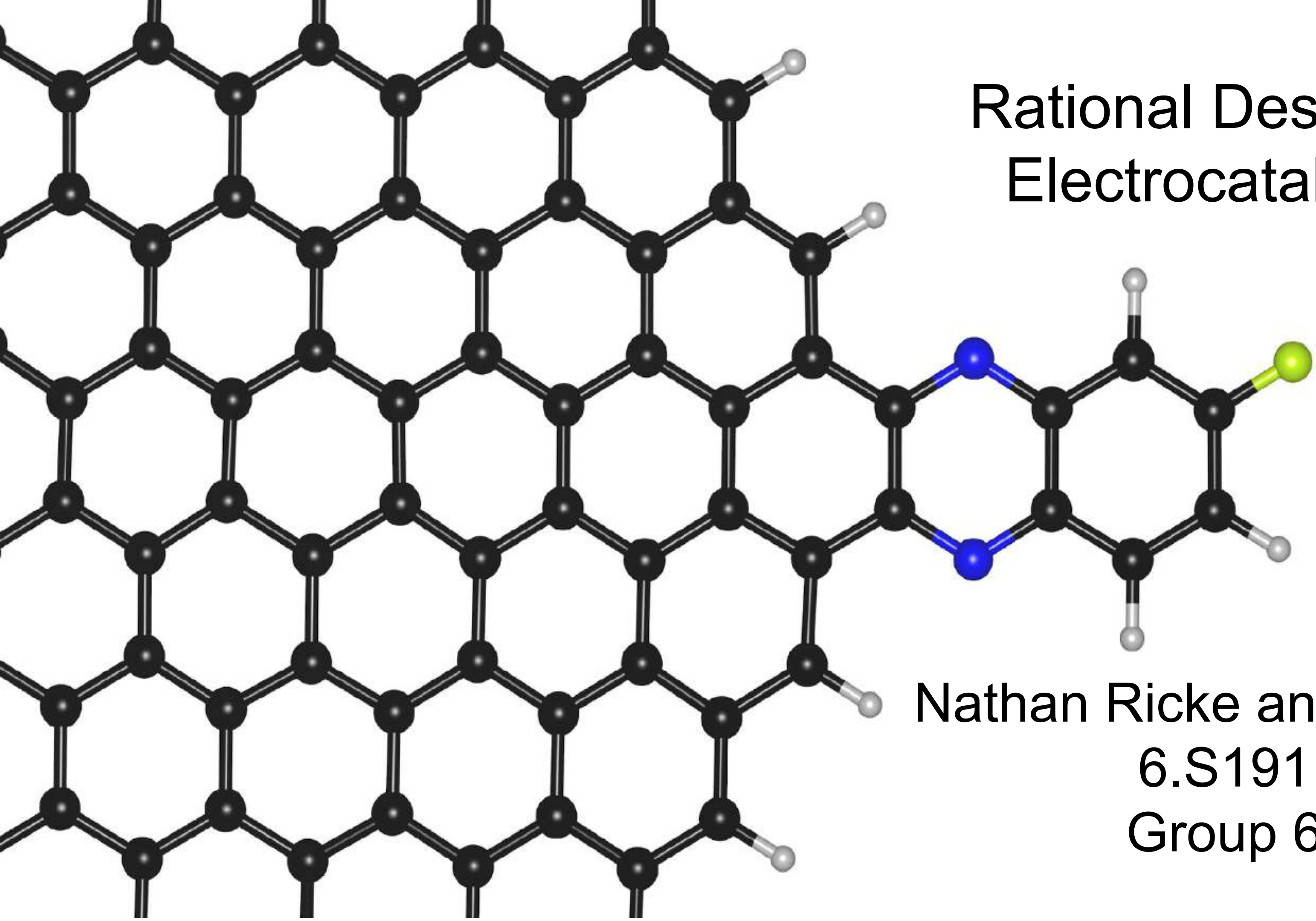
Pred1ct Network Architecture

- Feedforward neural network
- Input: 20 dimensional vector; each dimension can be one of four values
  - $(A, C, T, G)^{20}$
- Output: Percentage of insertions/deletions that are one nucleotide insertions
  - Value between 0 and 1
- Existing training set of ~42,000 sequences



Consequences

- Small frameshifts make up 24% of **mutations** that manifest in currently recognized **genetic disease**.
- Accurate prediction of +1 frequencies allows for the design of useful guide RNAs that would allow correction of these diseases
- For example:
  - Cystic Fibrosis
  - Crohn's Disease
  - Tay-Sachs Disease



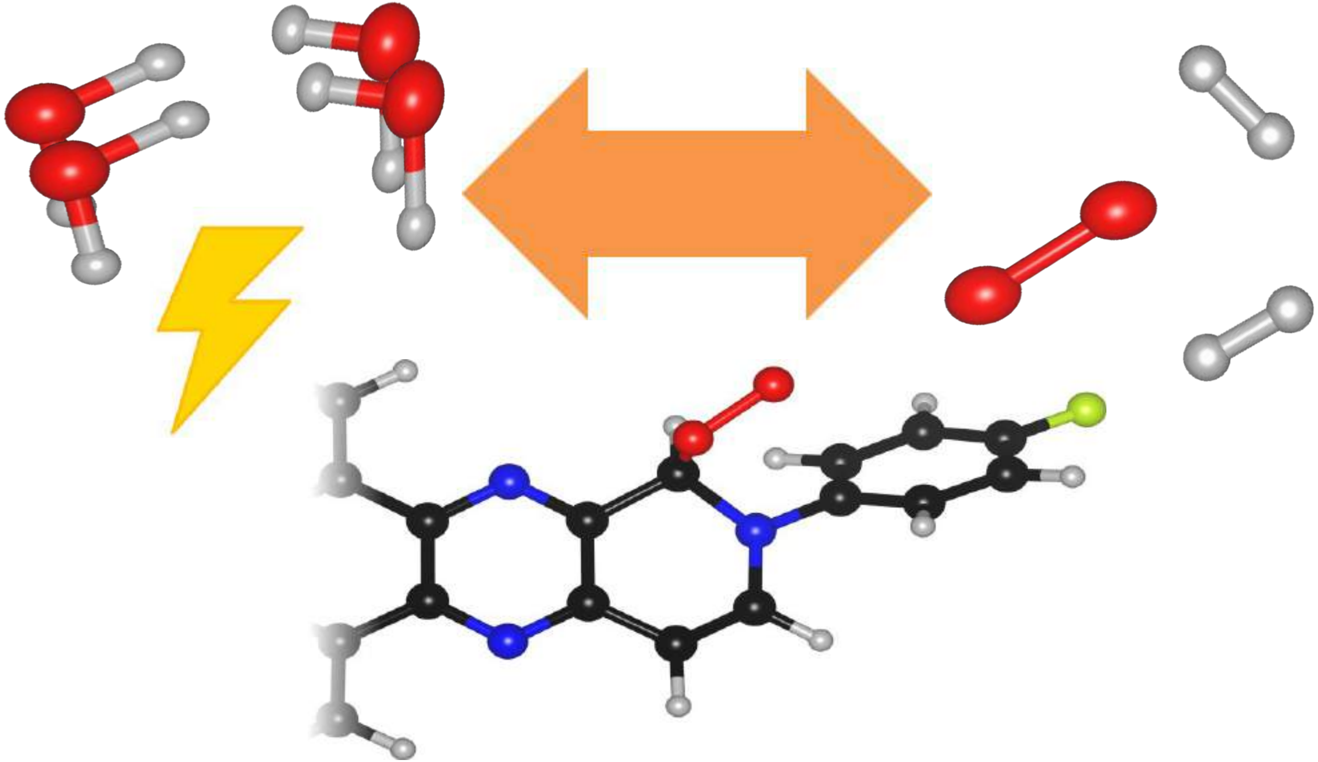
Rational Design of Electrocatalysts

Nathan Ricke and Eric Alt

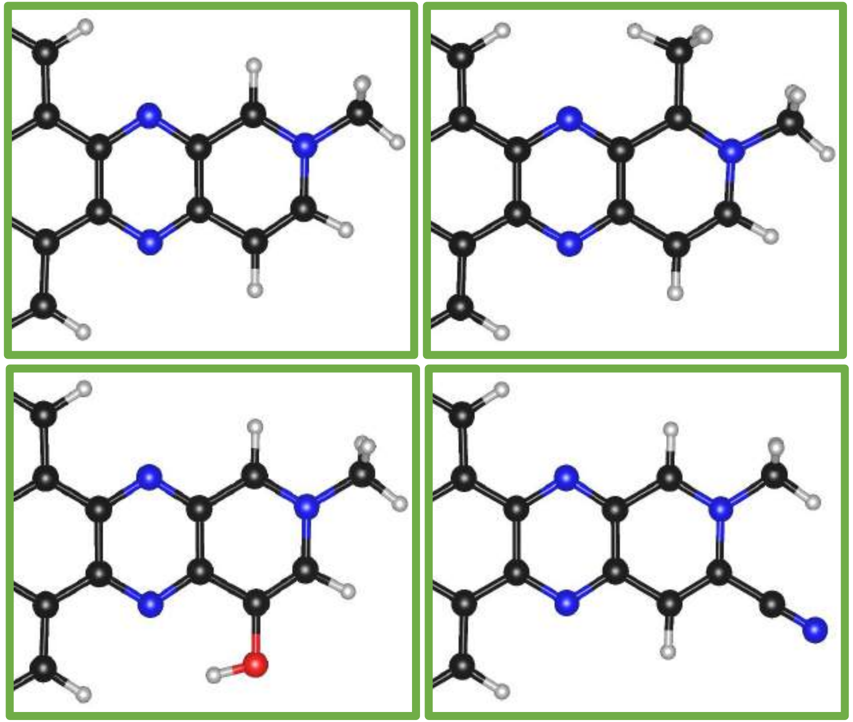
6.S191

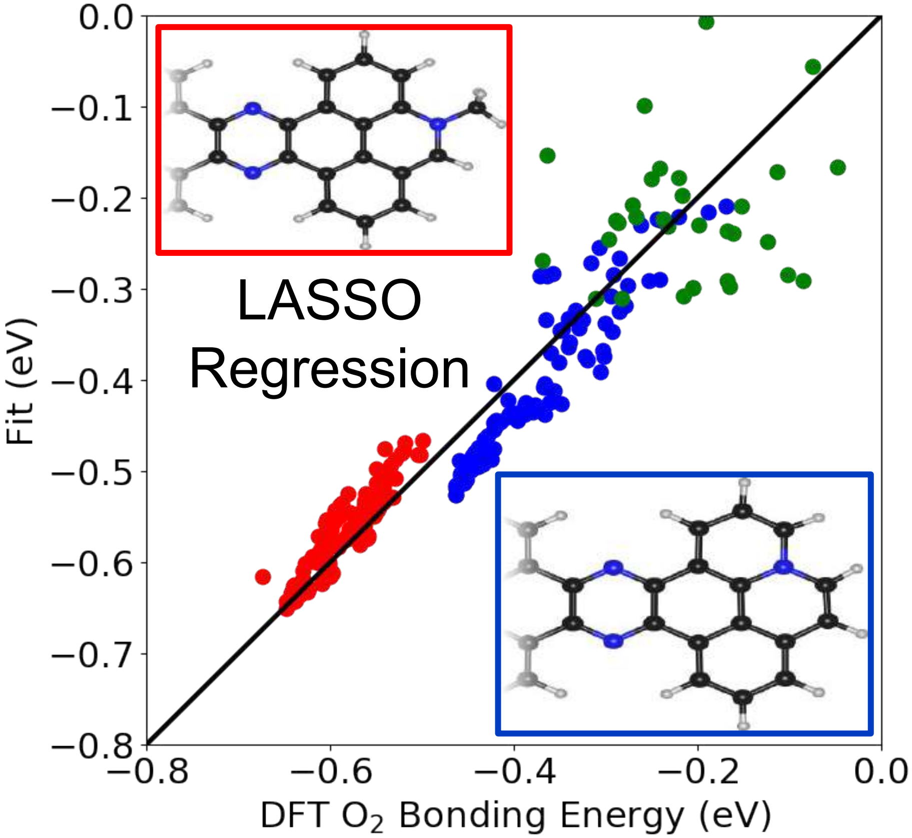
Group 6

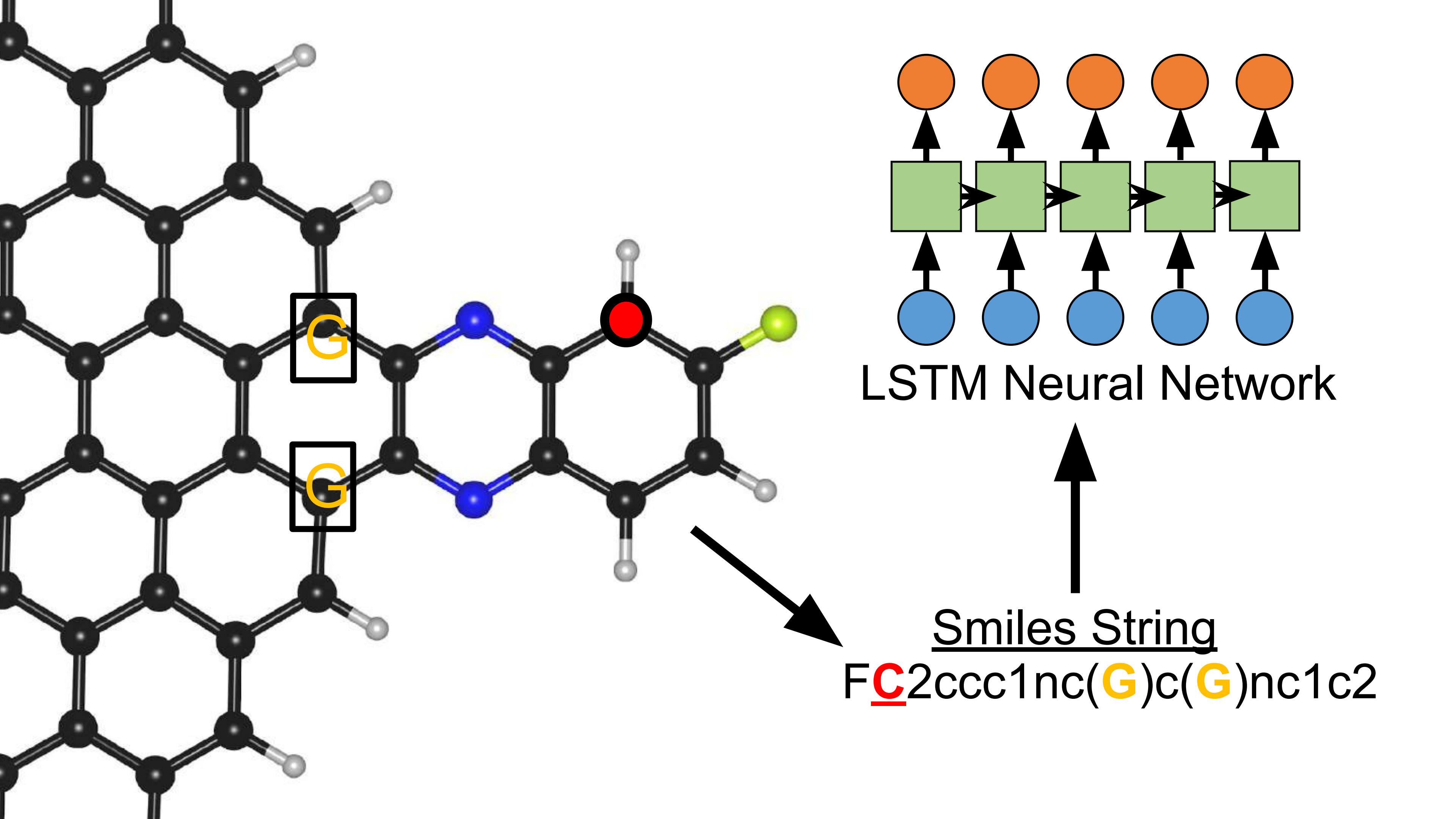
Electrocatalysts for Storing and Recovering Energy



Computationally Generate and Test Catalysts






G
G
LSTM Neural Network
Smiles String
FC2ccc1nc(G)c(G)nc1c2

[1]

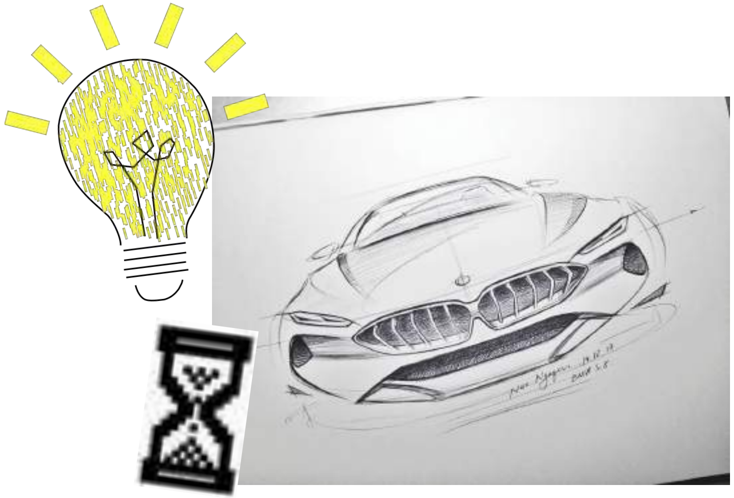
[2]

[3]

Group 7: Yiwen Huang, Greg Allan, Michael Schmid

GANs for Automotive Exterior Design

Automotive Design - State of the Art



BMW 8 series concept sketch [4]

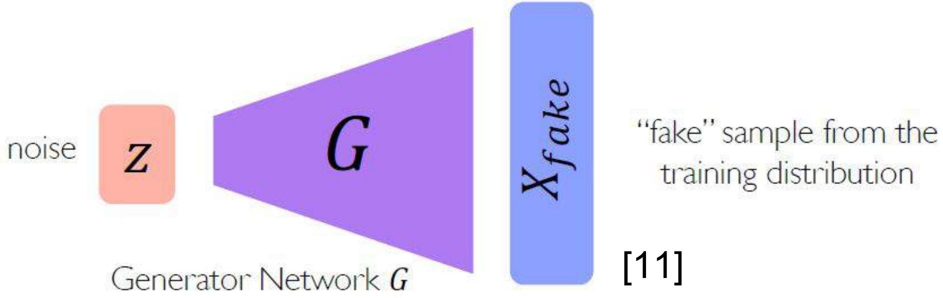
Attractive design requires creativity
BUT there are no new elements on cars!

BMW 8 series concept car [5]

BMW 8 series final design [6]

Idea: GANs in Automotive Design

Idea from lecture:
Exploit the creativity of Generative Networks

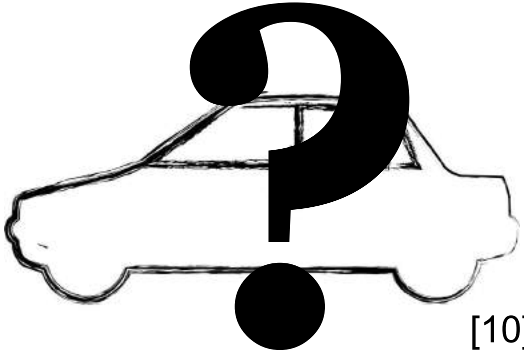


[11]

[7], [8], [9]

→ Generative Network →

Slowly increase or decrease single latent variables (luxury, sports, race)



[10]

design suggestions

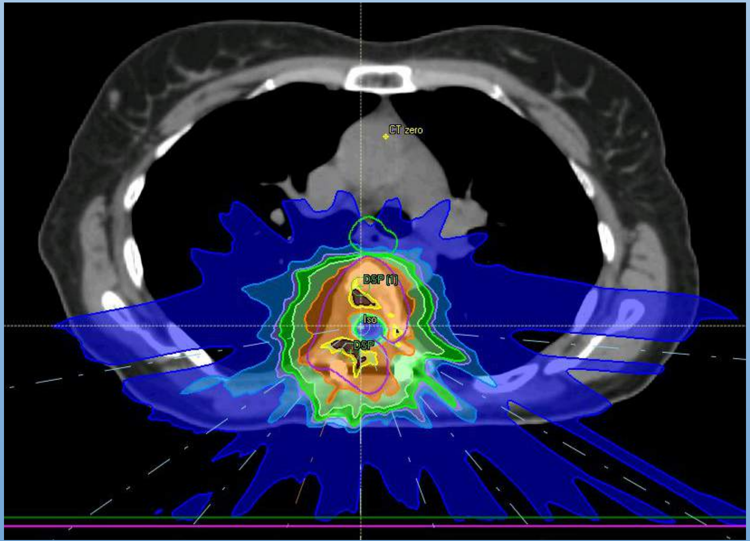
Thank you for your attention!

[12]

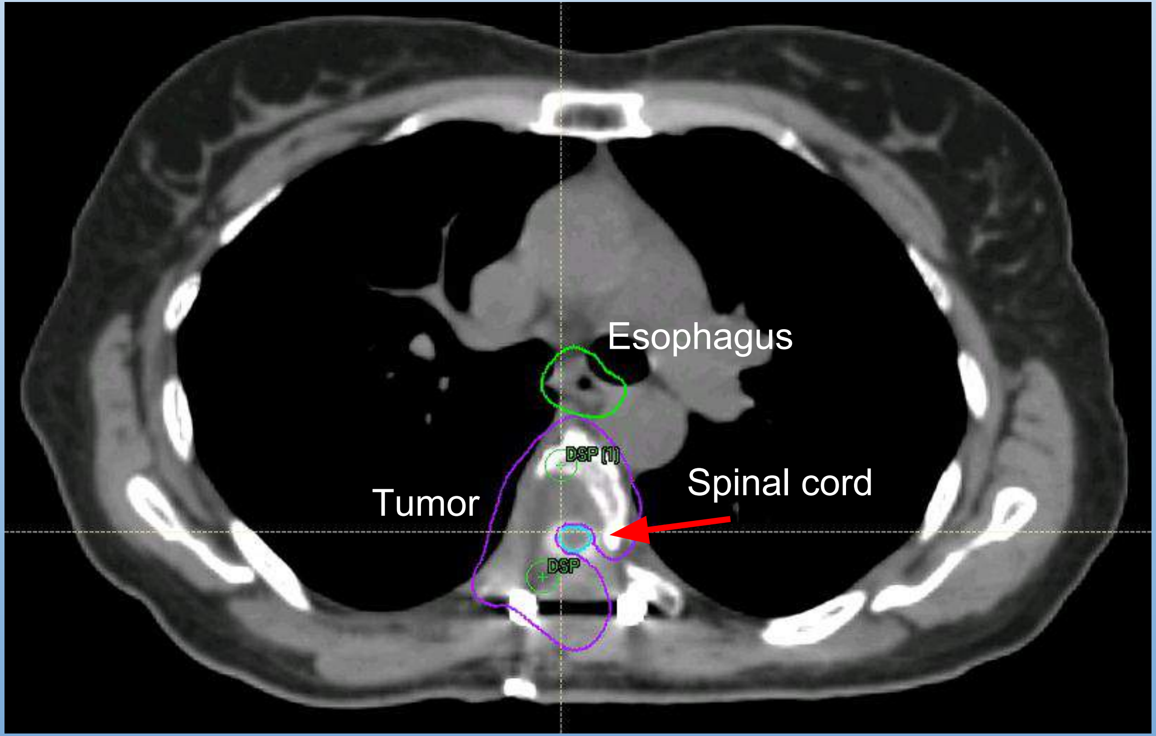
Deep Reinforcement Learning for Radiation Therapy Planning

Group 8: Susu Yan (Listener), Michelle Jiang (Credit)

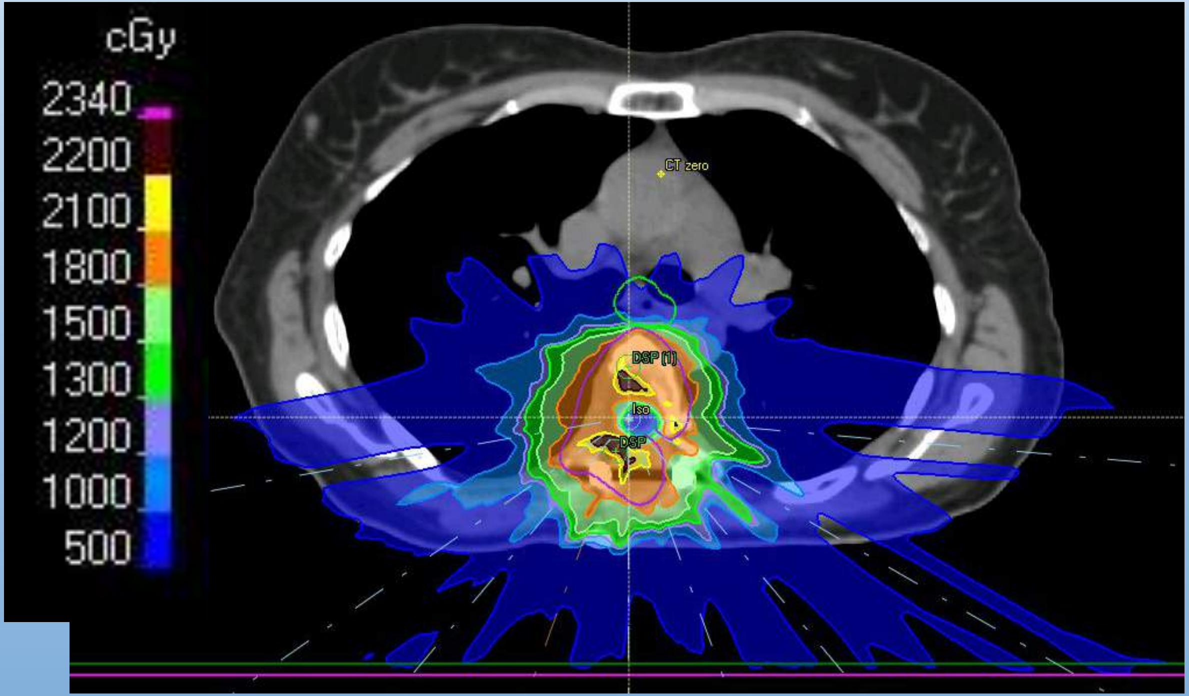
MIT 6.S191 presentation

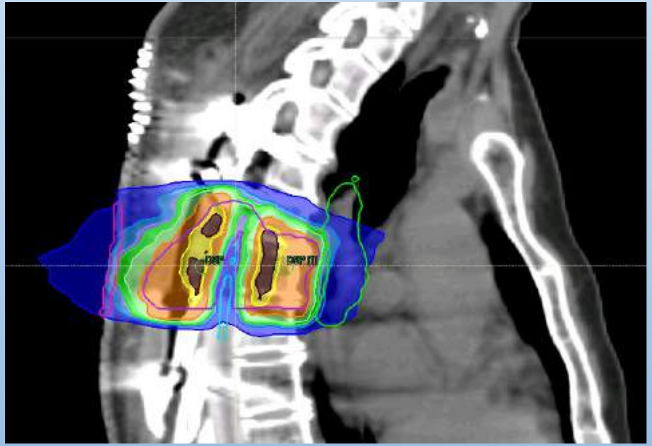


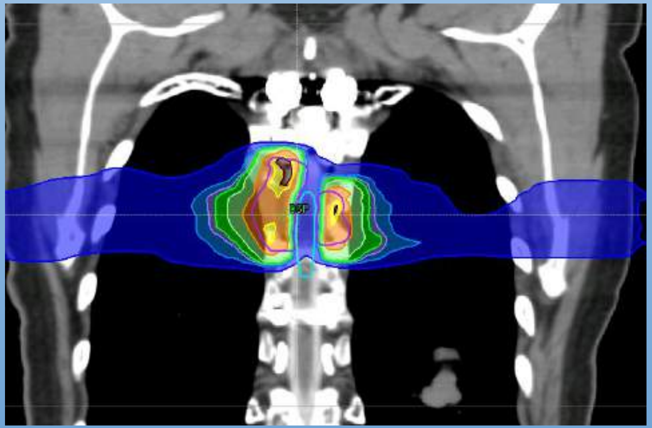
Radiation Treatment Plan: Tumor and Organs-at-risk



Radiation Treatment plan: Dose Distribution







3D distribution of dose in patient shown on CT

Actions

Isocenter [cm] Name	R-L	I-S	P-A	SSD [cm] To surface	To skin	Energy [MV]	Gantry angle [deg]	Coll. angle [deg]	Couch angle [deg]	No. segm	MU/fx	Bolus
T6	-2.72	1.66	-3.79	85.00	90.14	6	180.0	93.0	0.0	8	372.11	*(None)*
T6	-2.72	1.66	-3.79	84.03	89.50	6	200.0	90.0	0.0	8	333.31	*(None)*
T6	-2.72	1.66	-3.79	80.42	87.11	6	220.0	85.0	0.0	10	423.52	*(None)*
T6	-2.72	1.66	-3.79	75.96	82.76	6	235.0	82.0	0.0	13	468.94	*(None)*
T6	-2.72	1.66	-3.79	80.14	80.14	6	260.0	80.0	0.0	12	678.92	*(None)*
T6	-2.72	1.66	-3.79	73.43	73.43	6	95.0	12.0	0.0	12	941.50	*(None)*
T6	-2.72	1.66	-3.79	71.79	80.46	6	120.0	11.0	0.0	8	1103.28	*(None)*
T6	-2.72	1.66	-3.79	80.41	87.18	6	140.0	9.0	0.0	9	1068.20	*(None)*

Tradeoff objectives

Add Edit Delete

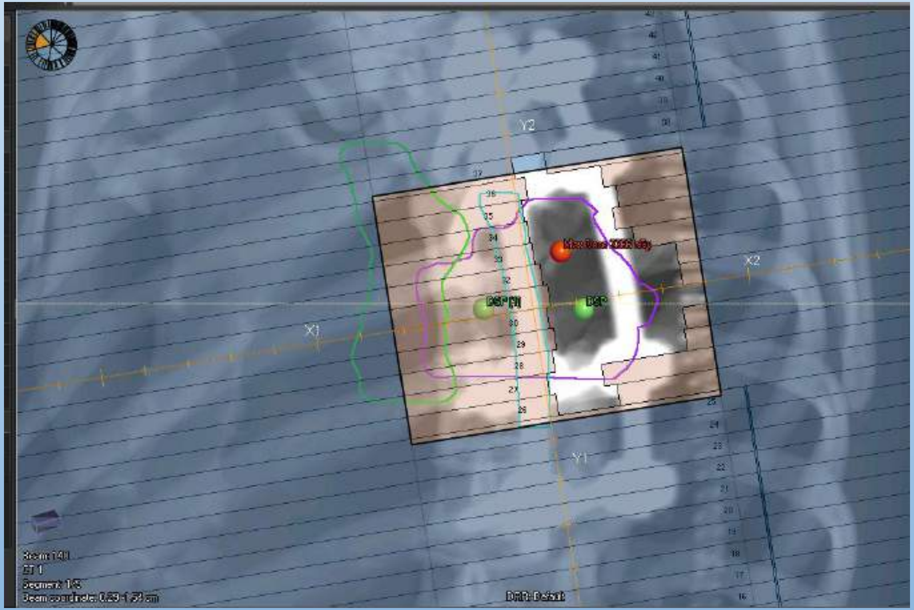
ROI	Description
PTV T6	Min DVH 1800 cGy to 100% volume
cord + 1 mm	Max DVH 1000 cGy to 9% volume
cord + 1 mm	Max Dose 1300 cGy
esophagus + 2 mm	Max Dose 1500 cGy
RingOuter1cmGap1mm	Dose Fall-Off [H]1800 cGy [L]0 cGy, Low dose distance 1.00 cm
RingInner5mm	Min DVH 1800 cGy to 100% volume

Constraints

Add Edit Delete

ROI	Description
PTV T6	Min DVH 1800 cGy to 94% volume
cord + 1 mm	Max Dose 1300 cGy
cord + 1 mm	Max DVH 1000 cGy to 9.1% volume
esophagus + 2 mm	Max Dose 1500 cGy
esophagus + 2 mm	Max DVH 1200 cGy to 30.5% volume
PTV T6	Max EUD 2050 cGy, Parameter A 8

Actions (cont.)



Weight MU | Weight dose | Balance weights | Scale to prescription

No.	Name	MU/fx	Beam dose to isocenter [cGy]	Clamp weight	Relative values Weight	MU weight [%]
1	180	372.11	151			6.09
2	200	333.31	170			5.46
3	220	423.52	145			6.94
4	235	468.94	123			7.68
5	260	678.92	190			11.12
6	95	941.50	55			15.42
7	120	1103.28	69			18.07
8	140	1068.20	92			17.49
9	160	716.37	66			11.73

There are thousands of parameters that can be modified to generate a radiation therapy plan.

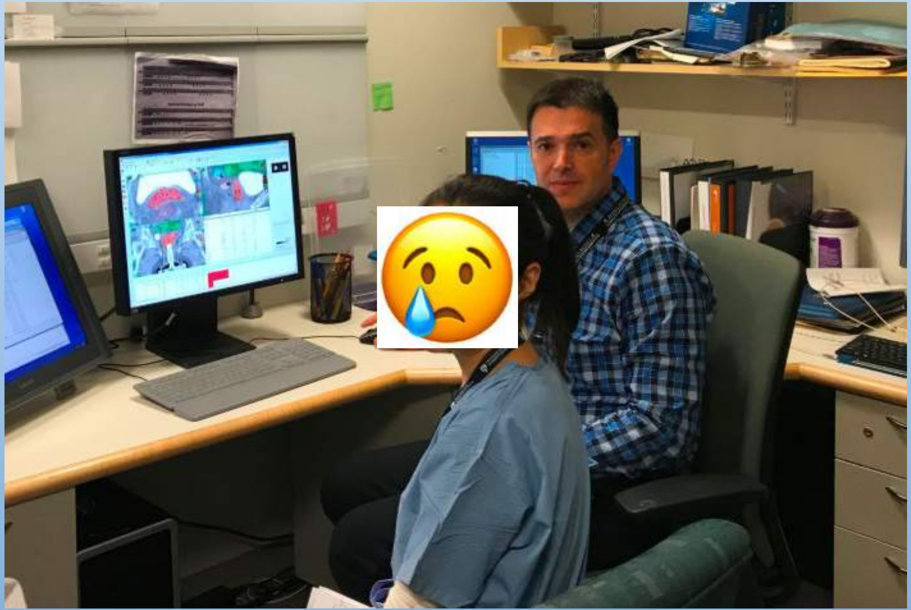
Reward: Minimizing or Maximizing Dose Values and Meeting Clinical Goals

ROI/POI	Clinical goal	Value	Result
cord + 1 mm	At most 0.4 cm^3 volume at 1000 cGy dose	0.3 cm^3	✓
cord + 1 mm	At most 0.25 % volume at 1300 cGy dose	0.11 %	✓
cord + 1 mm	At most 10.00 % volume at 1000 cGy dose	7.60 %	✓
esophagus + 2 mm	At most 0.25 % volume at 1500 cGy dose	0.13 %	✓
esophagus + 2 mm	At most 5.0 cm^3 volume at 1200 cGy dose	0.4 cm^3	✓
PTV T6	At least 91.70 % volume at 1800 cGy dose	91.71 %	✓

The goal is to kill all tumor cells and minimize radiation damage to healthy tissues.

Challenges

Challenges



- Requires years of training and experience
- Time consuming
- Never sure if a better plan exists
- Patient needs to be treated as soon as possible

Reinforcement Learning

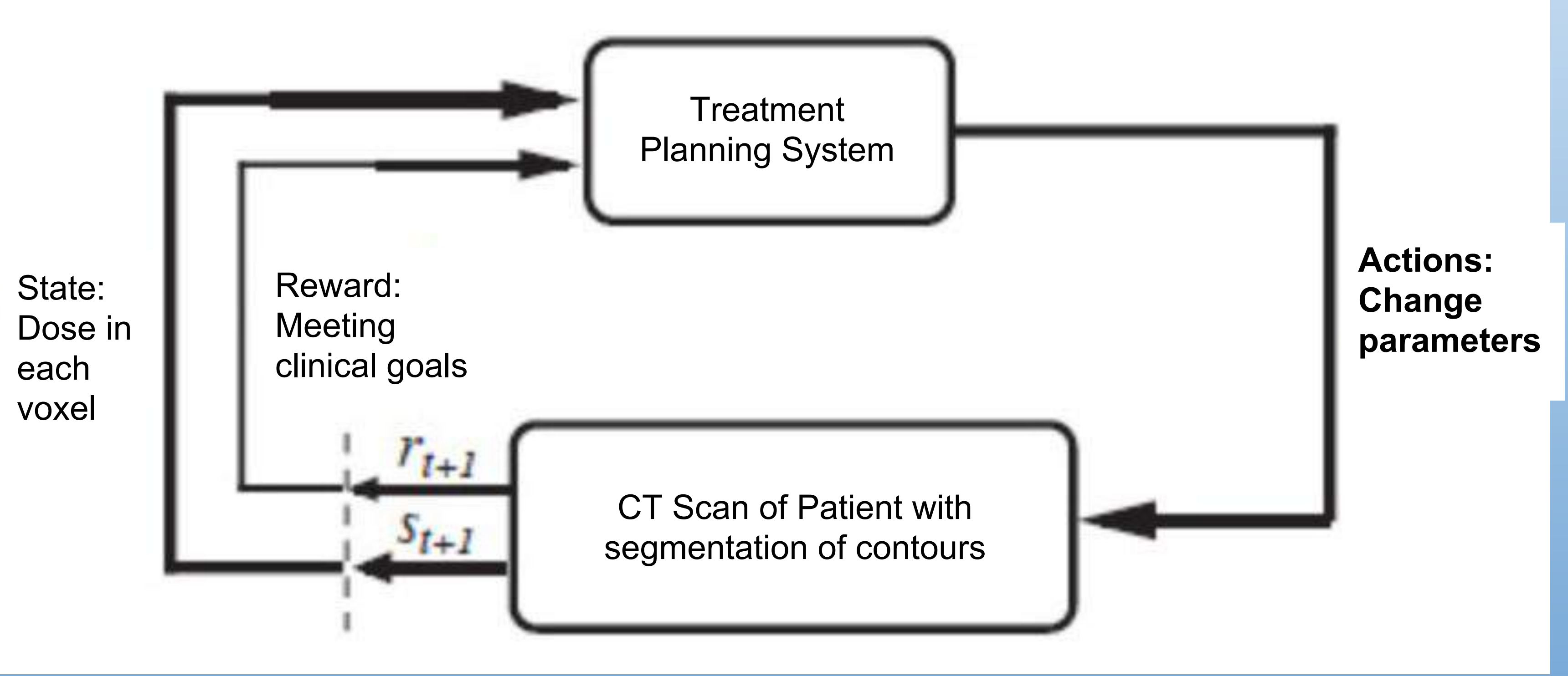
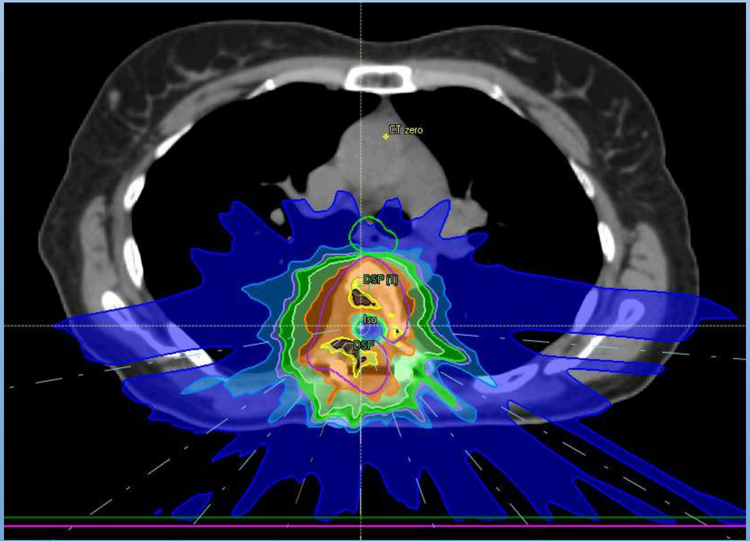
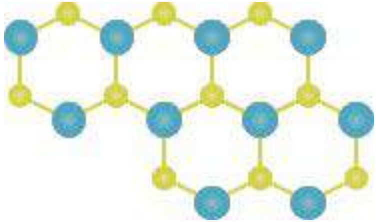


Image adapted from https://adeshpande3.github.io/Deep-Learning-Research-Review-Week-2-Reinforcement-Learning

Thank you!

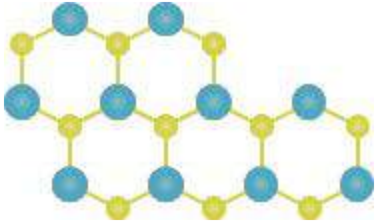
Group 8: Susu Yan (Listener), Michelle Jiang (Credit)





Diagnosing Defects in 2D Materials with Deep Learning

Nina & Jovana Andrejevic



Project Group 9

Introduction

2D materials exhibit tunable electronic and optical properties, exciting for development of next-generation electronic and optoelectronics devices

Quality is critical, but challenging to monitor

Raman spectroscopy provides one signature of material quality

Need a **high-throughput technique** for rapidly identifying and quantifying defects to satisfy industry-scale growth and processing

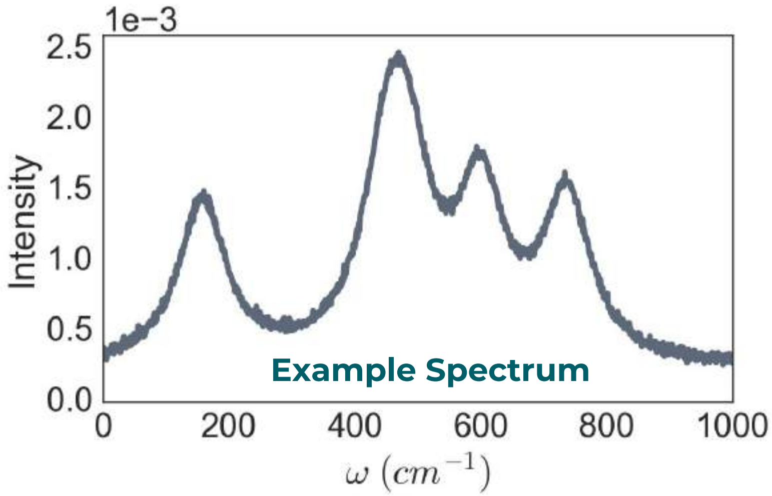
Proposal

Can unsupervised deep learning **automate the screening of “defect fingerprints”?**

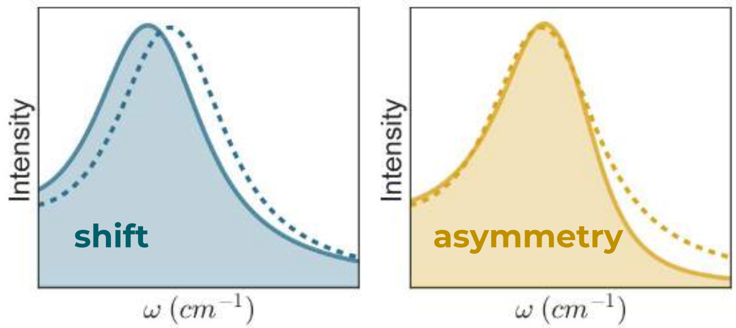
We use an autoencoder to learn a compressed representation of materials’ signatures that

- is **resistant to artifacts** produced by defects
- **distinguishes different materials** in an unsupervised manner

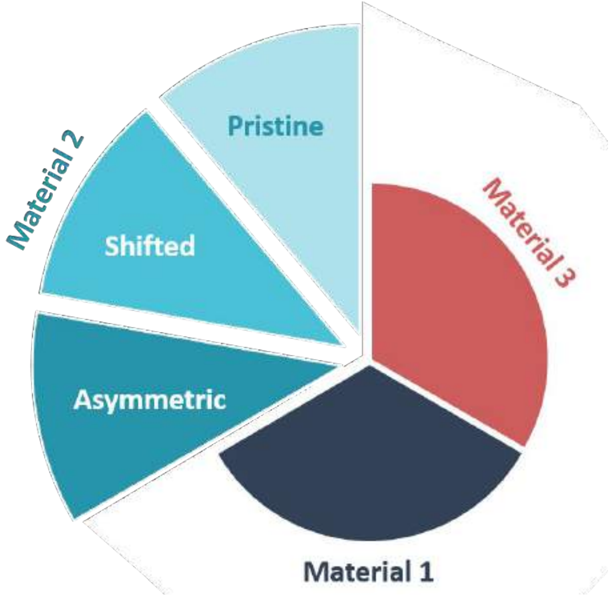
Data Generation



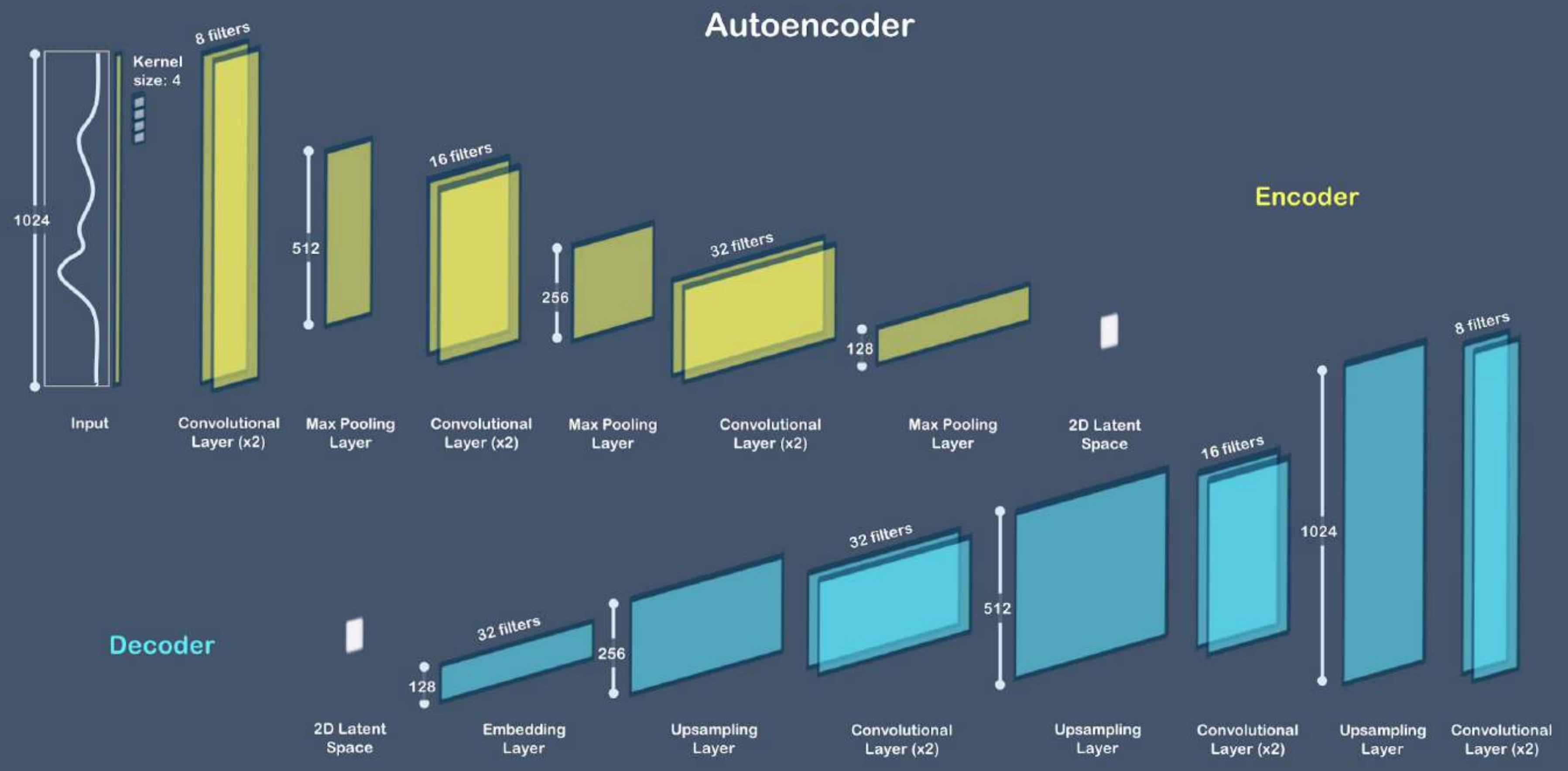
Defect Fingerprints



Generate 3 different materials classes with increasing complexity

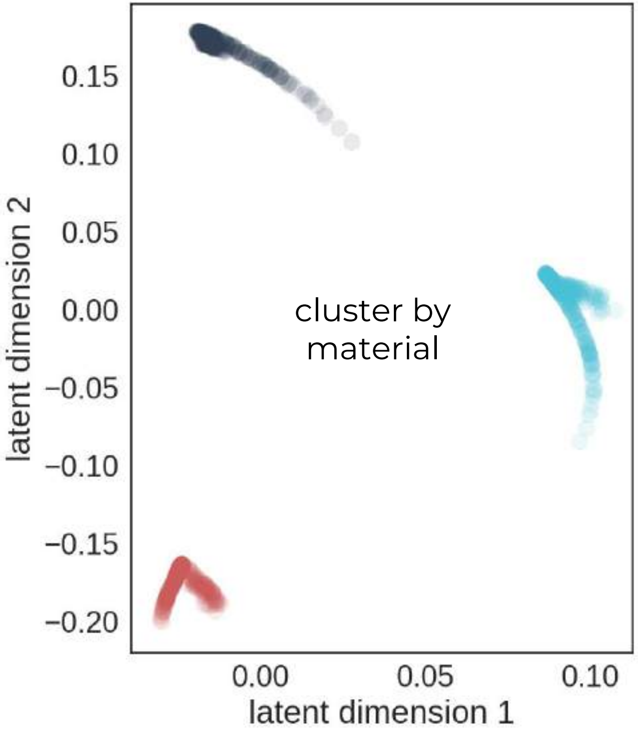


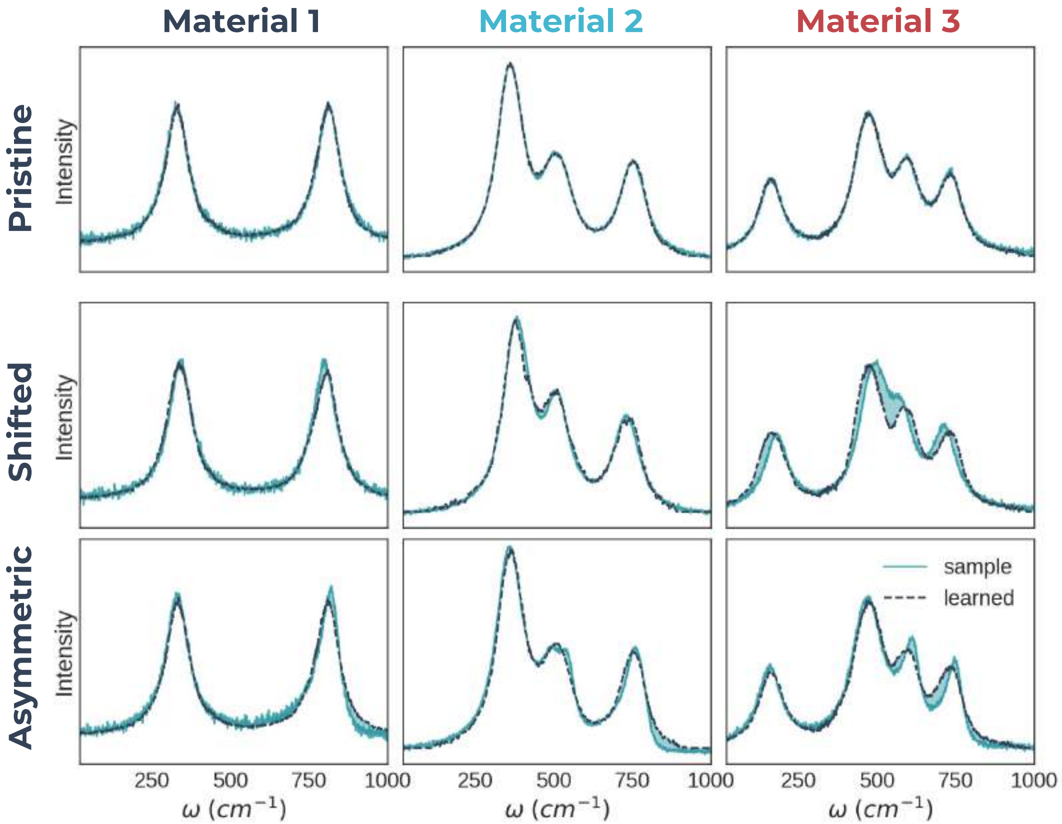
Project Group 9



Project Group 9

Preliminary Results





Conclusion

Our preliminary results show:

- the suitability of autoencoders for **recovering salient features** of Raman signatures corrupted by defects
- the network's ability to learn a **well-separated representation** of different materials' signatures in an unsupervised manner

Next steps:

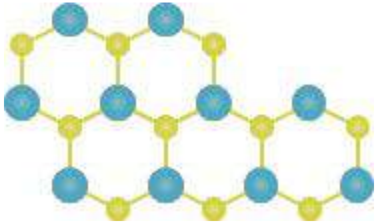
- Train on experimental data, possibly supplemented by simulation
- Quantify defect concentration

References

[1] “Raman Spectroscopy Quality Control of New 2D Materials.” *Spectroscopy Europe/Asia*, 12 July 2017, www.spectroscopyeurope.com/news/raman-spectroscopy-quality-control-new-2d-materials.

[2] “Keras: The Python Deep Learning Library.” Keras Documentation, https://keras.io/.

Thank you!



Using GANs in Filmmaking to replace traditional VFX

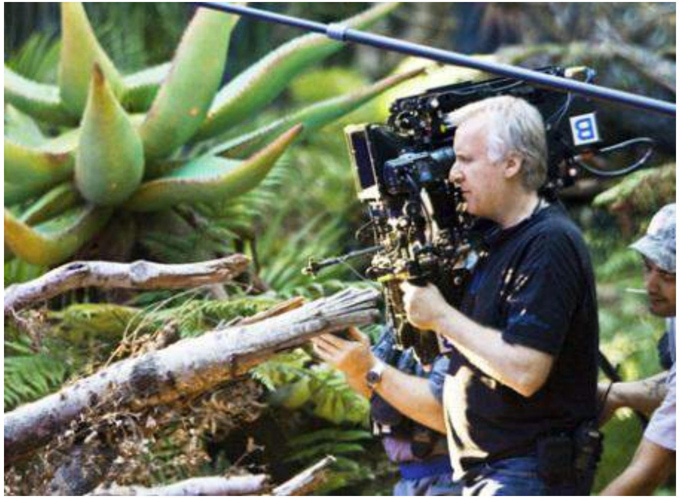
Baptiste, Nick, Suraj, Brandon - Group 10

Current CGI Implementation

- Generate 3D models

- Texture, lighting, and color

- Animate the CGI



- Avatar

- Music videos

Image courtesy of Imaginarium Studios

Current Uses of Machine Learning in VFX

- CGI overlaid on real images

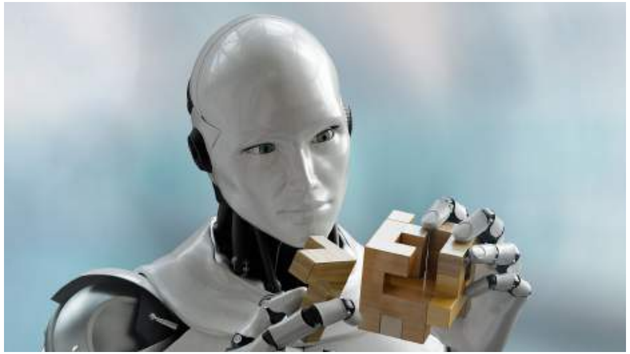
- Wire removal & green screen detection

- Rotoscoping

- Deepfakes

- Human faces created out of nothing

- Already large dataset

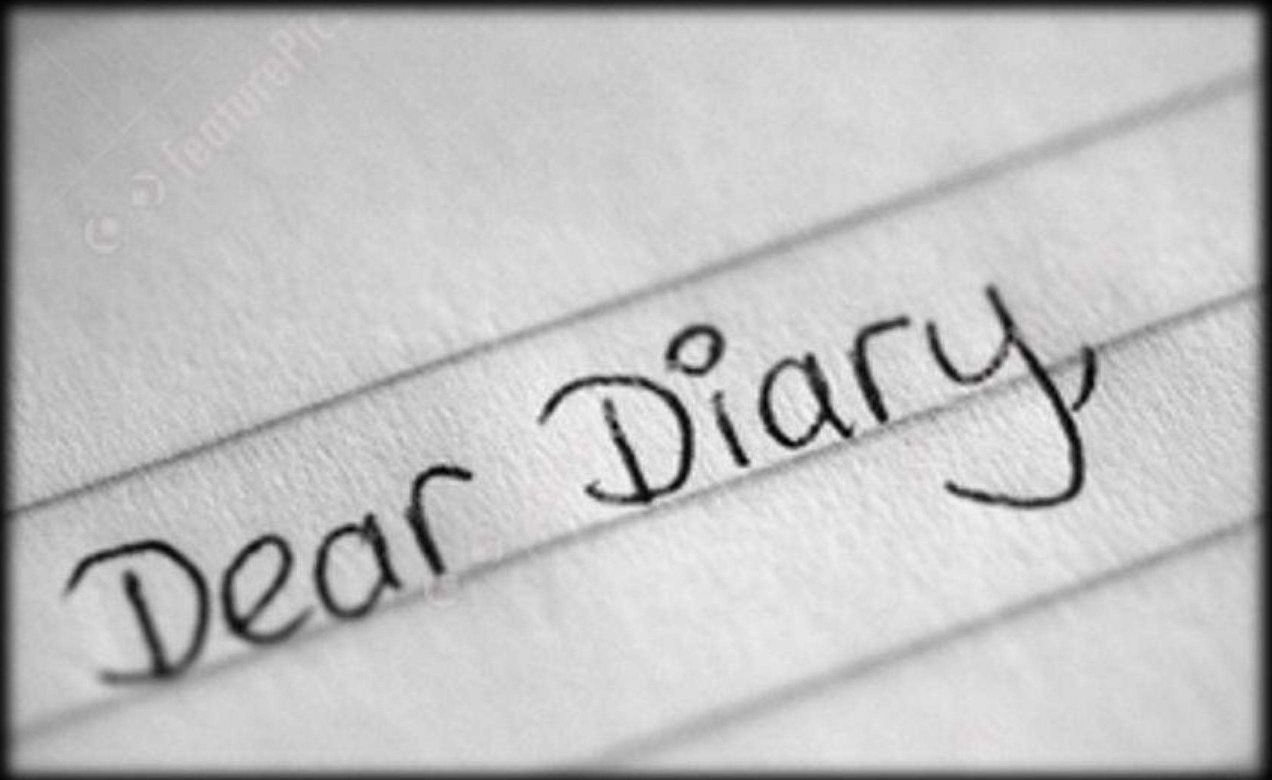


My. Inventory. Assistant.

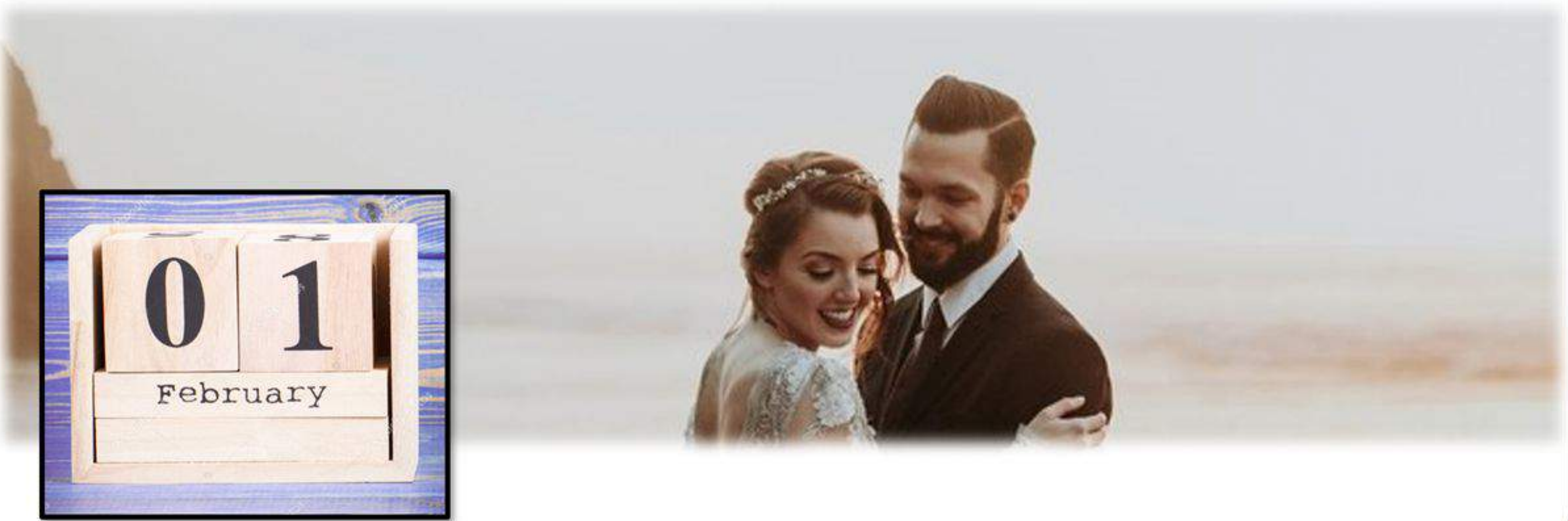
DEEP LEARNING FOR HOUSEHOLD INVENTORY MANAGEMENT

Group 11

J.S. ANG, C.TAN & S. LEE, SYSTEM DESIGN AND MANAGEMENT 2019 / MIT 6.S191



Entry #1



Today is my 5th Wedding Anniversary.

“We are out of coffee.” My wife said to me at breakfast.

No Caffeine - Bad start, but I believed in turning my day around.

I reached for a gift behind the door and presented it to my wife.

She glared at me, “You bought the same handbag last year! How could you have forgotten?”

Defeated, I turned to look at my angel, my 2-year old.

Except, she was no angel today. She let out the most terrible wail, demanding for her toy bunny.

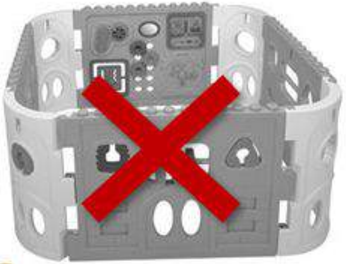
Toy bunny – Where is it?

Toy bunny – Where is it?

The cot?

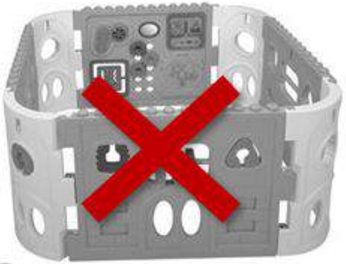
Toy bunny – Where is it?

The cot? No... The playpen?



Toy bunny – Where is it?

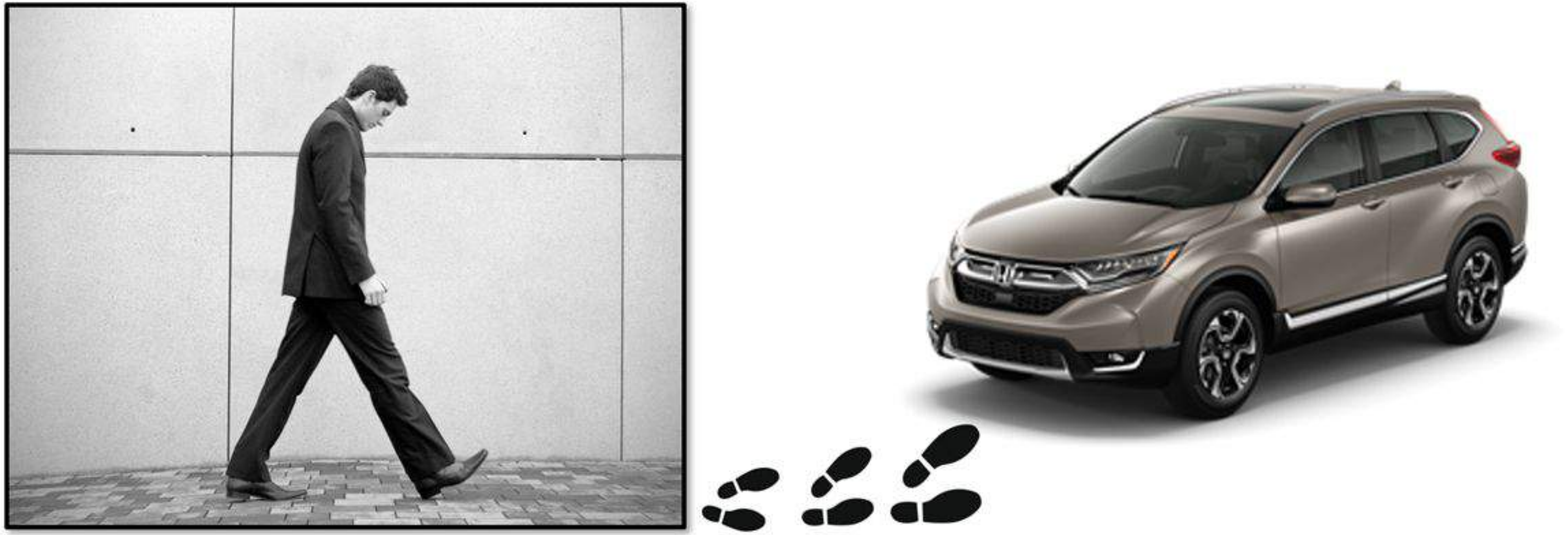
The cot? No... The playpen? No... The sofa?



Toy bunny – Where is it?

The cot? No... The playpen? No... The sofa? No!

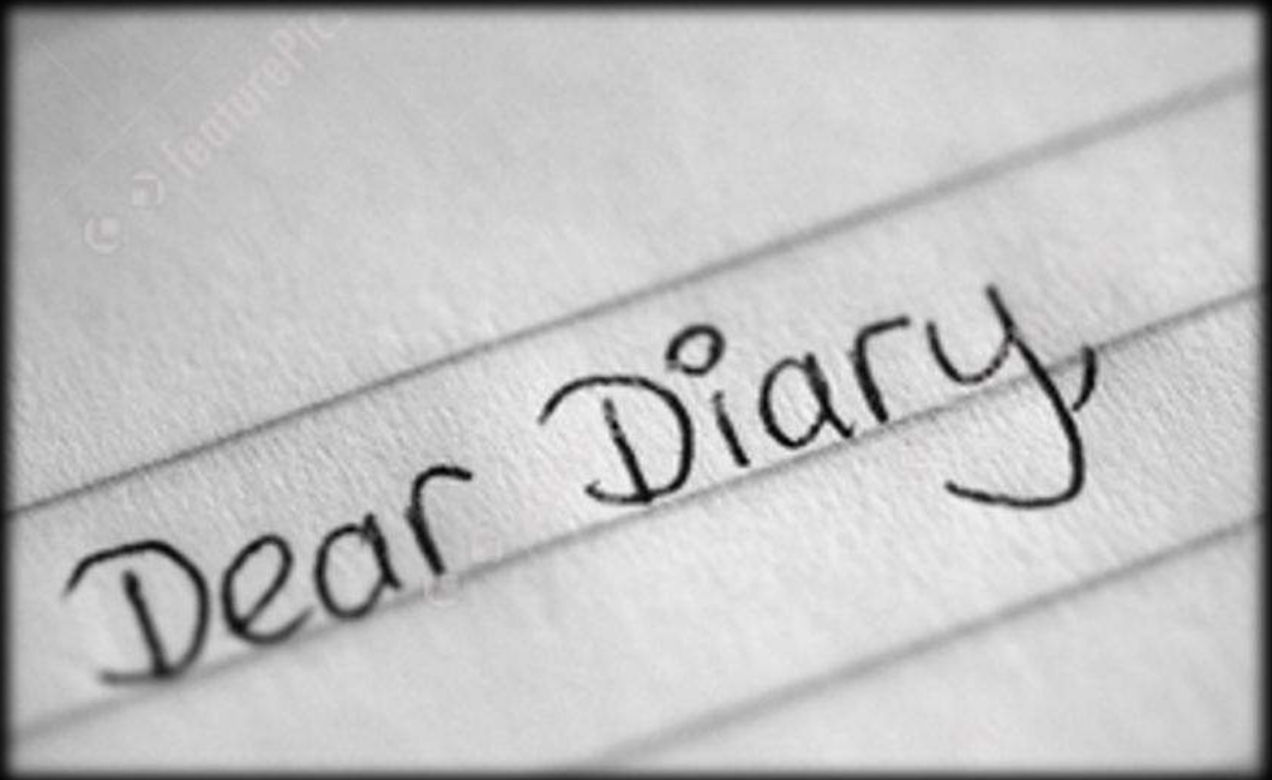
No coffee… A raging baby… A missing bunny…
An upset wife…



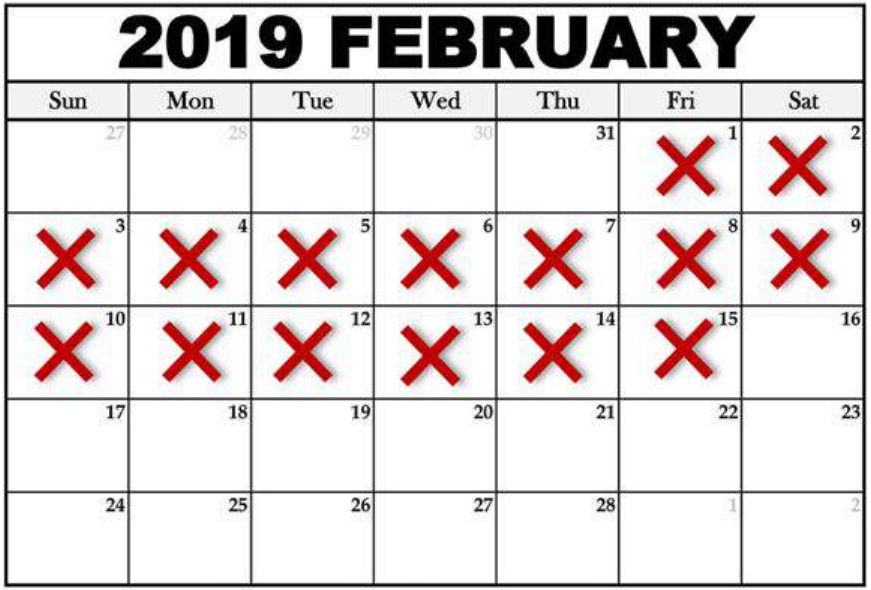
It can only get better right? I consoled myself as I approached my car.

Reaching into my pockets, I panicked...

Where is my car key?!!...



Entry #2



It has been two weeks.

2019 FEBRUARY

Sun	Mon	Tue	Wed	Thu	Fri	Sat
27	28	29	30	31	1	2
3	4	5	6	7	8	9
10	11	12	13	14	15	16
17	18	19	20	21	22	23
24	25	26	27	28	1	2

The bunny is still missing, the girl is still screaming, and the wife is still mad.

THE COOP MIT

I visited MIT COOP for a haircut, and perhaps some retail therapy.

“Looking for a gift?” A young promoter reached out to me. I listened.

NOT A DRONE…

MORE THAN
A DRONE

"This is more than a drone…"

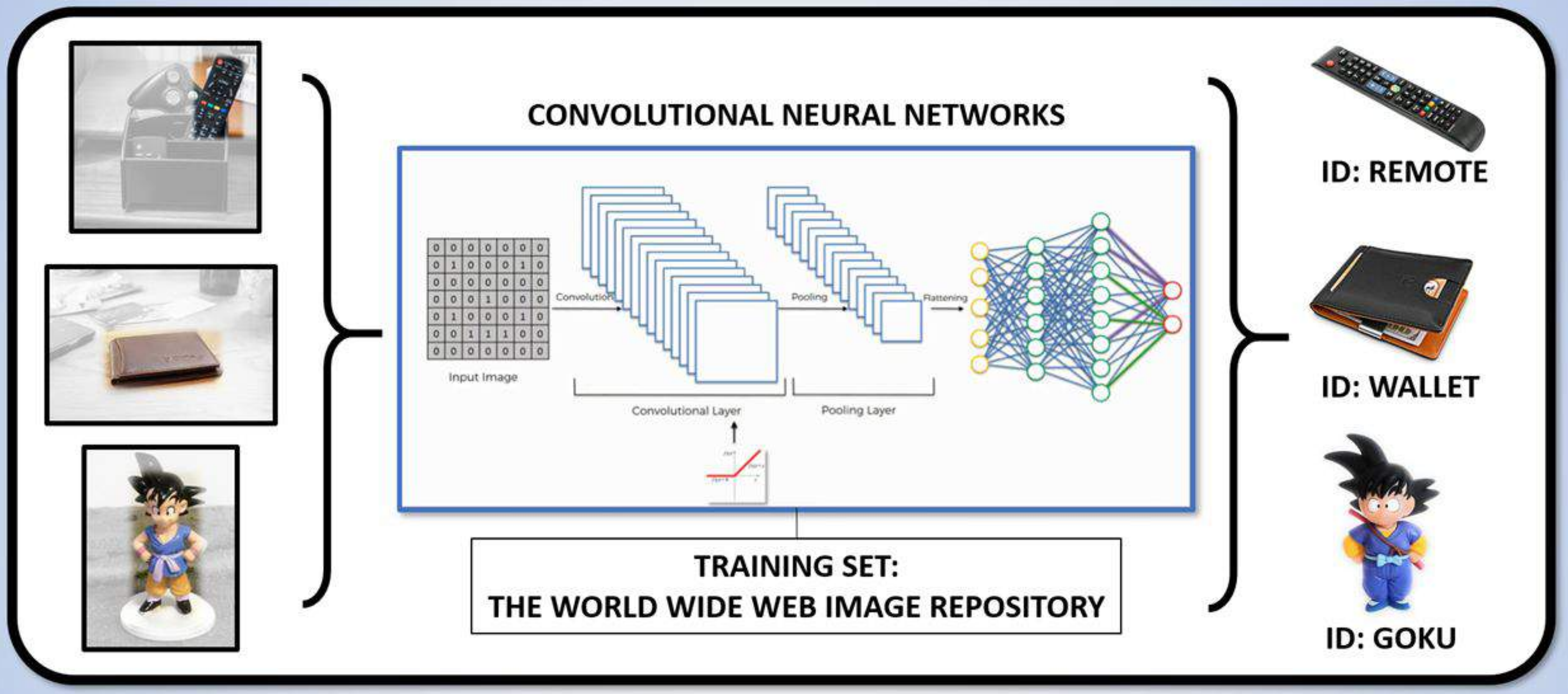
MY. INVENTORY. ASSISTANT.

This is M.I.A. – My Inventory Assistant, except it can be yours, of course. Came straight out of MIT.

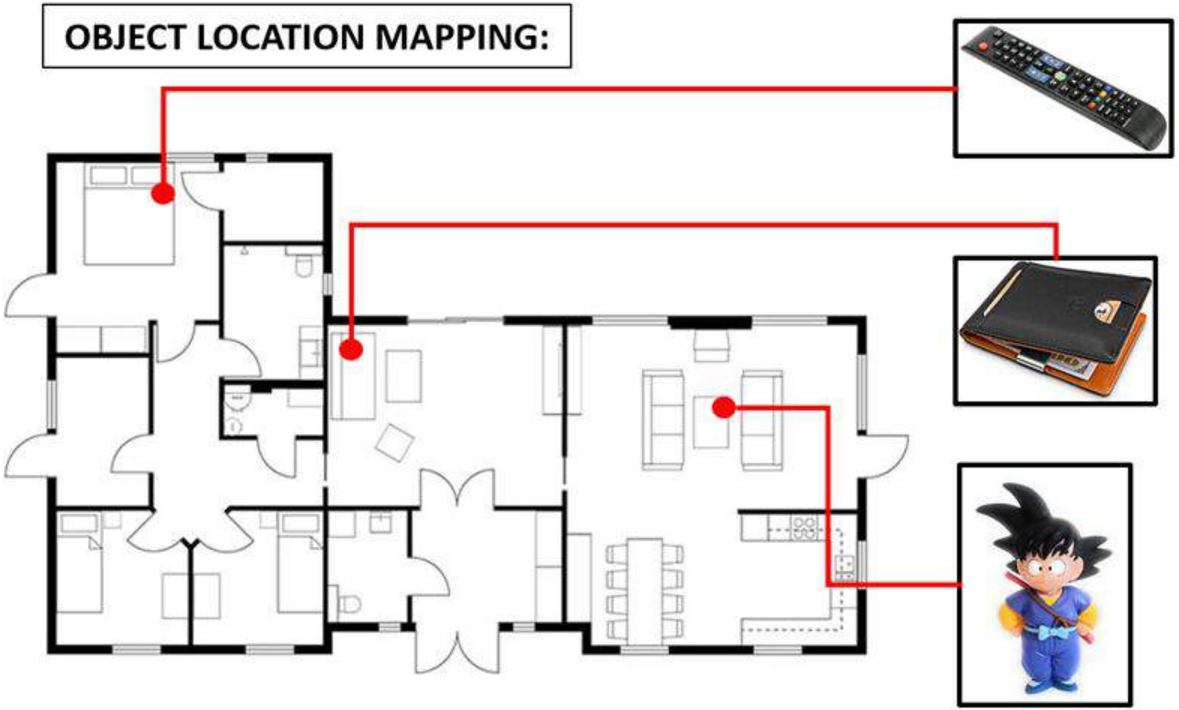
AREA OF COVERAGE:

This gadget navigates around your house while you are at work.

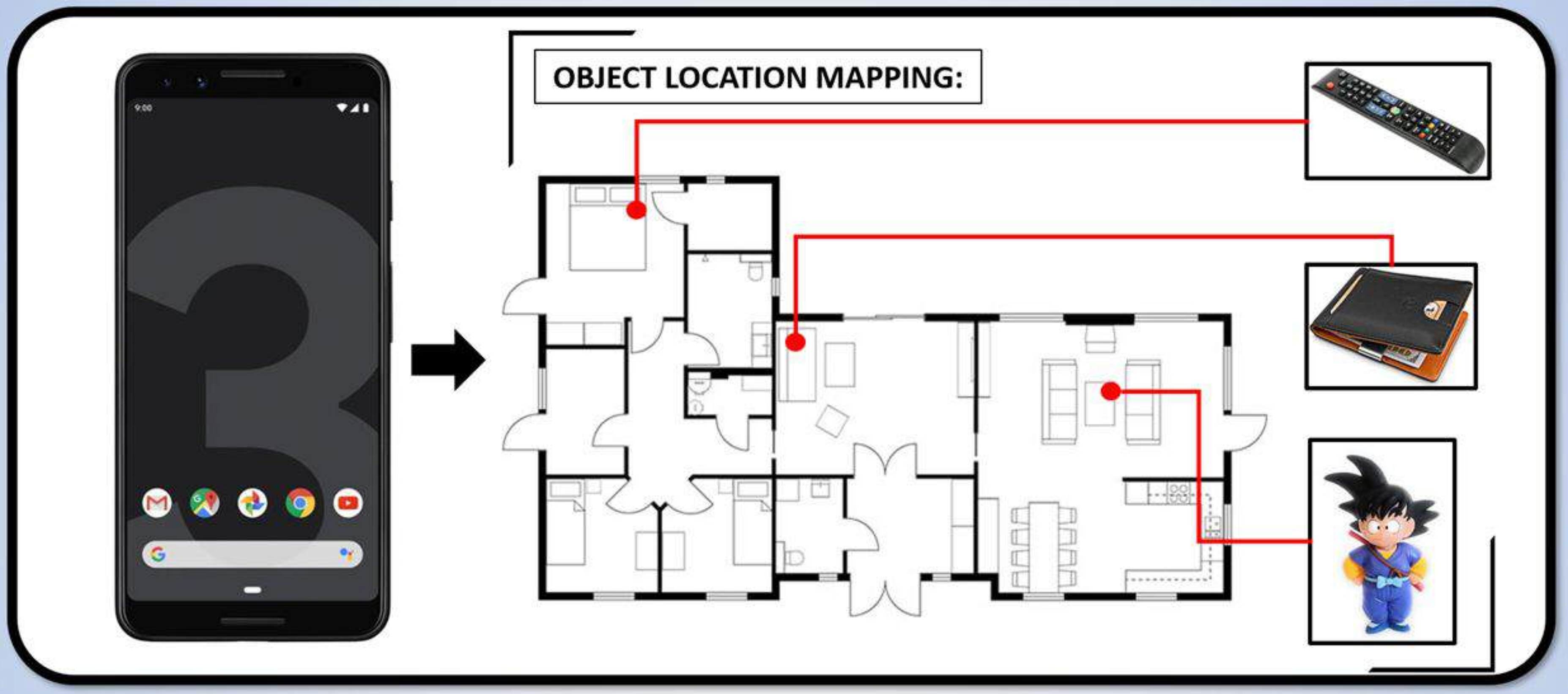
It captures images from every corner of your home and transmits them to a base station.



Using deep learning image recognition, the base station identifies every item in these images…



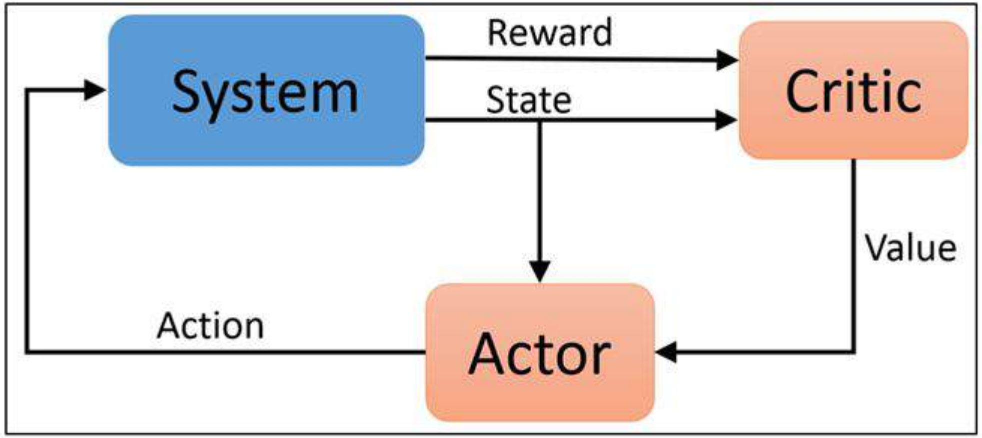
… and maps out their location onto a floorplan.



With a click from your device, you will know the quantity and location of the items.

This gadget gets smarter from here.

REINFORCEMENT DEEP LEARNING

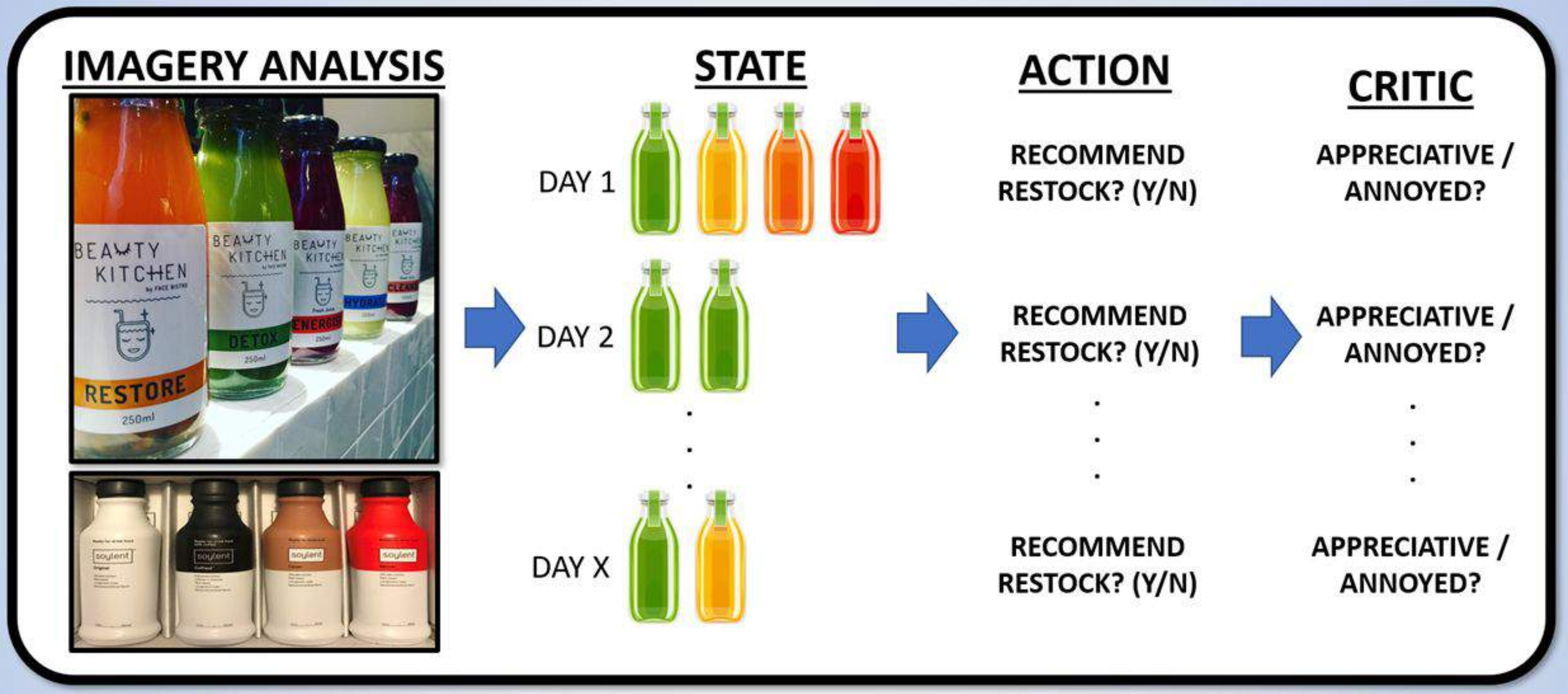


State:
Inventory Level for N Items

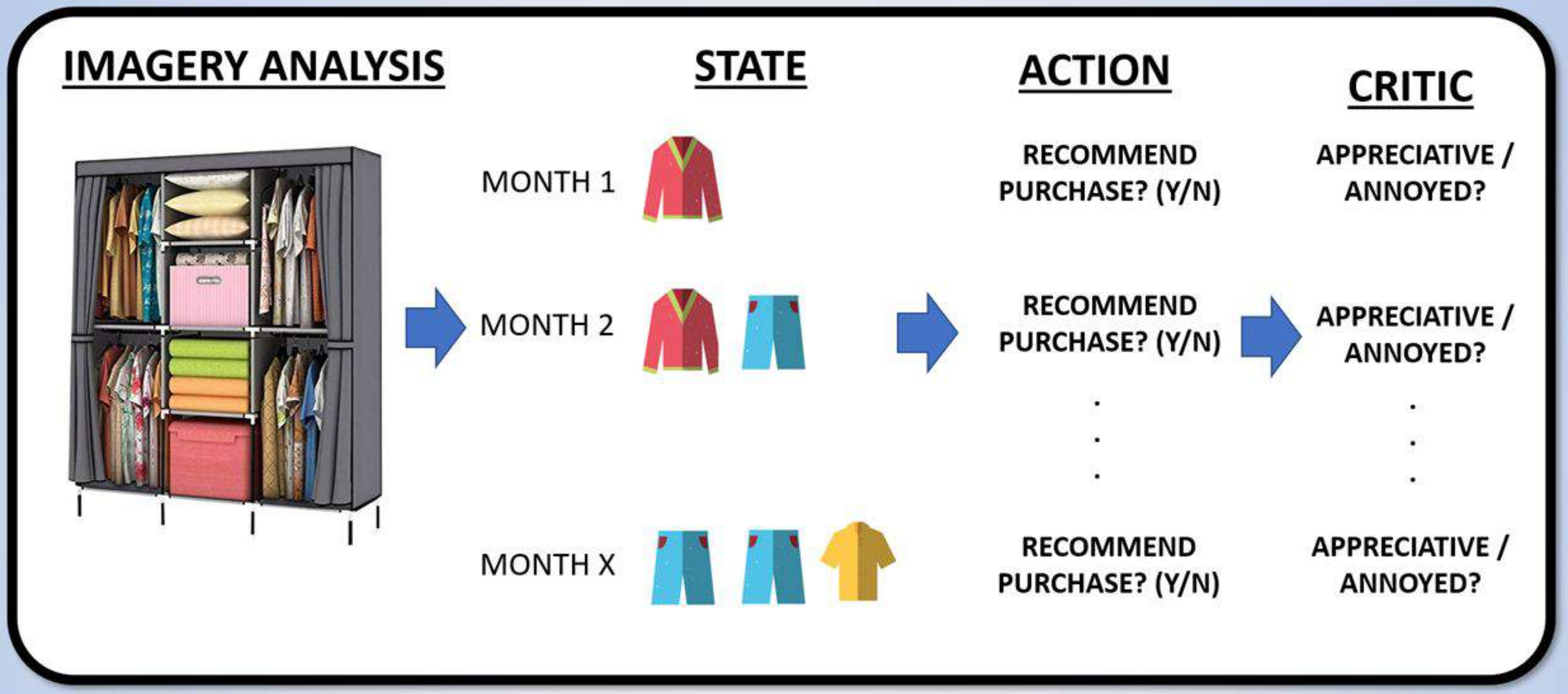
Action:
Prompt Restock for Item Category

Reward:
When Shortfall Predicted Correctly

It also uses reinforcement neural networks to understand and adapt to your consumption patterns.

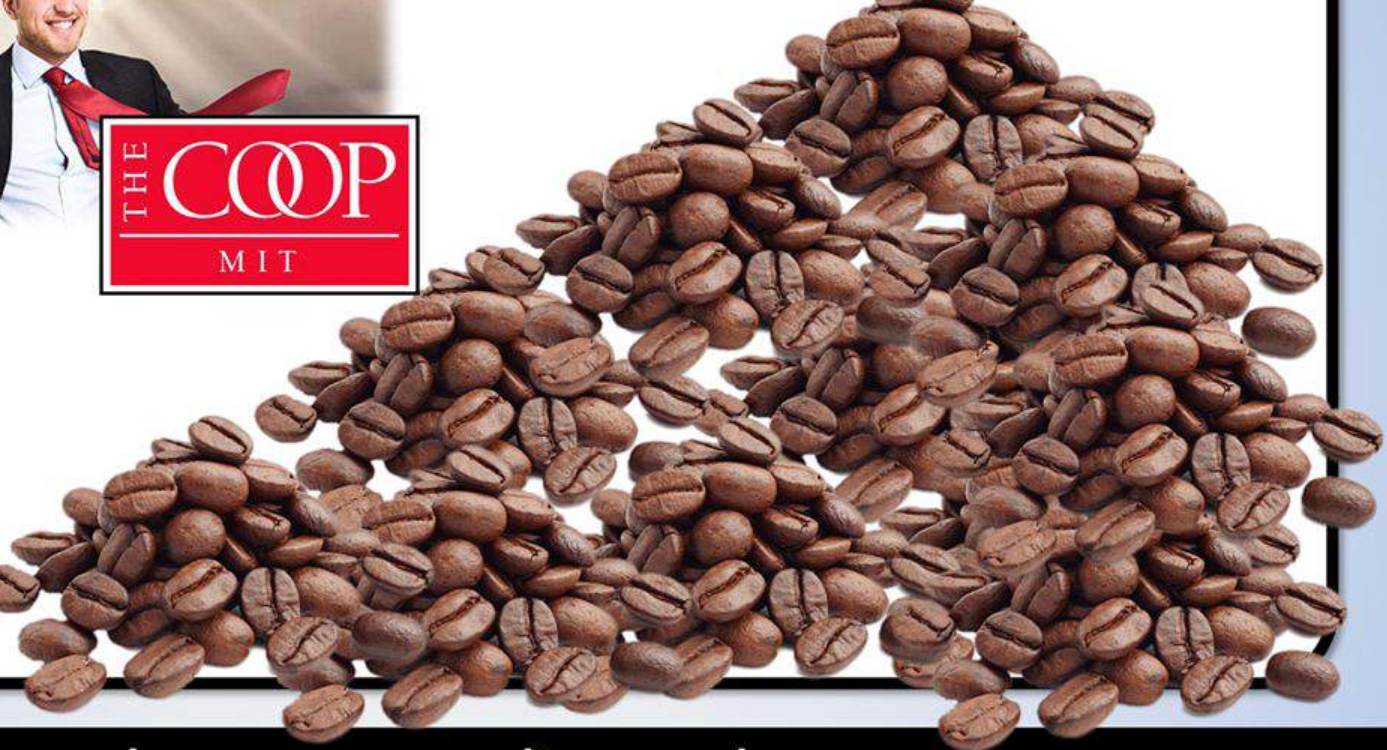


For example, by analyzing daily images captured from your kitchen, it learns if any item type is running low.



It also profiles your wardrobe based on their color, style, and quantity.

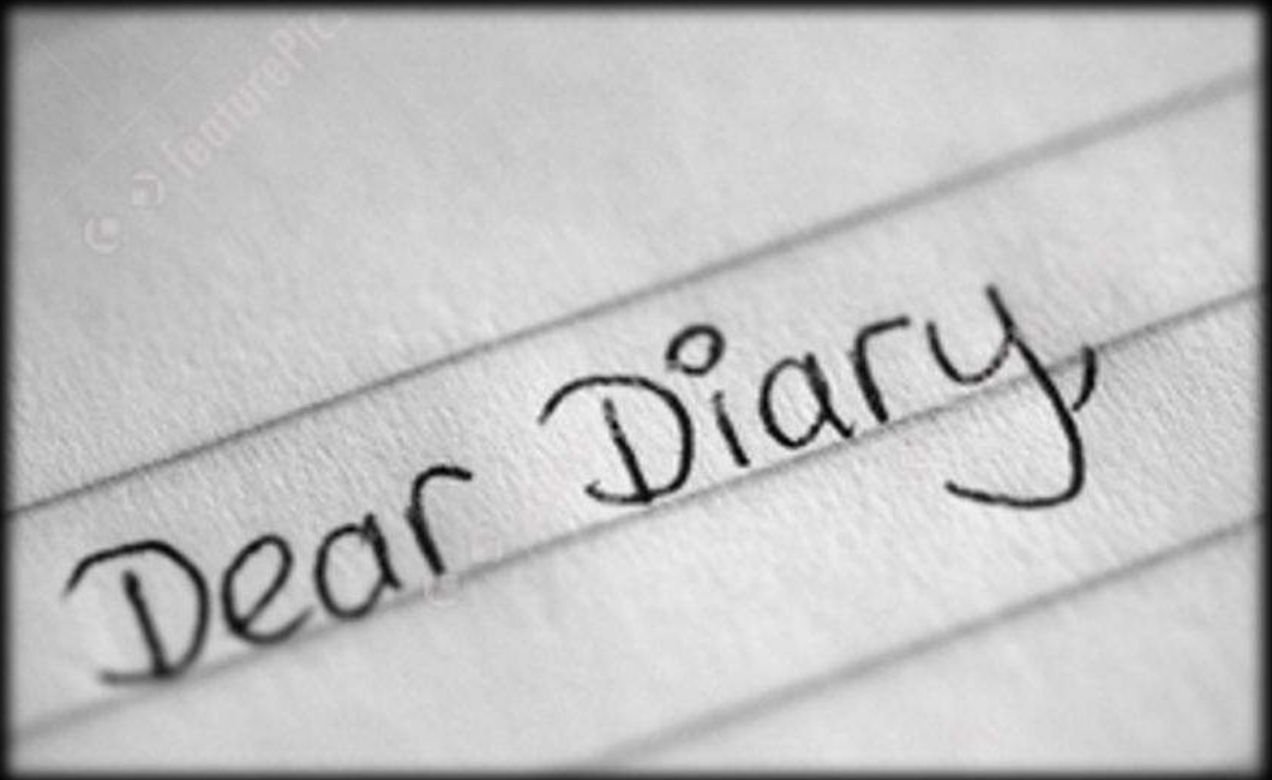
THE COOP MIT



You will never run low on supplies or buy unnecessary stuff again."

THE COOP
MIT

Awesome! I grabbed the gadget and headed towards the checkout counter.



Entry #3

We found the bunny within minutes of deploying my newest gadget.

I returned to the city to look for the perfect anniversary gift.

With my household inventory at my fingertips, I was confident that I would not make the same mistake.

As I parked my car, my cellphone let out a beep. “You are low on coffee.” I was reminded.

As I lay my hand on the door handle, I realized that I left my wedding ring… somewhere at home.

MY. INVENTORY. ASSISTANT.

DEEP LEARNING FOR HOUSEHOLD INVENTORY MANAGEMENT

"It's ok." I reassured myself.

"***My Inventory Assistant*** has my back."

MY. INVENTORY. ASSISTANT.

DEEP LEARNING FOR HOUSEHOLD INVENTORY MANAGEMENT

THANKS FOR LISTENING!

J.S. ANG, C.TAN & S. LEE, SYSTEM DESIGN AND MANAGEMENT 2019 / MIT 6.S191

AI-assisted parenting

Zhenhua (Ray) Rui
&
Kai Jin

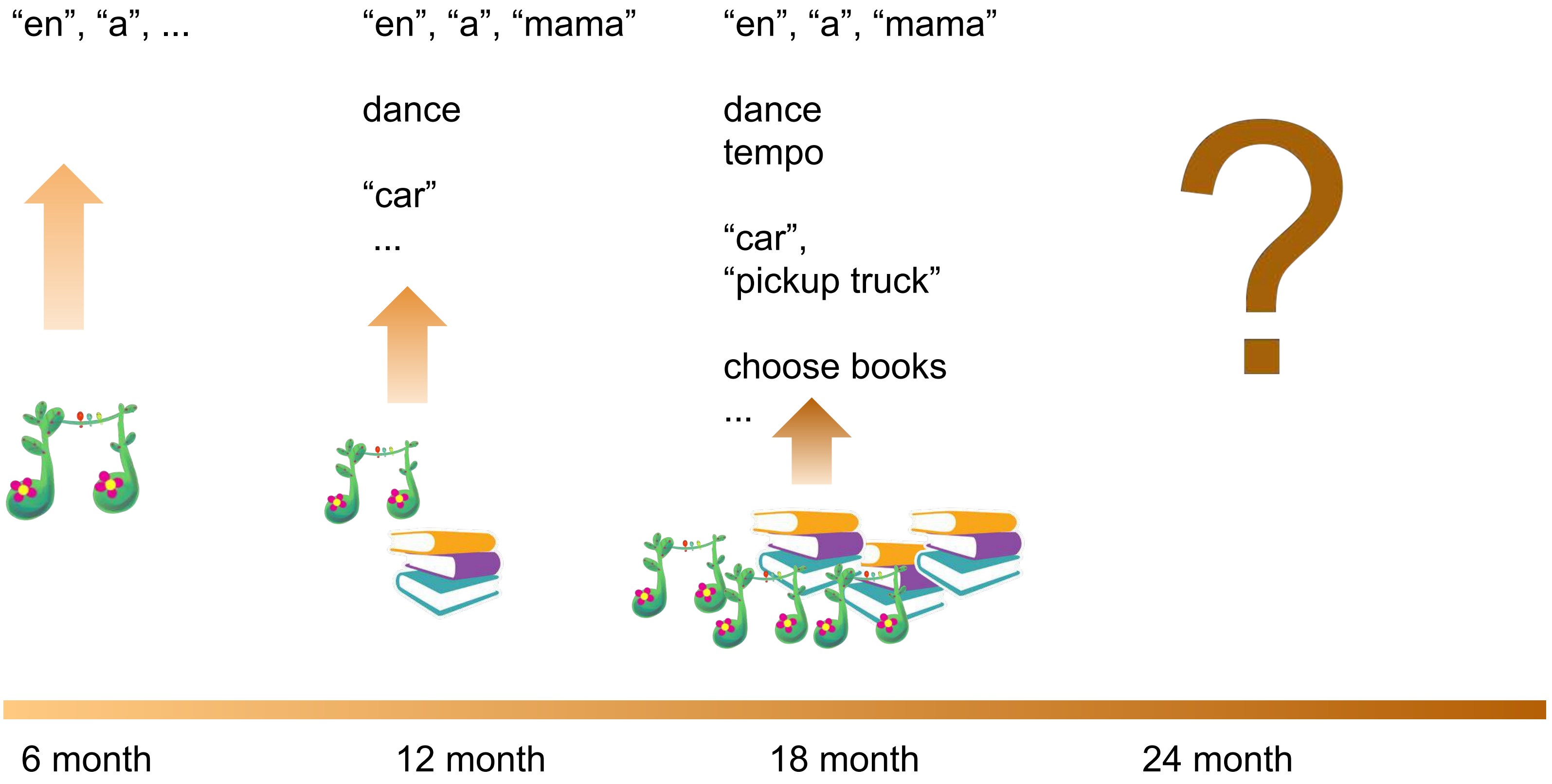
Group 12

parenting is a sophisticated job

Kids development

Language
Motor skills
Mental
Habits
...

learn how kids learn and suggest the next move



challenge

Can AI help parents raise **better** humans?

Using Deep Learning to assist Colorblind people

Victor Horta
Luis Covatti

Agenda

What is **Color blindness**, and why it matters?

What is **the problem** we are trying to solve?

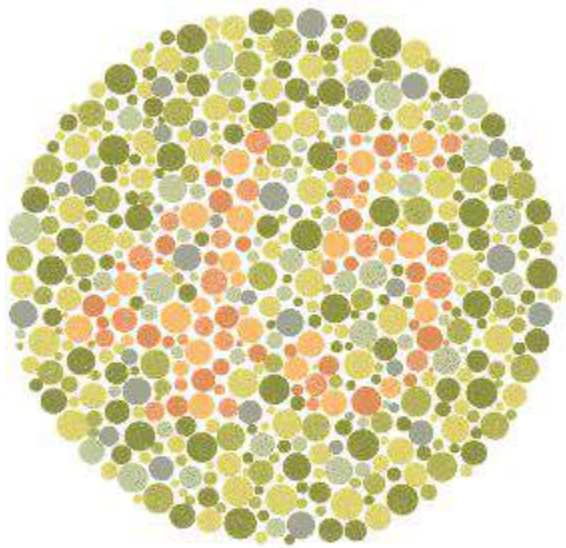
Proposed solution

Potential **applications**

What is Color blindness, and why it matters?

8% of men are colorblind [1]

1 in every 200 women is colorblind [1]



What number do you see?

Source: L. T. Sharpe, A. Stockman, H. Jagle, and J. Nathans, “Color vision: From genes to perception chapter Opsin genes cone photo pigments,” in Color Vision and Color Blindness. Cambridge, U.K.: Cambridge Univ., 1999, pp. 3–51.

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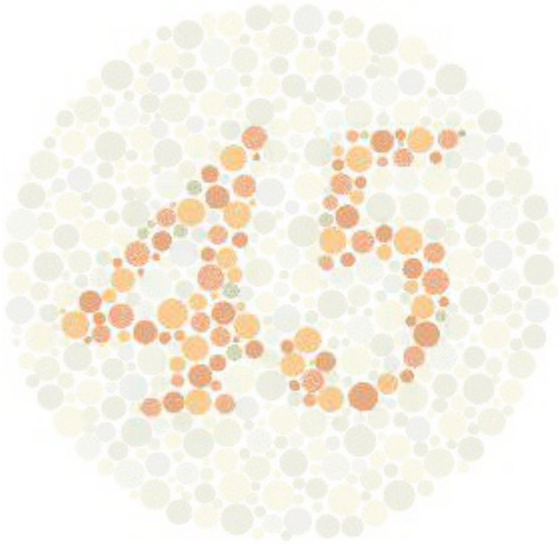


Source: L. T. Sharpe, A. Stockman, H. Jagle, and J. Nathans, “Color vision: From genes to perception chapter Opsin genes cone photo pigments,” in Color Vision and Color Blindness. Cambridge, U.K.: Cambridge Univ., 1999, pp. 3–51.

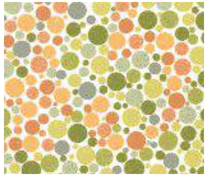
The problem

Colorblind people usually can distinguish standalone colors

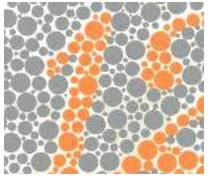
Red

Green

But things get harder when certain shades are very small and close to each other



????



Easy!

Surroundings seem to matter

How can we generate **image filters** that increase the world readability by **slightly tilting colors**, while still maintaining them **as true to their original as possible**?

What has been done so far?

Mechanical solutions

Enchroma glasses

enchroma.
see the difference


Do EnChroma glasses improve color vision for colorblind subjects?

L. Gómez-Robledo, E. M. Valero, R. Huertas, M. A. Martínez-Domingo, and J. Hernández-Andrés

Author Information ▾ Find other works by these authors ▾

"The results show that the glasses introduce a variation of the perceived color, but ***neither improve results in the diagnosis tests nor allow the observers with CVD to have a more normal color vision.****" [1]*

Recoloring algorithms

Aim to improve color differentiation

Drastic change in original colors (unnatural)
Do not preserve **image details**

Original | *Corrected*

Adaptive Fuzzy[2]

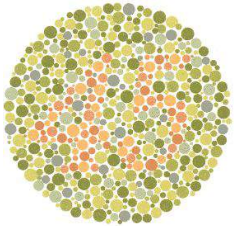
Deep Correct[3]

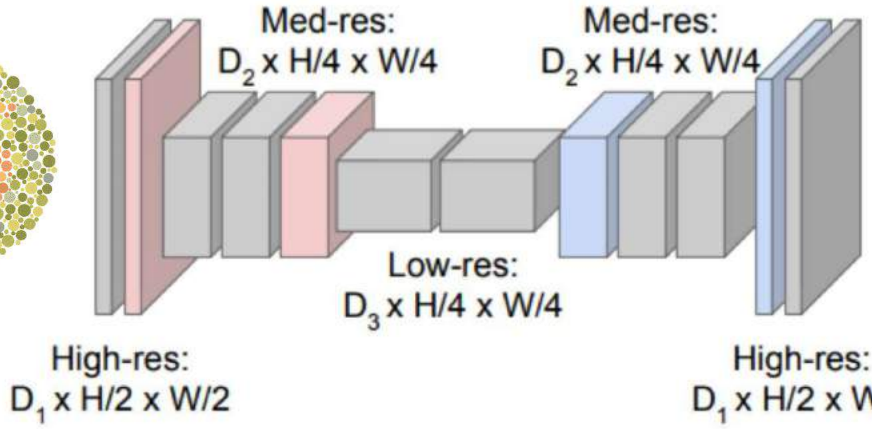
Source: [1] https://www.osapublishing.org/oe/abstract.cfm?uri=oe-26-22-28693
[2] Jimmi Lee, Wellington P. dos Santos. An Adaptive Fuzzy-Based System to Simulate, Quantify and Compensate Color Blindness
[3] Gajo Petrovic, Hamido Fujita. Deep Correct: Deep Learning color correction for color blindness

The model/system

[Illustrative]

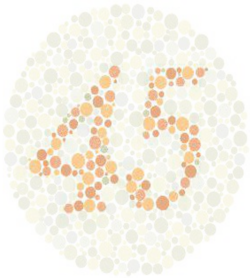
Input image





CNN

Output image



Using colors within the domain of visualization for colorblind people

Loss-function dependent on:

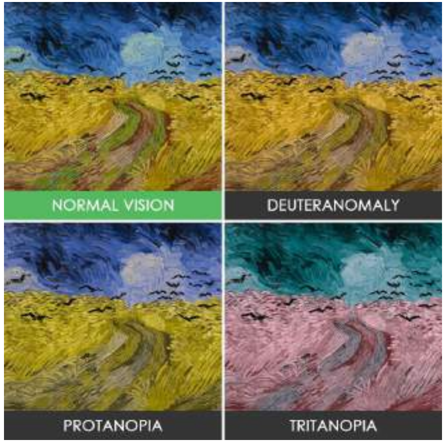
Interpretability by colorblind people **max**

Assessed by mathematical transformation and field tests (feedback)

Distortion from original image **min**

Potential applications

Improve accessibility to digital content



Visual Arts
(paintings, movies)

Entertainment
(games)

Internet
(maps readability, web design)

Thank you

All Dolled Up:
How Deep Learning Can Teach Children to Love Themselves

By: DIna Atia, Faduma Khalif, Yousef Mardini

Group 17

Background

- National Black Doll Museum
- Topsy Turvy Dolls
- Mattel Barbie: 1968, 1980

All Dolled Up:

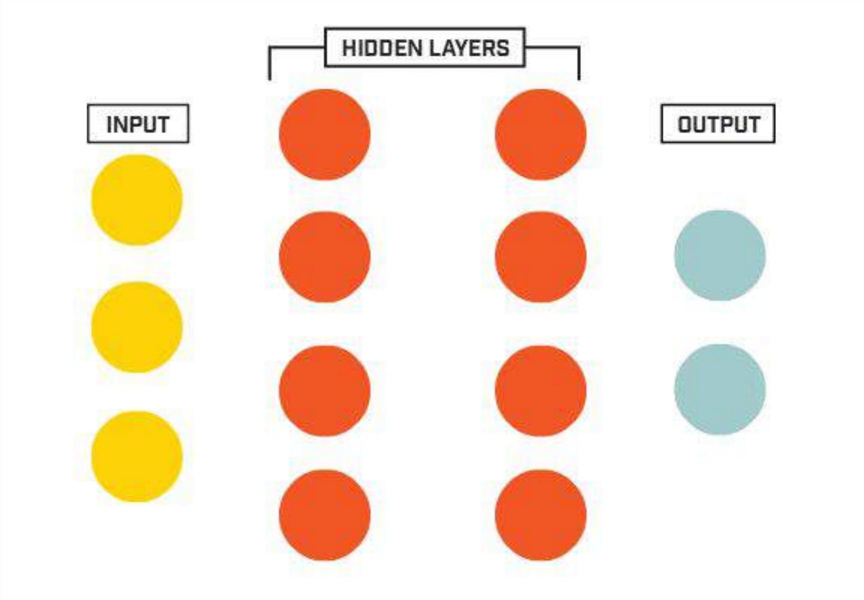
- Learns what you look like
- Maps your features to doll feature set
- Doll that looks like you!

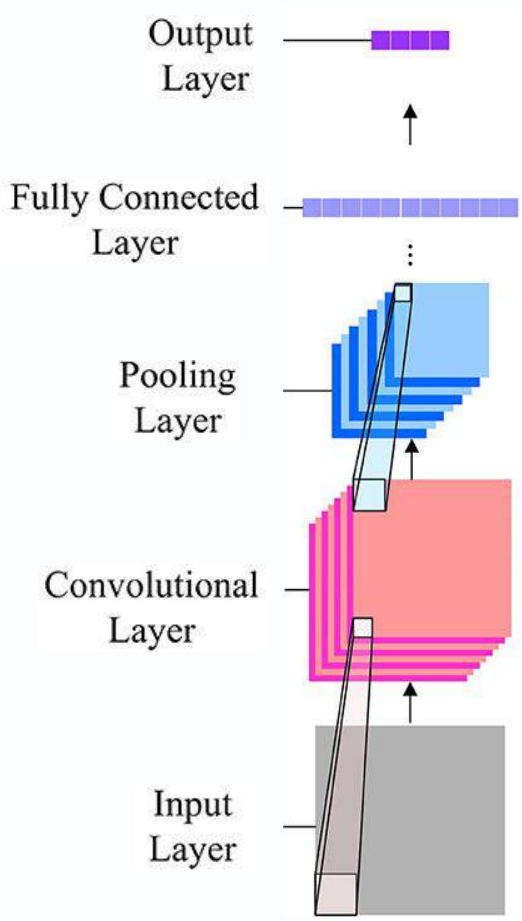
Methodology

- collecting ground truth data
- training a set of Classifiers
- applying the most accurate classifier to raw, unannotated data.
- making the necessary corrections to focus on the weak points of the classifier

The Classifier

A CNN





Thanks For Listening!!

Please Give Us Prizes

Background

- National Black Doll Museum
- Topsy Turvy Dolls
- Mattel Barbie: 1968, 1980

Customized interior design using generative models

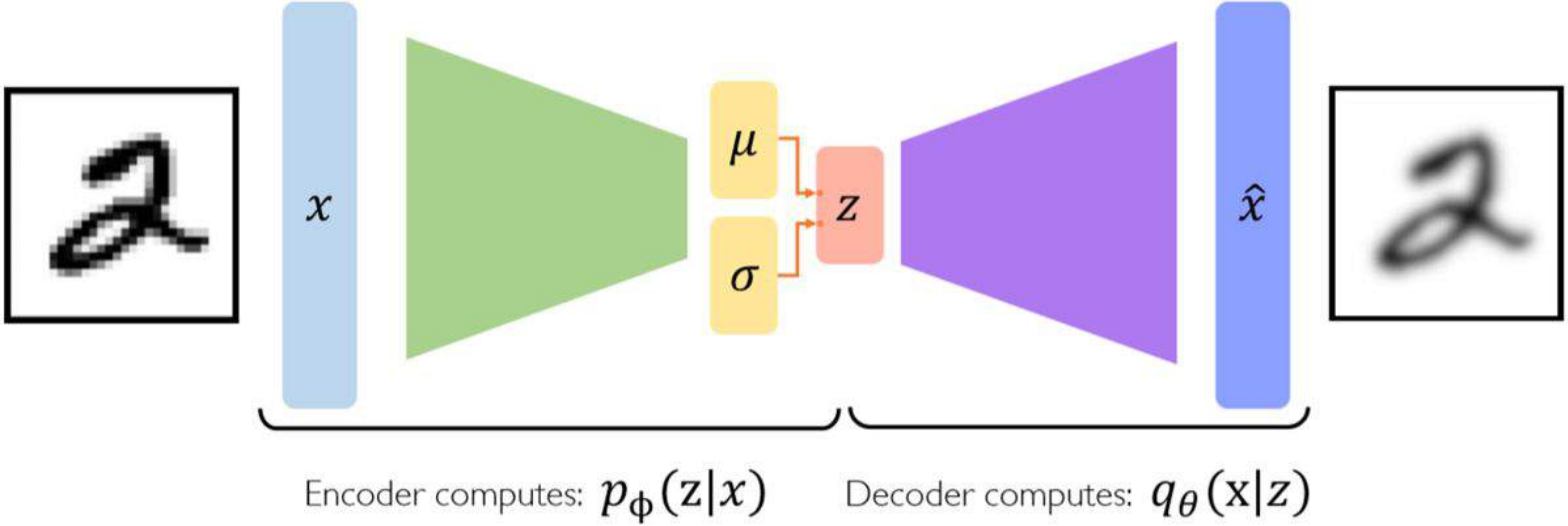
Group 18: Keran Rong ; Mia Hong

Customized interior design using generative models

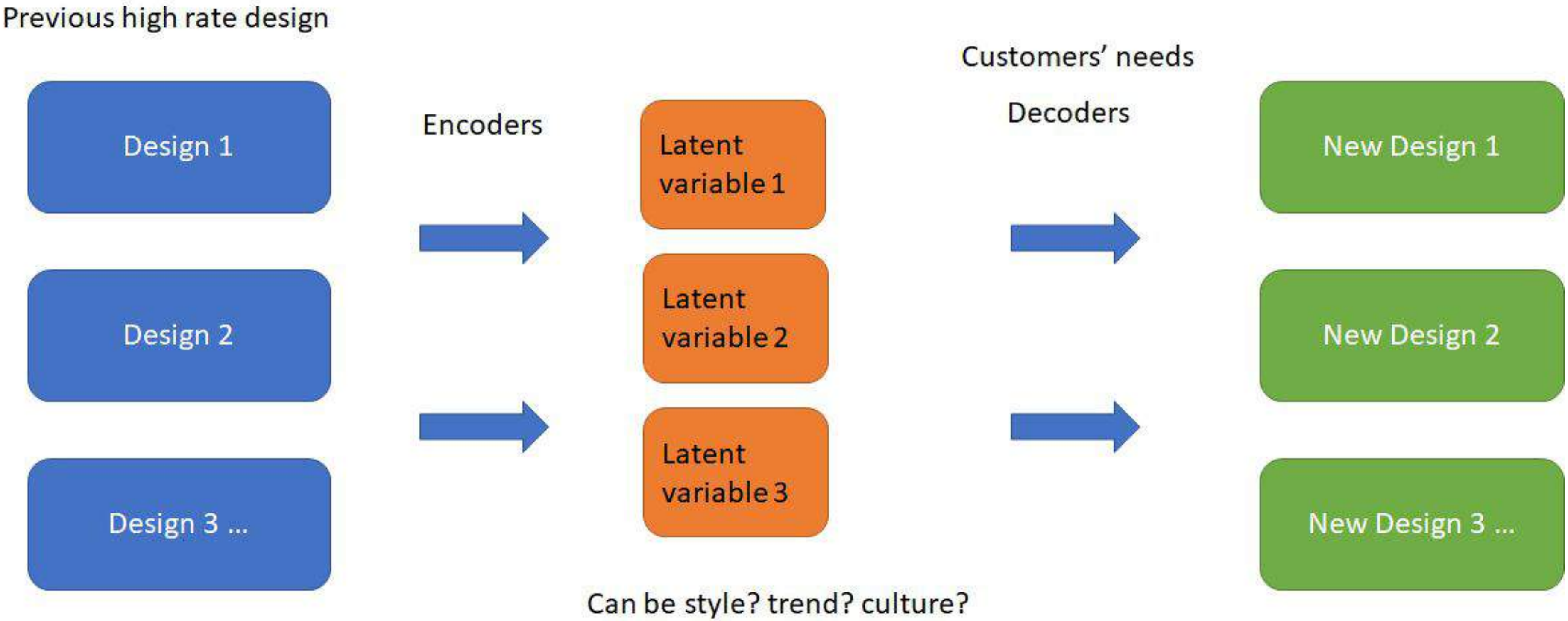
Interior design Current situation:

- A high demand in market
- High expertise is needed
- Fashion – sensitive
- Customized design is expensive

VAE optimization



Customized interior design using generative models



Thank you! Any Questions?

Neural Networks as an early-stage Architecture Design & Sustainability Tool

6.S191

Group 23
Yu Qian Ang (credit)
Klo'e Ng (listener)

PROBLEM

THE BUILT ENVIRONMENT:

LARGE AMOUNT OF WASTE

>3 Billion tonnes of raw materials consumed annually

ENERGY INTENSIVE

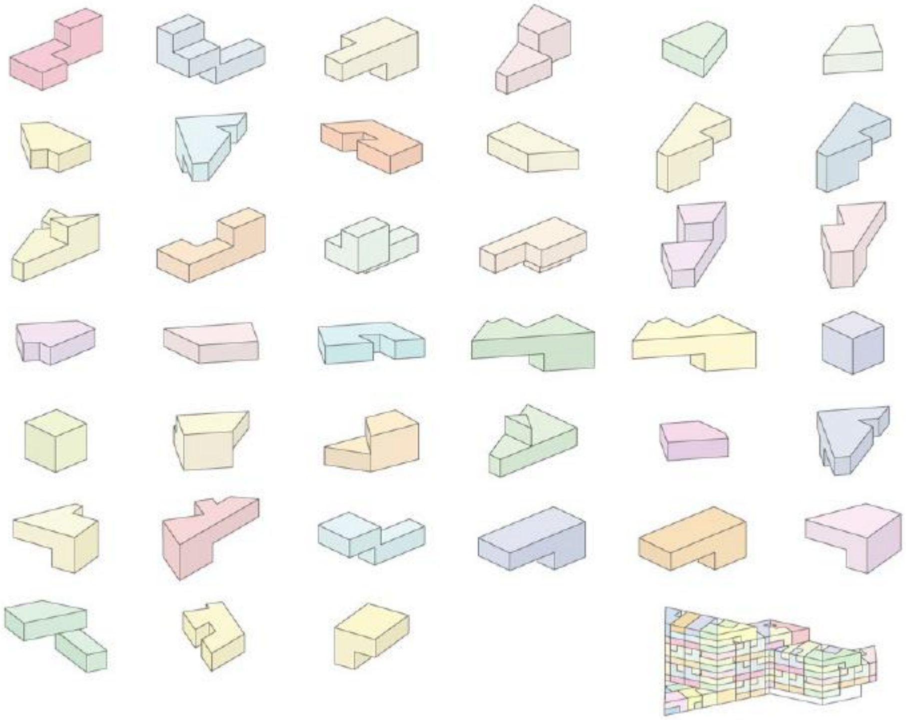
Built environment consumes >30% to 70% of total primary energy use

CARBON EMISSIONS

Buildings are key contributor to greenhouse gas emissions around the world

PROPOSED APPLICATION

EARLY STAGE DESIGN IN BUILT ENVIRONMENT



WHY MACHINE LEARNING / NEURAL NETWORK:

- Human design inherently subjective
- Opportunity for impact downstream (enhance sustainability)
- Insufficient time/manpower to explore many design options
- Human error, blind-spots, and bias

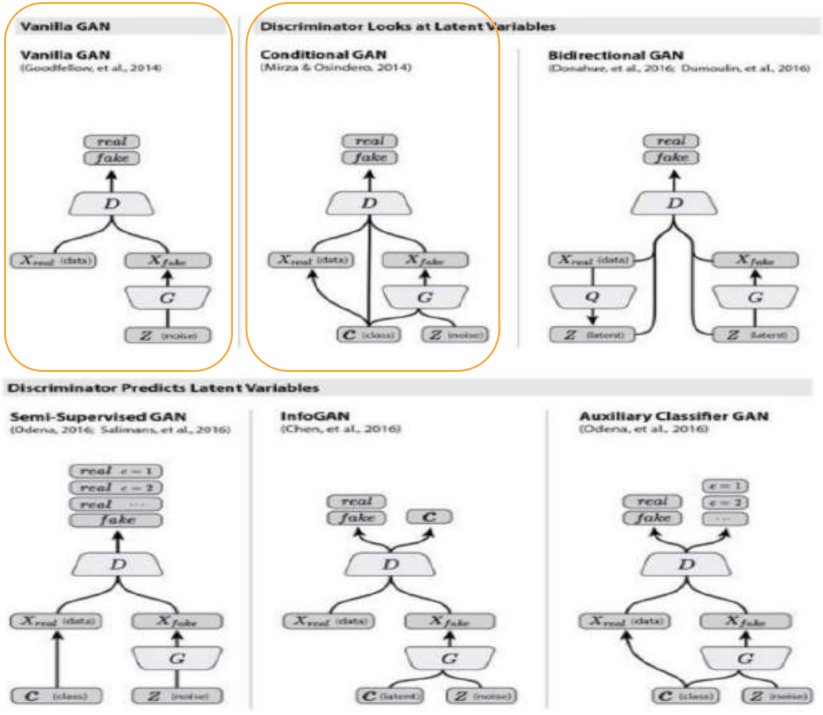
PROPOSED APPLICATION

GENERATIVE ADVERSARIAL NETWORKS (GAN)

A Identify key parameters/features to optimise

- (Low) carbon footprint
- Cost efficiency
- (Low) energy use/wastage
- (Low) material wastage

B Design and develop GAN model



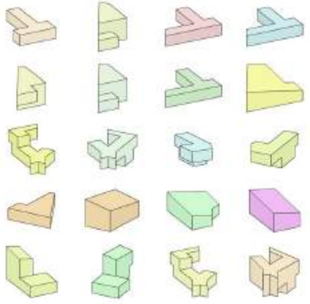
Group 23

PROPOSED APPLICATION

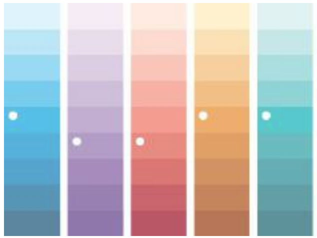
GENERATIVE ADVERSARIAL NETWORKS (GAN)

1 Data | Samples

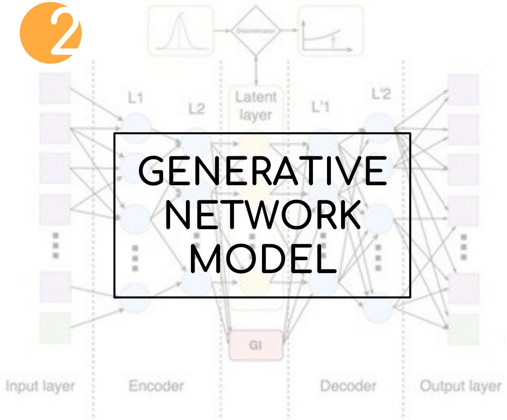
Data/samples from past projects, or design options developed manually



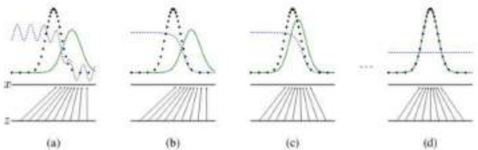
Latent Space



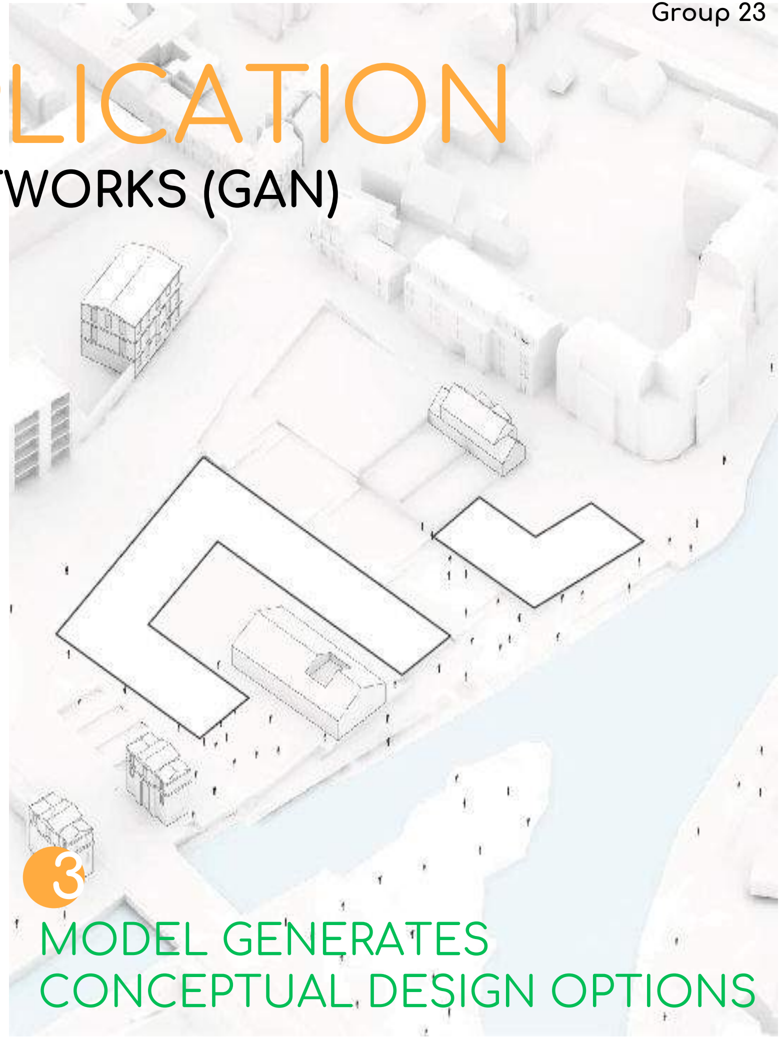
2



GENERATIVE NETWORK MODEL



Feed data into model to train iteratively, aim to minimize loss



3

MODEL GENERATES CONCEPTUAL DESIGN OPTIONS

IMPACT & CHALLENGES

POTENTIAL IMPACT

- more/better building design options
- Enhanced sustainability
- Less wastage
- Less human error/bias

CHALLENGES

- Mode collapse: generator keeps generating similar designs

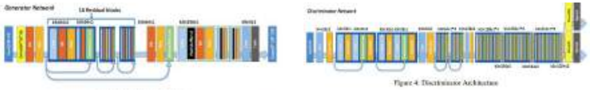
  (limited diversity of samples)
- Validation of GAN outputs

  (may need to run physics based simulations)
- Contextualizing the GAN outputs

  (architecture is sometimes highly contextualized)

SIMILAR APPROACHES/APPLICATIONS

1 Generating Anime Girls

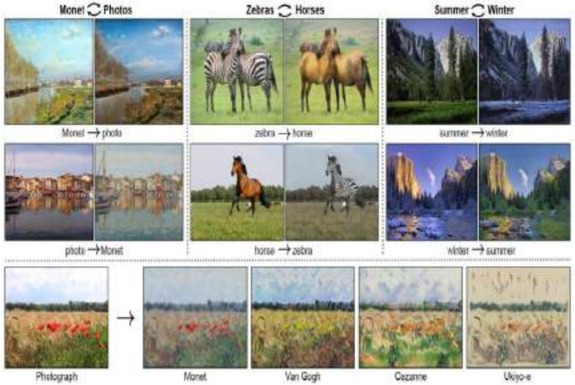


Jin et al (2017)
(Fudan & Carnegie Mellon)

2 Generating Pose-guided Apparel

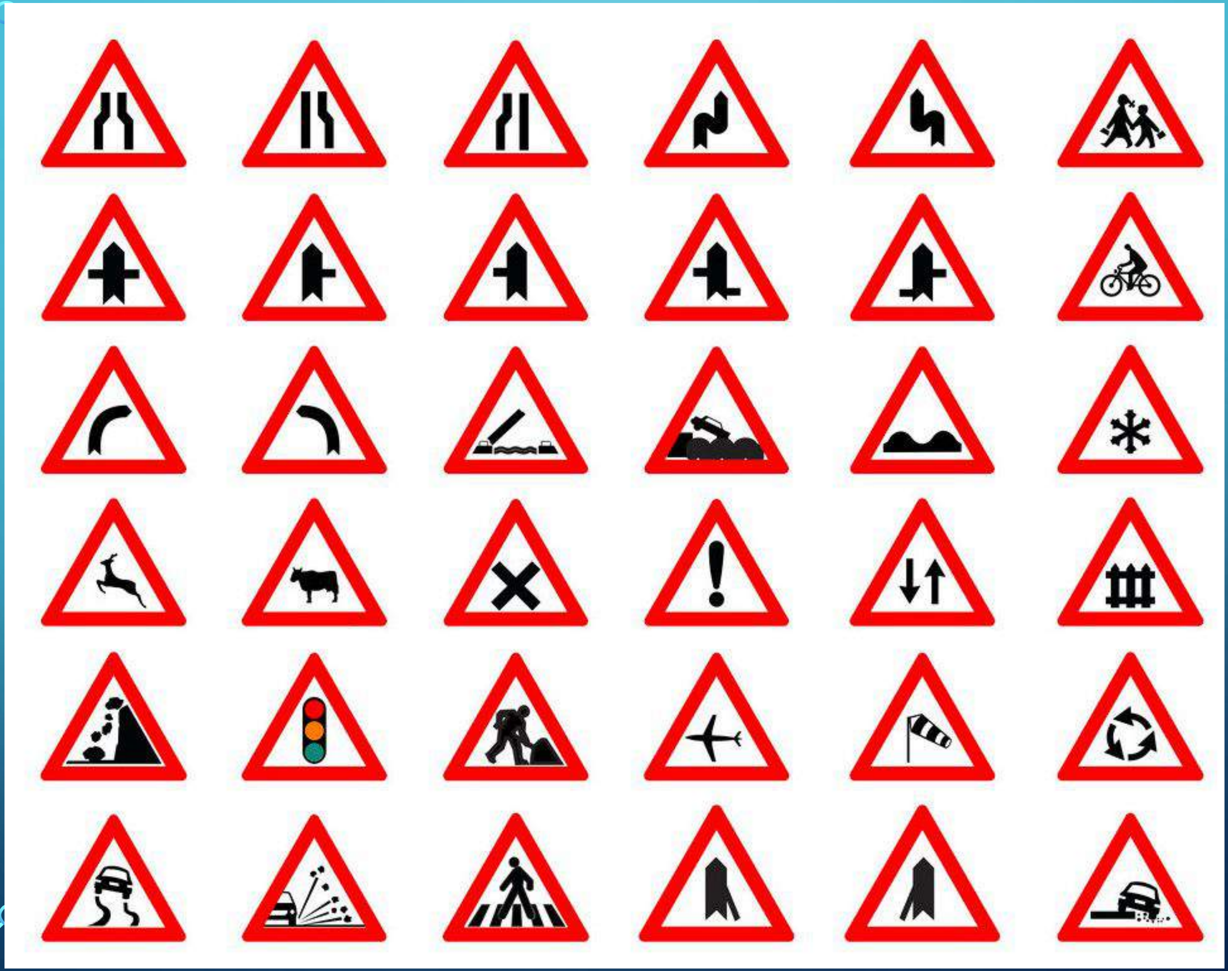
Ma et al (2018)
(KU-Leuven & ETH Zurich)

3 CycleGAN: Generating photos from paintings etc



Zhu et al (2017)
(UC Berkeley)

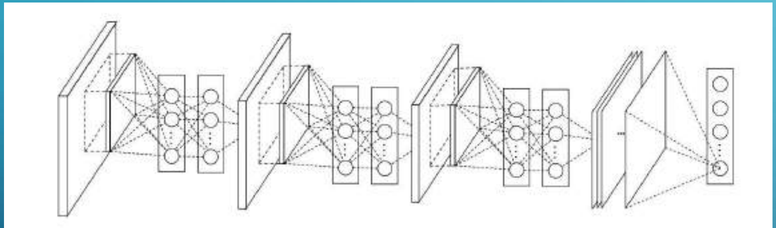

THANK YOU

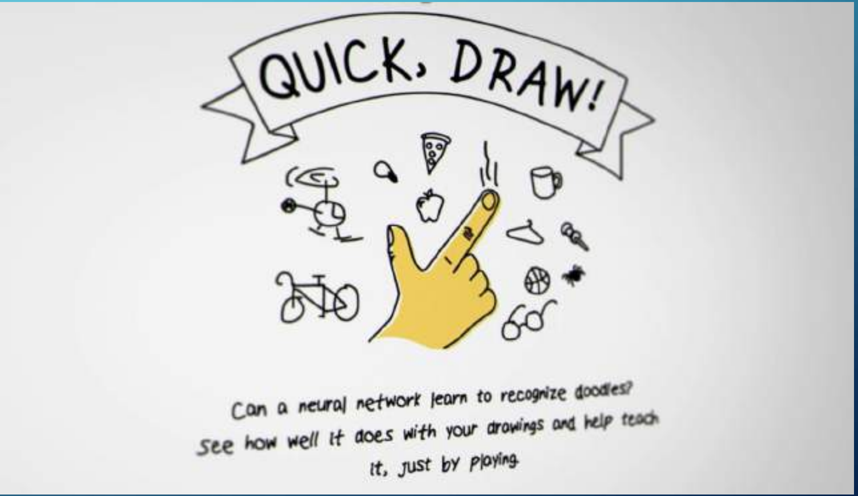


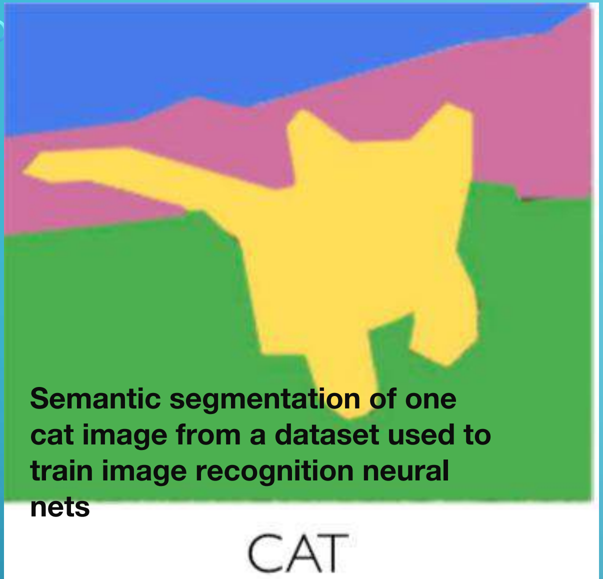
DEEP DOODLE

DEEP LEARNING METHODS TO GENERATE SKETCHES FROM LABELS

WHAT DEEP LEARNING CONCEPTS ARE WE USING?



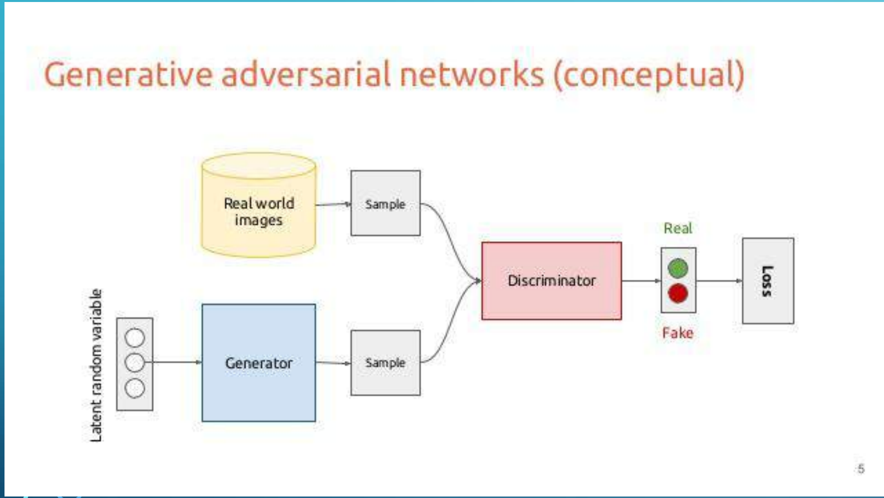


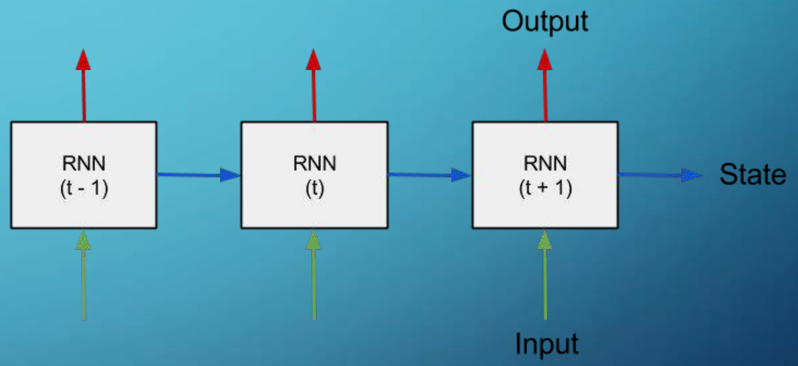


Semantic segmentation of one cat image from a dataset used to train image recognition neural nets

Some cat doodles from Google QuickDraw

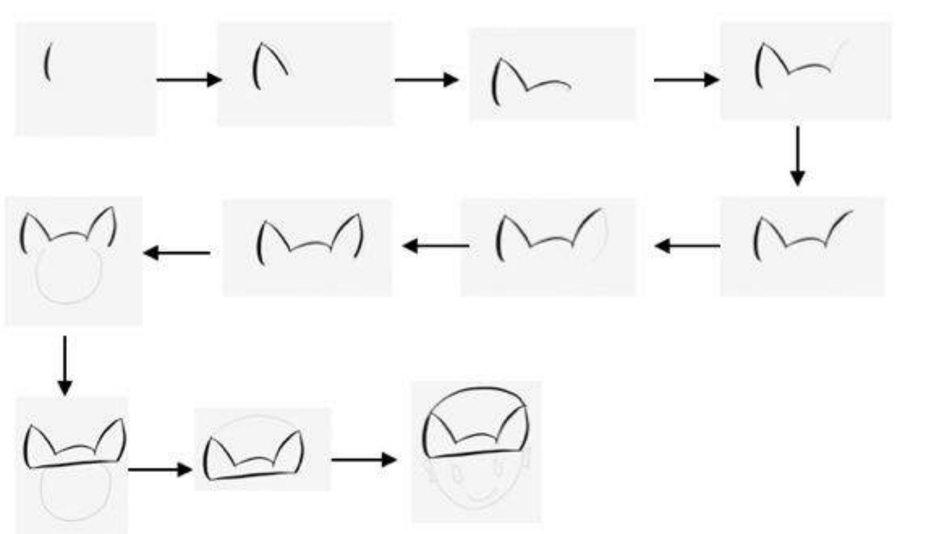
WHAT DEEP LEARNING CONCEPTS ARE WE USING?





POSSIBLE APPLICATIONS

- Used in cognitive interviews
- Animating children's books in real time.
- Assistive technology for teaching kids to draw.



Demo

https://colab.research.google.com/drive/1hHMR3Q2-Iugs8fb5GXG3SGmwXkMpo2FC

https://magenta.tensorflow.org/assets/sketch_rnn_demo/index.html

Deep Learning in Major League Baseball

Maximilian Porlein and Jack Phifer, MIT 2022

Inspiration

MLB Beat the Streak: choose up to two Major League players daily. String together a 57-game hit streak to beat Joe DiMaggio’s record of 56 games and you win $5.6 million dollars. If either of your players goes hitless, you start all over.

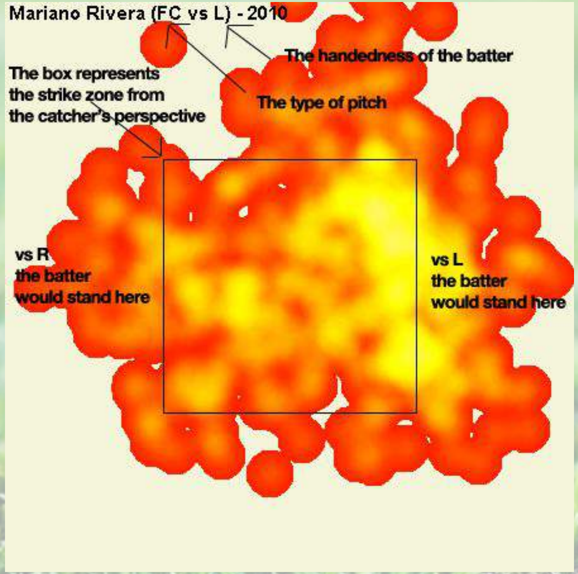
Why not just pick the top hitters in the MLB?

Why not just pick the top hitters in the MLB?

- Too many factors can influence a player’s ability to make a hit

Why not just pick the top hitters in the MLB?

- Too many factors can influence a player’s ability to make a hit
  - Pitcher:



Source: FanGraphs PITCHF/x, Feb 2011

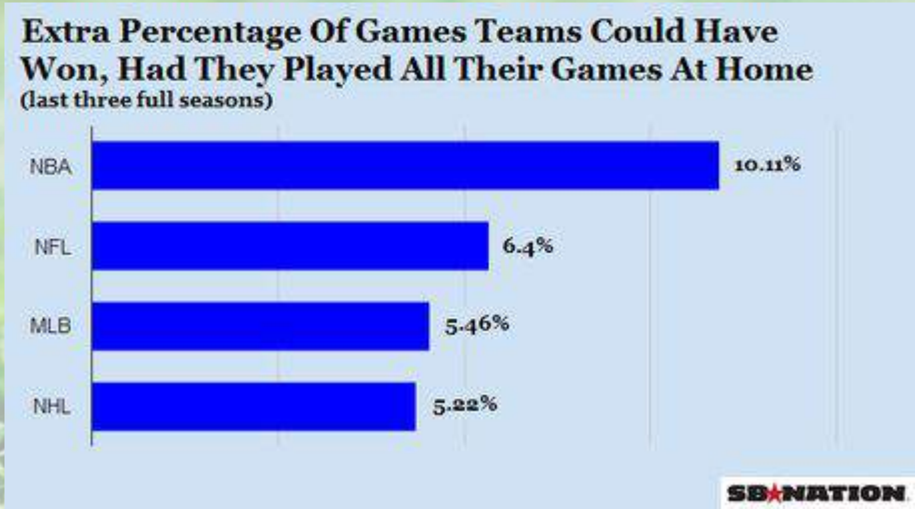
Why not just pick the top hitters in the MLB?

- Too many factors can influence a player’s ability to make a hit
- Weather:
  - Air temperature can change a baseball's trajectory
  - Air density can play a role in how far a ball travels
  - High and low temperatures can affect a pitcher's grip
  - Cloud coverage can affect how players see the ball
  - Windy conditions

Source: Alan Nathan, University of Illinois Department of Physics

Why not just pick the top hitters in the MLB?

- Too many factors can influence a player’s ability to make a hit
- Location:
  - Home team advantage



Source: SB Nation, Jan 2011

Our Model - Formulation

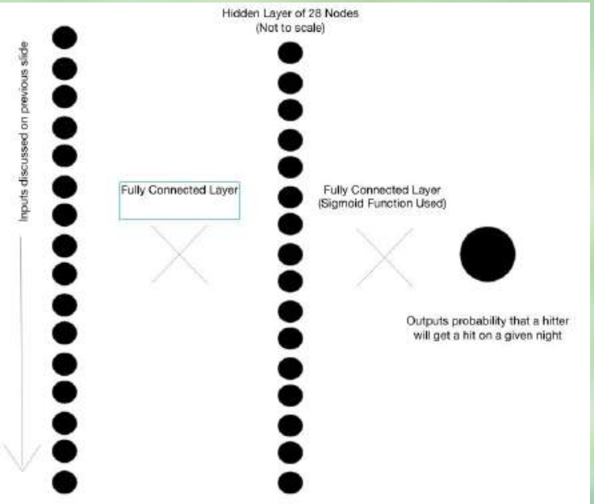
- 16 Different Variables
    - Data compiled from several different sources including mlb.com and baseball-reference
    - Most categories didn’t directly exist but were compiled in python
    - All categories were scaled to a value between 0 and 1

```python
class Batter():
    def __init__(self,player_dict):

        player = player_dict['Player']

        self.career_ba = player['career'][0]['avg']
        self.season_ba = player['season'][0]['avg']
        self.month_ba = player['month'][0]['avg']
        self.walks_per_ab = (player['career'][0]['bb']/player['career'][0]['ab'])

        self.ba_against_rhp = player['month'][0]['vs_RHP']
        self.ba_against_lhp = player['month'][0]['vs_LHP']

        self.ballpark_rank = 1
        self.bullpen_rank = 1

        if player['Team'][0]['des'] == 'Home':
            self.home = 1
        else:
            self.home = 0

        got_hit = False
        for ab in player['atbats'][0]['ab']:
            if 'Single' or 'Double' or 'Triple' or 'Home Run' in ab['event']:
                got_hit = True

        if got_hit:
            self.got_hit = 1
        else:
            self.got_hit = 0
```


```json
],
"vs_LHP": [
  {
    "avg": ".263",
    "ab": "95",
    "h": "25",
    "bb": "10",
    "so": "16",
    "r": "9",
    "sb": "2",
    "cs": "0",
    "hr": "0",
    "rbi": "6",
    "ops": ".667"
  }
],
"vs_RHP": [
  {
    "avg": ".238",
    "ab": "143",
    "h": "34",
    "bb": "20",
    "so": "37",
    "r": "11",
    "sb": "6",
    "cs": "0",
    "hr": "3",
    "rbi": "13",
    "ops": ".680"
  }
],
"vs_P": []
```

Our Model - Implementation

- Used 1 hidden layer
  - Consisted of 28 nodes
- Outputted probability of a hit
- All active players are fed into NN and player with the highest output is selected for that night



```
# number of neurons in each layer
input_num_units =
hidden_num_units =
output_num_units =

# define placeholders
x = tf.placeholder(tf.float32, [None, input_num_units])
y = tf.placeholder(tf.float32, [None, output_num_units])

# set remaining variables
epochs =
batch_size =
learning_rate =

### define weights and biases of the neural network (refer this article if you don't understand the terminologies)

weights = {
    'hidden': tf.Variable(tf.random_normal([input_num_units, hidden_num_units], seed=seed)),
    'output': tf.Variable(tf.random_normal([hidden_num_units, output_num_units], seed=seed))
}

biases = {
    'hidden': tf.Variable(tf.random_normal([hidden_num_units], seed=seed)),
    'output': tf.Variable(tf.random_normal([output_num_units], seed=seed))
}

#Define structure of nueral netwok
hidden_layer = tf.add(tf.matmul(x, weights['hidden']), biases['hidden'])
hidden_layer = tf.nn.sigmoid(hidden_layer) ##Network uses sigmoid function
output_layer = tf.matmul(hidden_layer, weights['output']) + biases['output']
```

Our Model - Conclusion

- Model was trained using data from 2016 and 2017 season
  - 2018 was used as the testing data
- Model was largely unsuccessful as it could never put together high streaks
  - Highest streak was 9
- Reasons the model fell short
  - Baseball is an imperfect game with human variation
  - Not enough testing data (data for previous years wasn’t as accessible)
  - Not enough training time

Extensions of Our Model

- Allows individual teams to choose rosters before playing specific teams
- Teams can use to determine their most consistent players
- Can be used in recruitment for colleges and teams
  - See which players are most consistent

Extensions of Our Model

MLB Beat the Streak:

- Even if the model is not completely perfect…
    - MLB frequently gives “off-day” exceptions to streaks longer than 10-15 days
    - Prizes (like merchandise) are still awarded to streaks as short as 5 days

Thank you!

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Jack Phifer - jphifer@mit.edu

Final Project Presentations

MIT 6.S191
February 1, 2019