



Final Project Presentations

MIT 6.S191
February 1, 2019



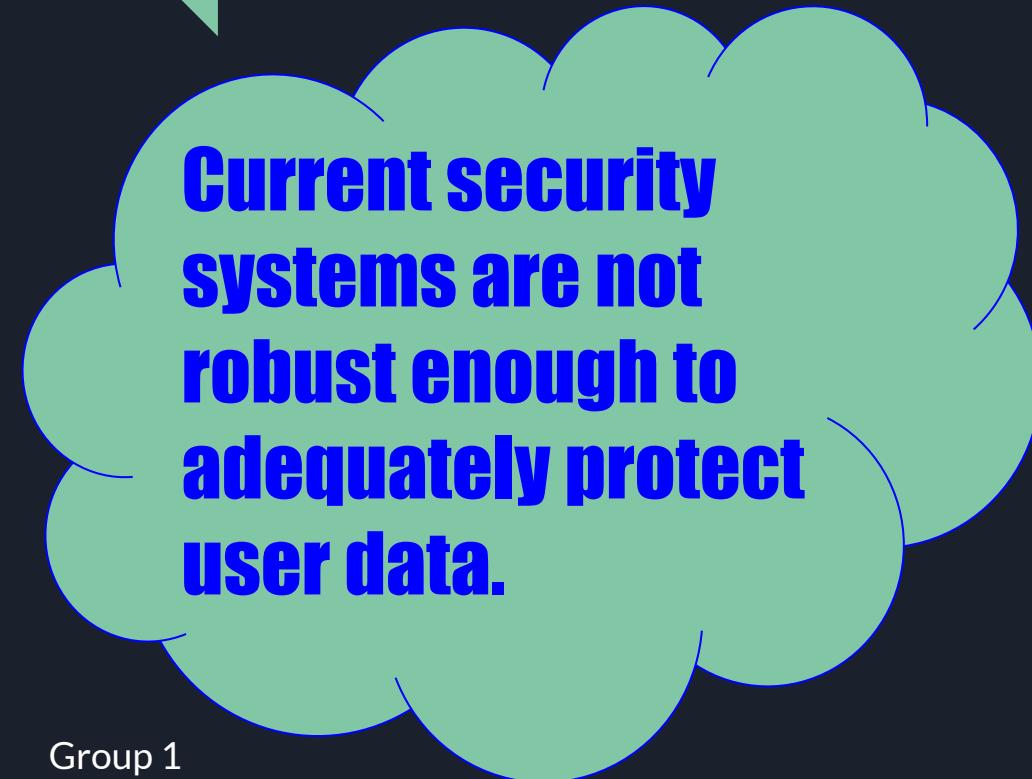


6.S191 Project Group 1

Varnika Sinha
Julia Wang
Emily Zhang



Problem



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

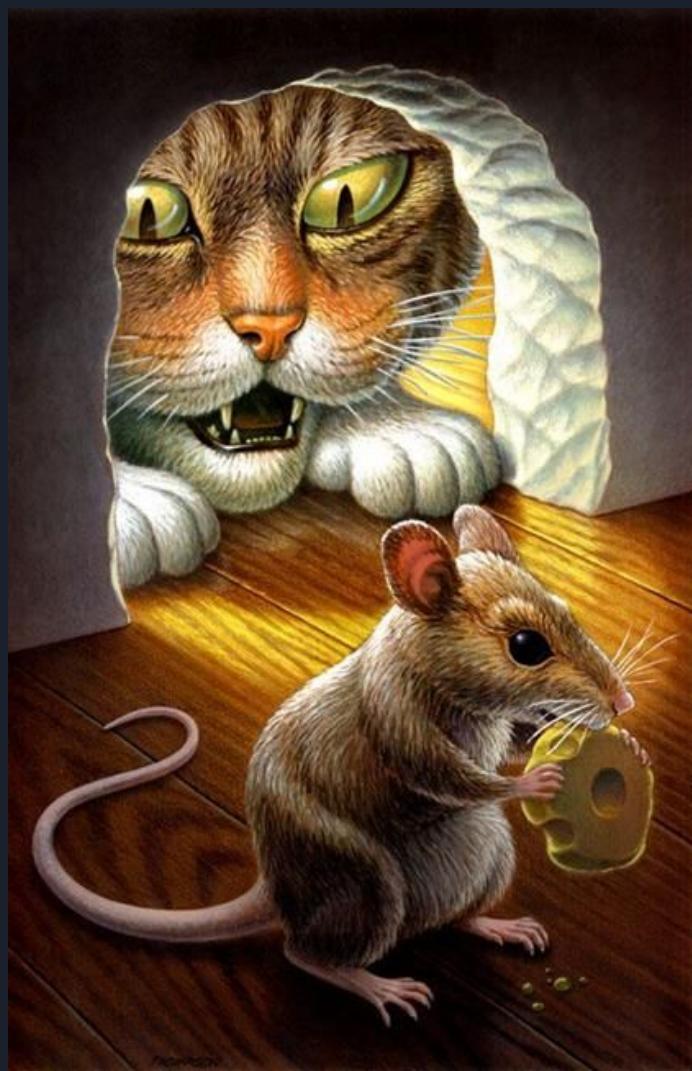
Cybersecurity Challenges:

- ❖ 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**

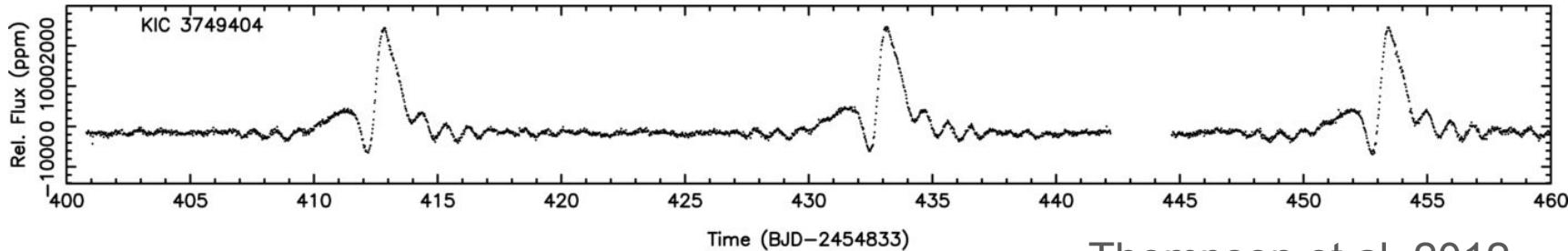


Identification of Heartbeat Systems in Photometric Surveys

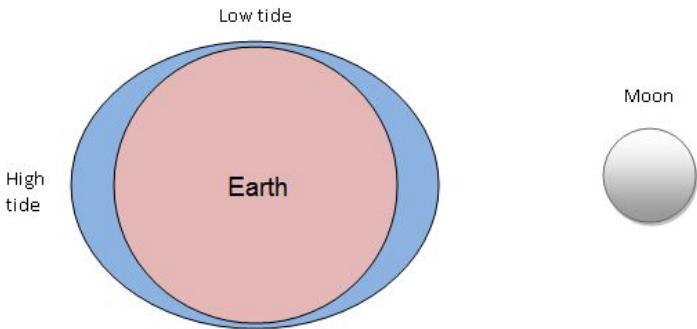
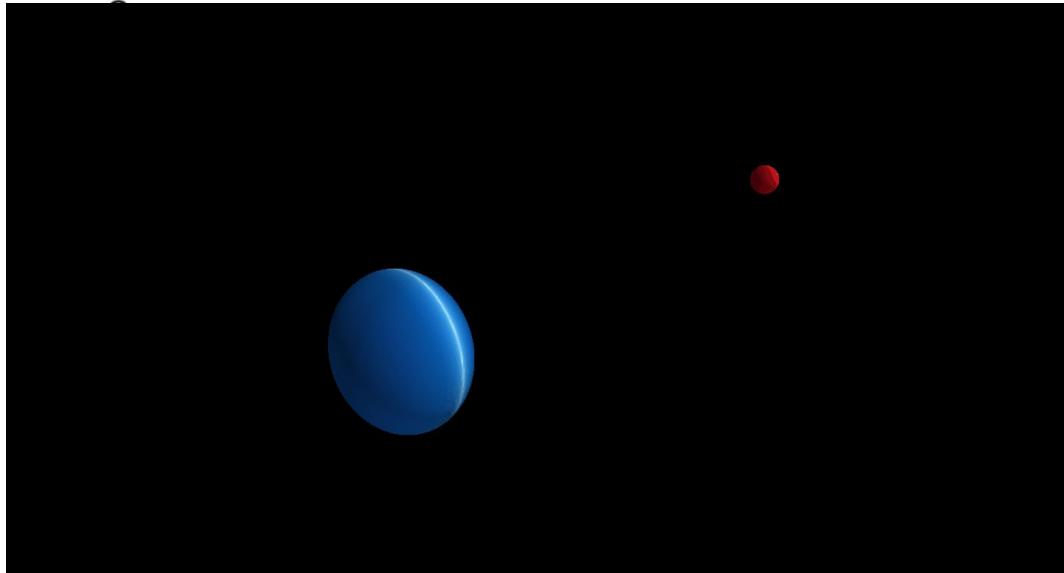
Baichuan Mo, Erik Tamre,
Prajwal Niraula, Yunpo Li

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Feb 1, 2019

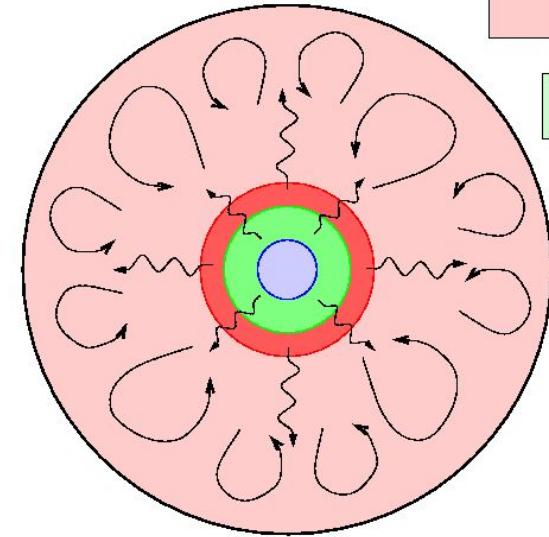
Heartbeat Systems



Thompson et al. 2012



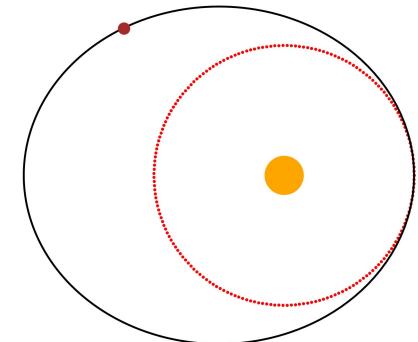
Scientific Motivations



Probing the Internal
Stellar Structure



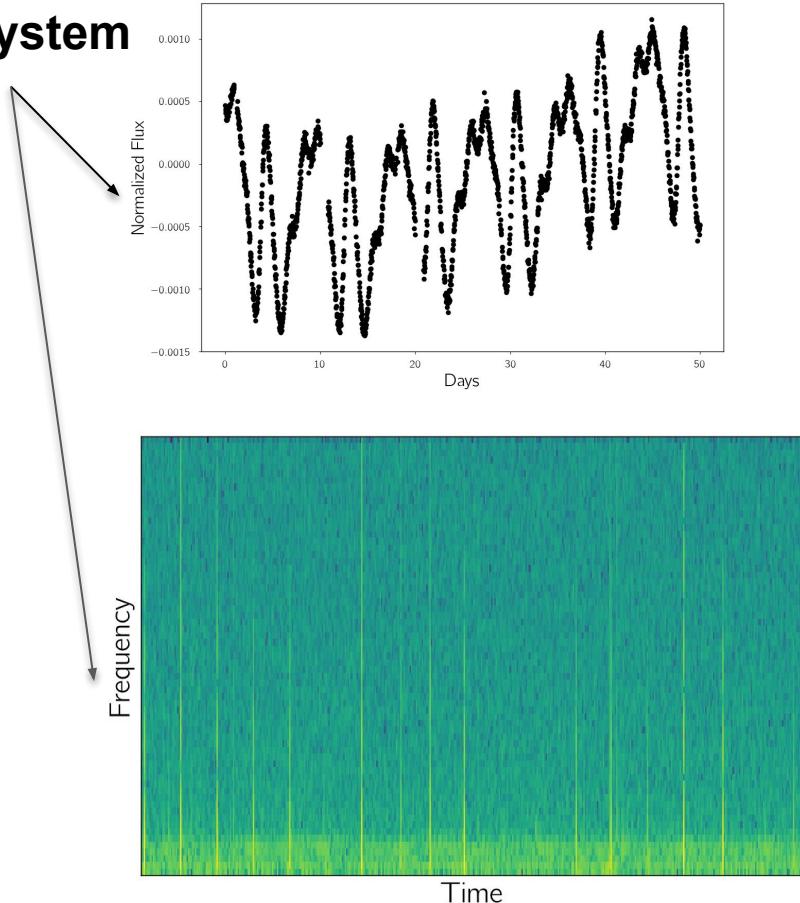
As method of finding
exoplanet



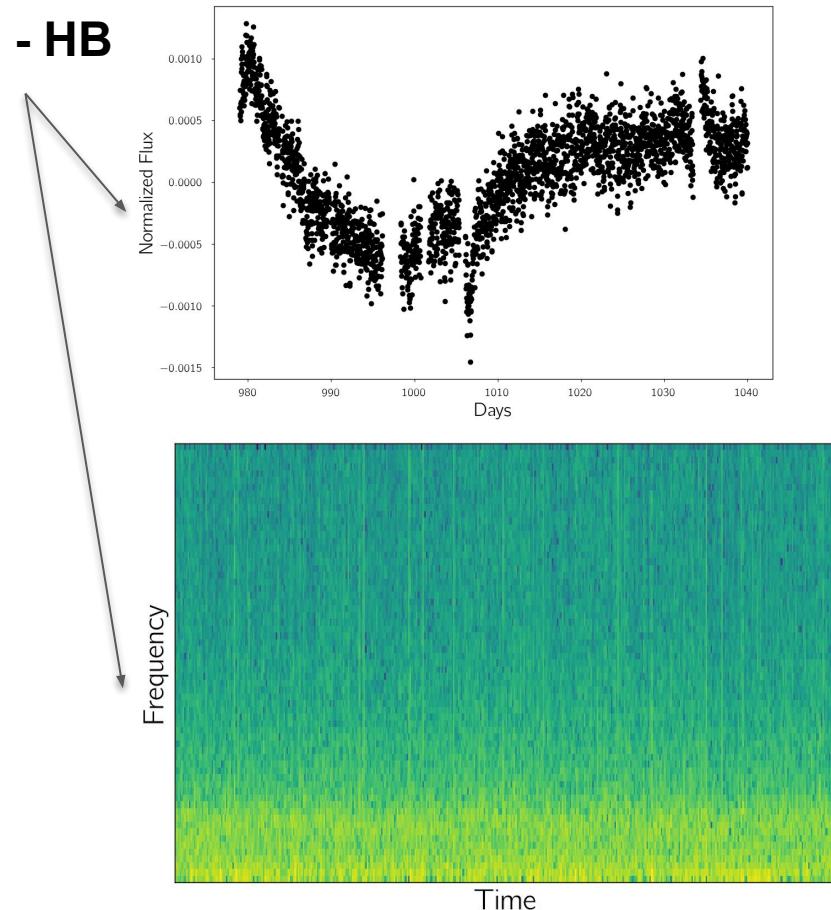
Tidal Circularization

Distinguishing the HeartBeat Systems

HB System



Non - HB



Proposed method

Deep Learning! But why?

Method one: 1-D Convolutional Neural Network

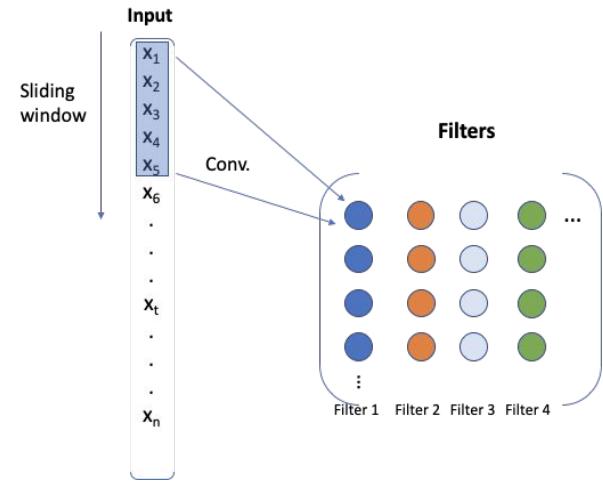
Motivation: Extract local features in the time domain (e.g., peaks, valleys, etc.)

Method Two: Recurrent Neural Network (LSTM)

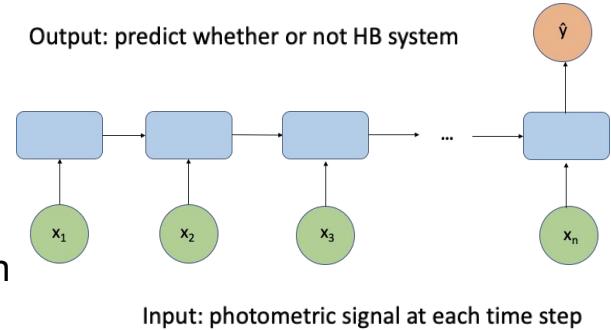
Motivation:

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



Output: predict whether or not HB system



Challenges and path forward

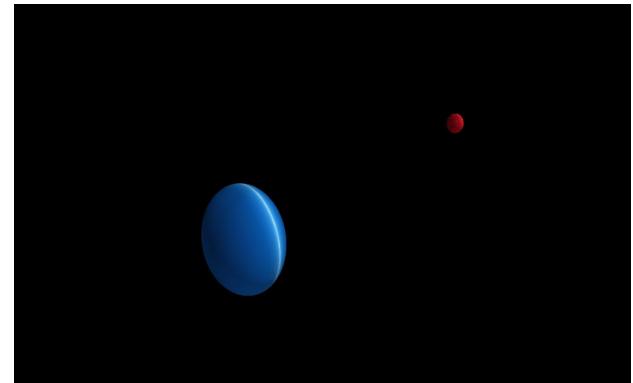
Challenges at current stage

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

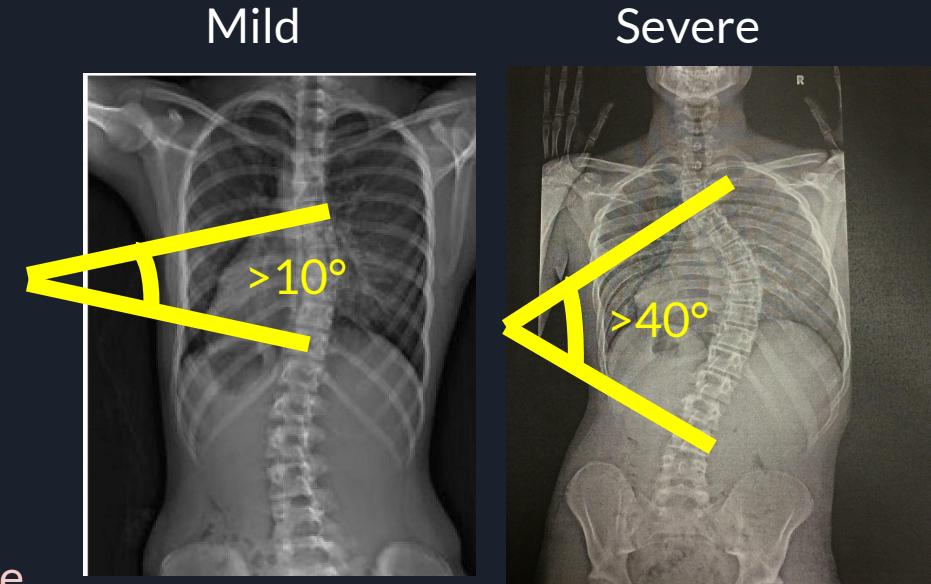
- Starts before 15 yrs. old
- 600,000 patient visits/year
- 30,000 children fitted w/brace
- 40,000 undergo spinal fusion surgery



Brace
May 2014-July 2015

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





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

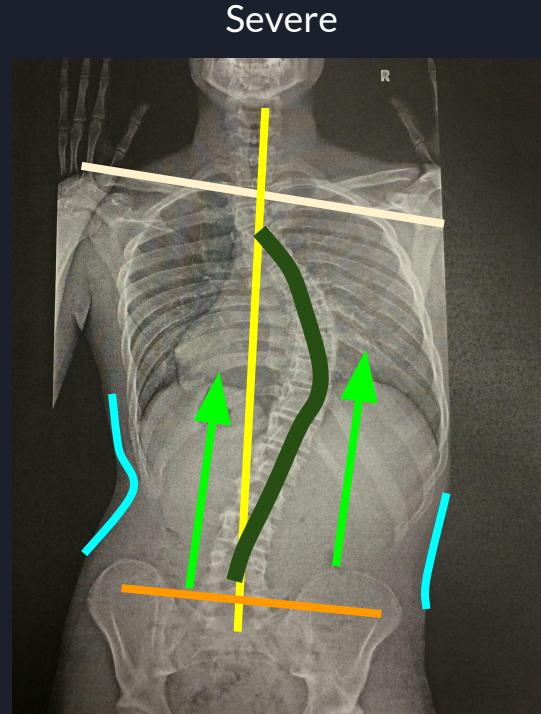
Class 2:
Moderate Scoliosis after time T

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





What are the challenges?

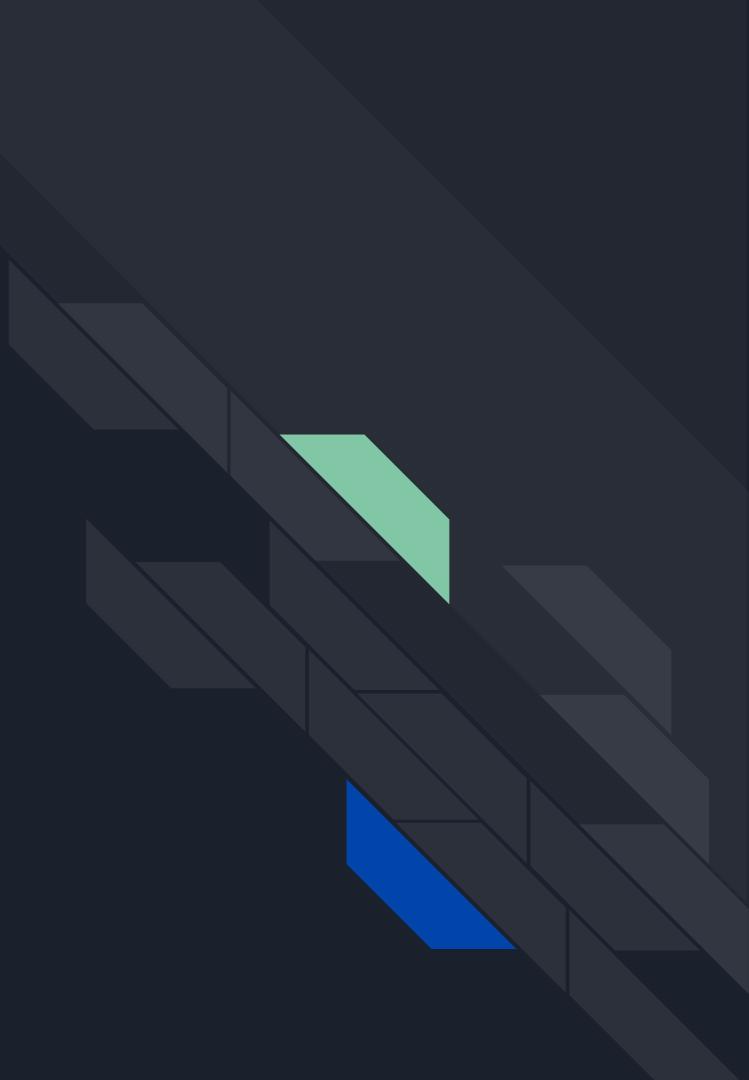
- Validation
- Data Acquisition
 - **600,000** patient visits/year
 - Potential privacy issues with hospitals

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



Thank you!



Dementia



One case every **3 seconds**.

131.5 million by 2050.

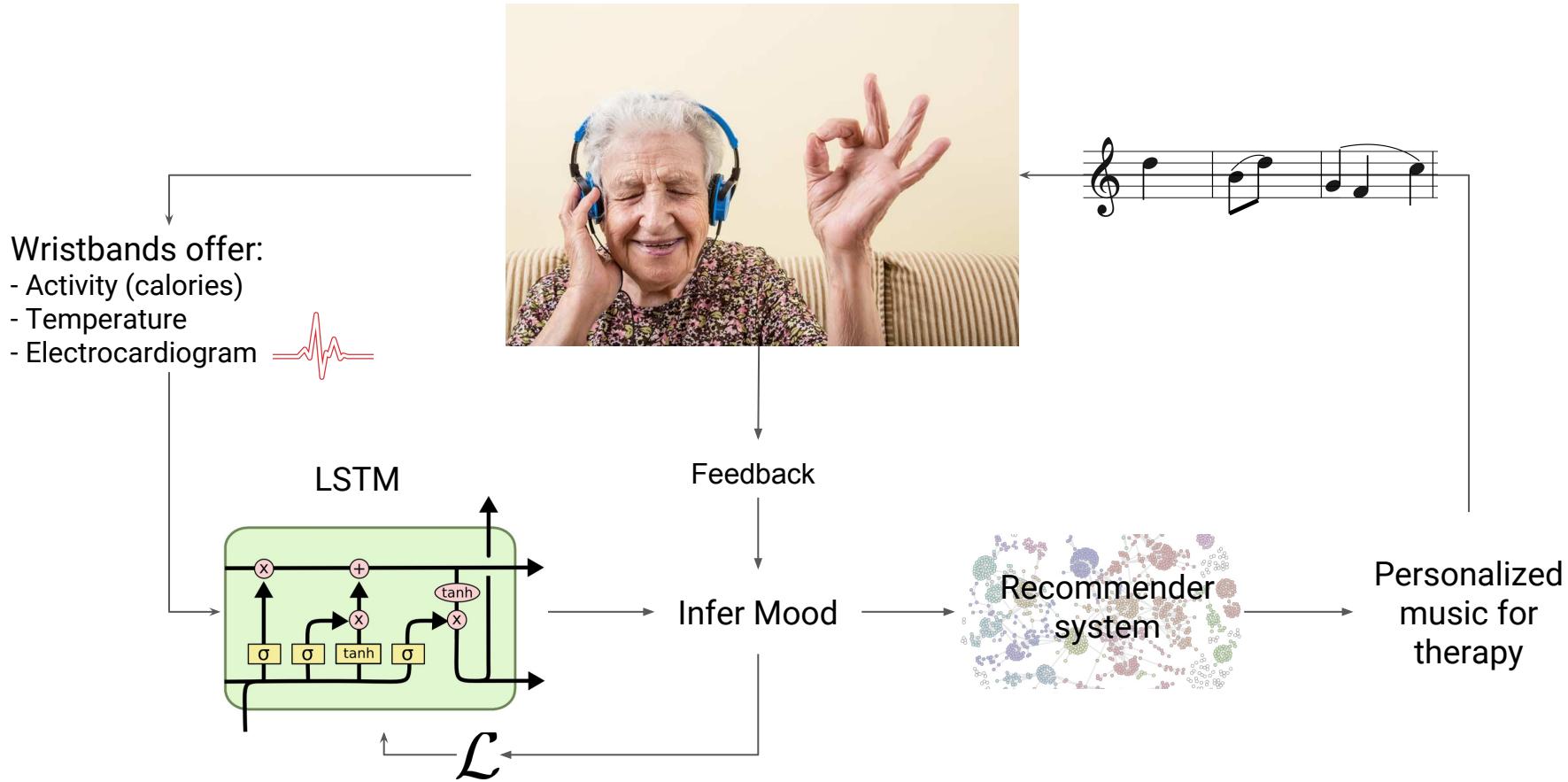
Costs above a **\$1 trillion** in 2018.

Music can help...



...but which music works best?

TheraTune. Personalized music therapy



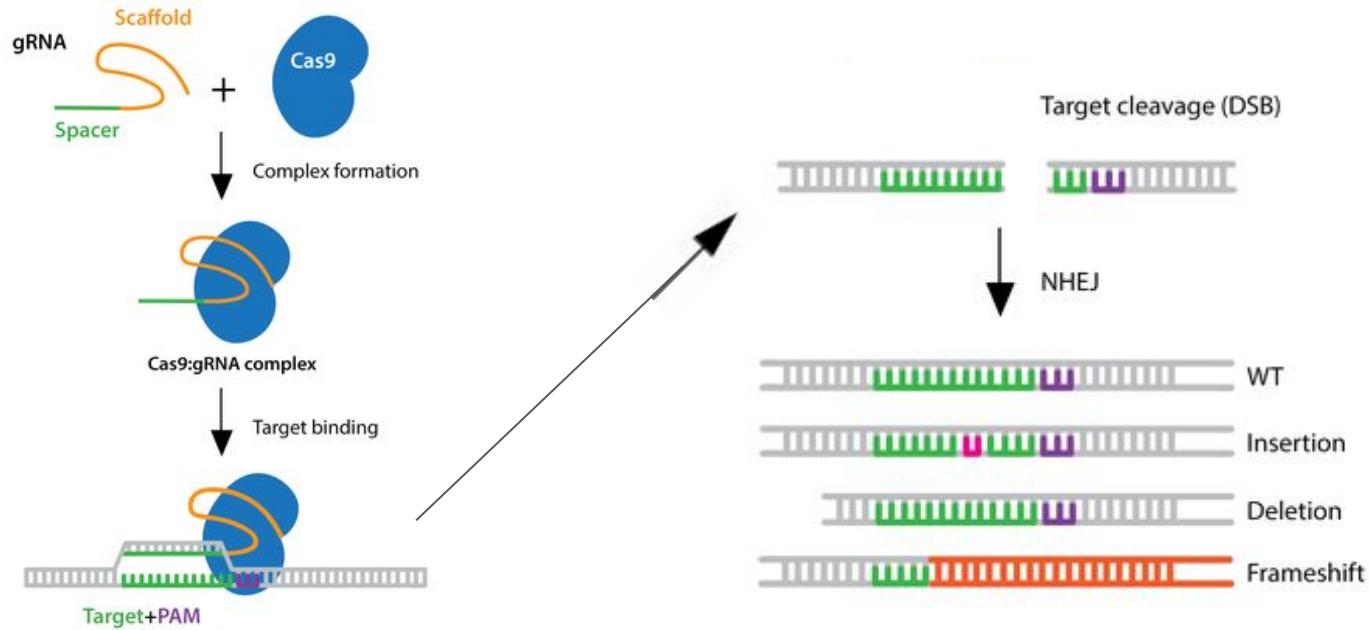
Pred1ct: Predicting Useful CRISPR-Cas9 Outcomes



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-z>

Predictable and precise template-free CRISPR editing of pathogenic variants

Max W. Shen^{1,7,12}, Mandana Arbab^{3,4,5,12}, Jonathan Y. Hsu^{6,7}, Daniel Worstell⁸, Sannie J. Culbertson⁸, Olga Krabbe⁸, Christopher A. Cassa^{8,10}, David R. Liu^{3,4,5*}, David K. Gifford^{2,6,10,11*} & Richard I. Sherwood^{8,9*}

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 precision, reaching a predicted genotype, enabling correction of disease-associated mutations in humans. We constructed a library of 2,000 Cas9 guide RNAs (gRNAs) targeting genes and transcripts belonging to a machine learning model that predicted genes associated with a range of 1 to 60 percent pair-wise edit rates, based on gRNA sequences with high homology ($\pi = 0.87$) to human and mouse cell lines. In-depth predictions suggest that 5–11% of Cas9 guide RNAs targeting the human genome are able to produce ~5–10% editing, a single genotype, in living organisms, creating greater than or equal to 50% of all major editing products. We expect that template-free Cas9 editing will be applicable to a wide range of diseases, including correction of point mutations in primary patient-derived fibroblasts or pathogenic alleles at wild-type genotype for Hemophilia B, Parkinson syndrome and Menkes disease. This study establishes an approach for precise, template-free genome engineering.

Clustered regularly spaced short palindromic repeats (CRISPR)-Cas has revolutionized genome editing, providing powerful research tools and prospecting agents for the potential treatment of genetic diseases. CRISPR-Cas9 technology is based on Cas9 protein, which is encoded by the development of guide RNA (gRNA) design principle, modeling of factors leading to off-target DNA cleavage, enhancement of Cas9 sequence fidelity by off-target DNA cleavage, enhancement of the evolution and engineering of Cas9 variants with alternative PAM sequences¹. Eventually, combining the base of Cas9 system with CRISPR, developed by the development of base-pair matching, achieving to achieve precise and efficient single-nucleotide mutations², and the improvement of template-directed single-nucleotide repair (HDR) of double-stranded breaks³. Despite these developments, base pair mismatch repair is still a challenge. In addition, it is limited by homologous recombination (HR) pathway, which is a process that can target site is reproducible and dependent on local sequence context³⁻⁴, but no general methods have been described to predict genomic effects following Cas9-induced double-stranded DNA breaks.

ARTICLES



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

Felicity Allen^{1,7}, Luca Crepaldi^{1,7}, Clara Alsine¹, Alexander J. Strong¹, Vitalii Kleshchevnikov^{1,8}, Pietro De Angelis¹, Petra Páleníková⁴, Anton Khodak¹, Vladimir Kiselev^{1,9}, Michael Kosicki¹, Andrew R. Bassett^{1,0}, Heather Harding², Yaron Galanty^{3,4}, Francisco Muñoz-Martínez^{3,4}, Emmanuel Mattheoulian^{1,5}, Stephan B. Jacobson^{3,4}, & Imanol Dotin^{1,6}

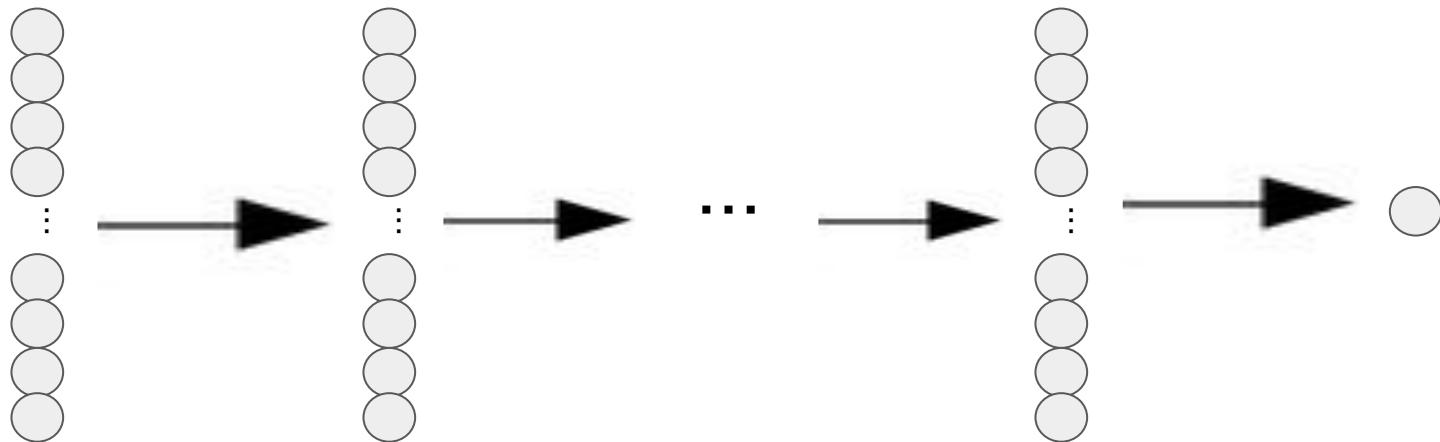
The DNA mutation produced by cellular repair of a CRISPR-Cas9-generated double-strand break determines its phenotypic effect. It is known that the mutational outcomes are not random, but depend on DNA sequence at the targeted location. Here we systematically study the influence of flanking DNA sequence 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 >10⁶ mutational outcomes. The majority of repairable mutations are caused by a single base, short deletions or longer microhomology-mediated edits. Each gRNA has an individual edit-line dependence 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.

CRISPR-Cas9 is a transformative DNA editing technology.¹ It operates by recruiting the Cas9 nuclease to a genomic locus with a *spacer-protospacer-protospacer adjacent motif (SPG)*.² If the protospacer sequence matches the desired target, Cas9 cleaves DNA at that location, and when the double-strand break is repaired by cellular machinery, frameshift mutations can occur, disabling translation of the target gene.

Cas9-generated mutations result from imperfect action of DNA repair pathways that are activated to remedy the double-strand break. The main repair mechanisms include nonhomologous end joining, the

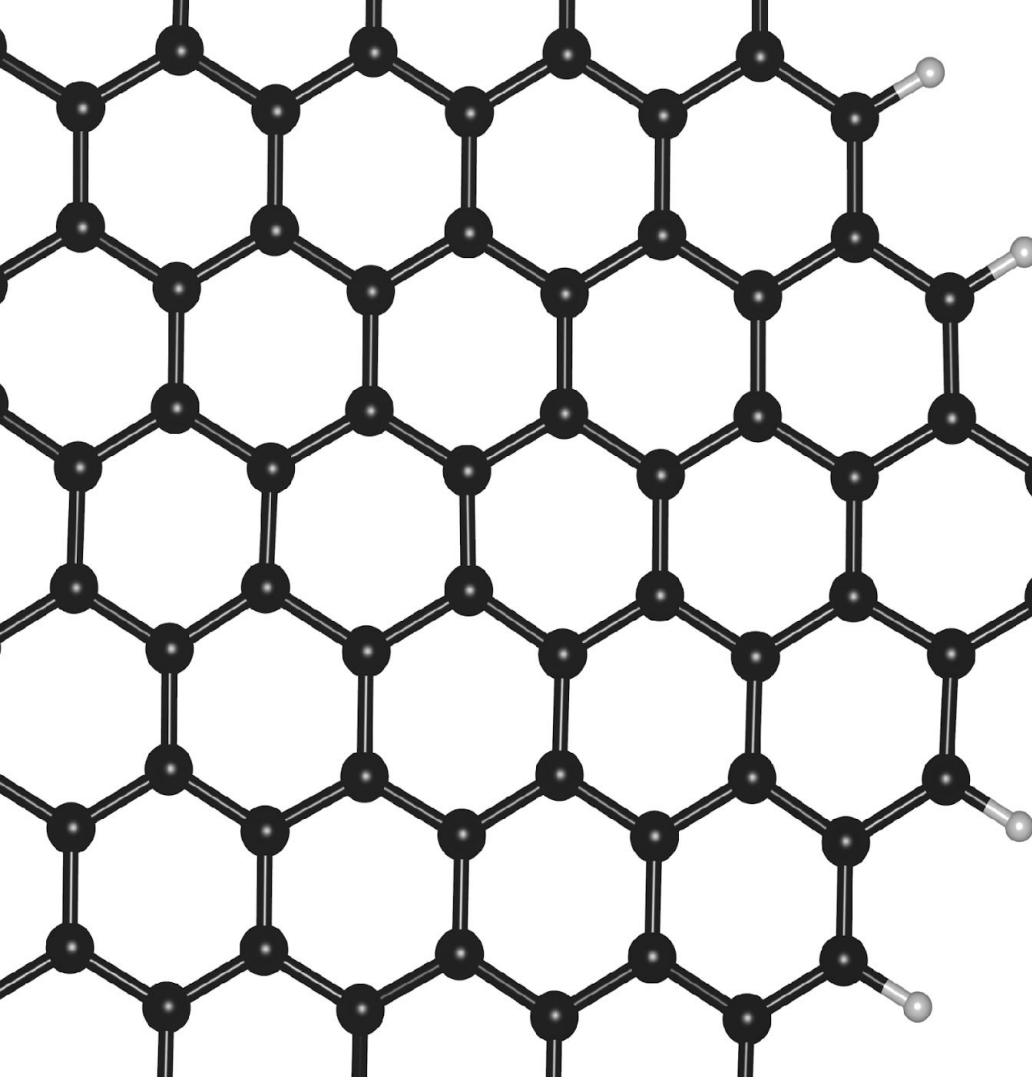
Pred1ct Network Architecture

- 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

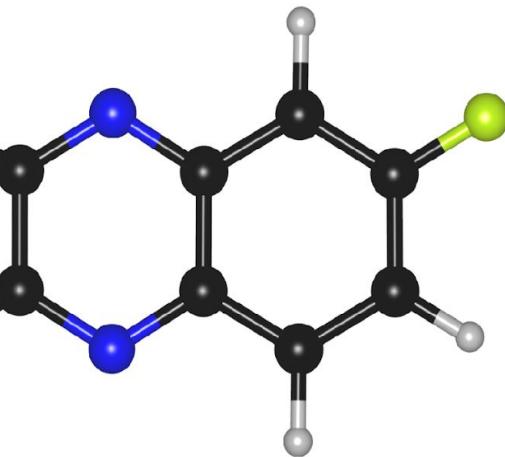


Consequences

- 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

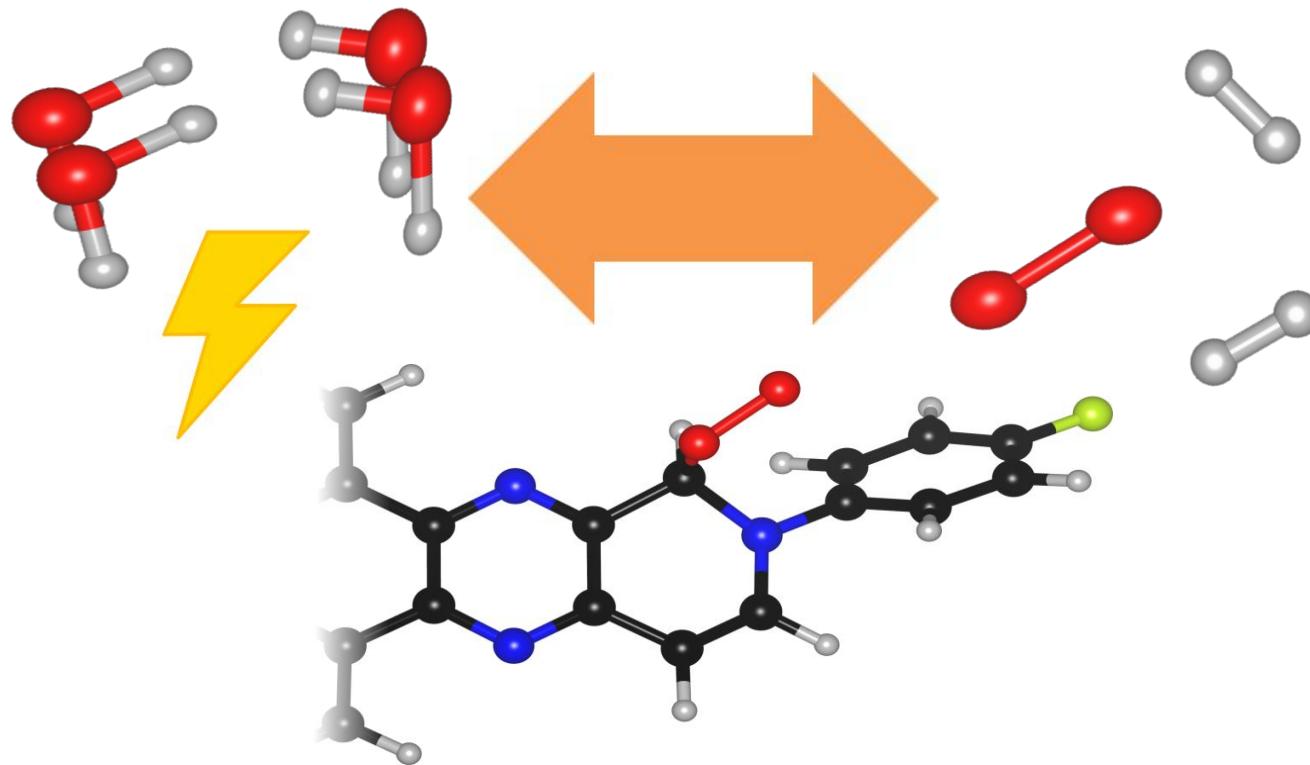


Rational Design of Electrocatalysts

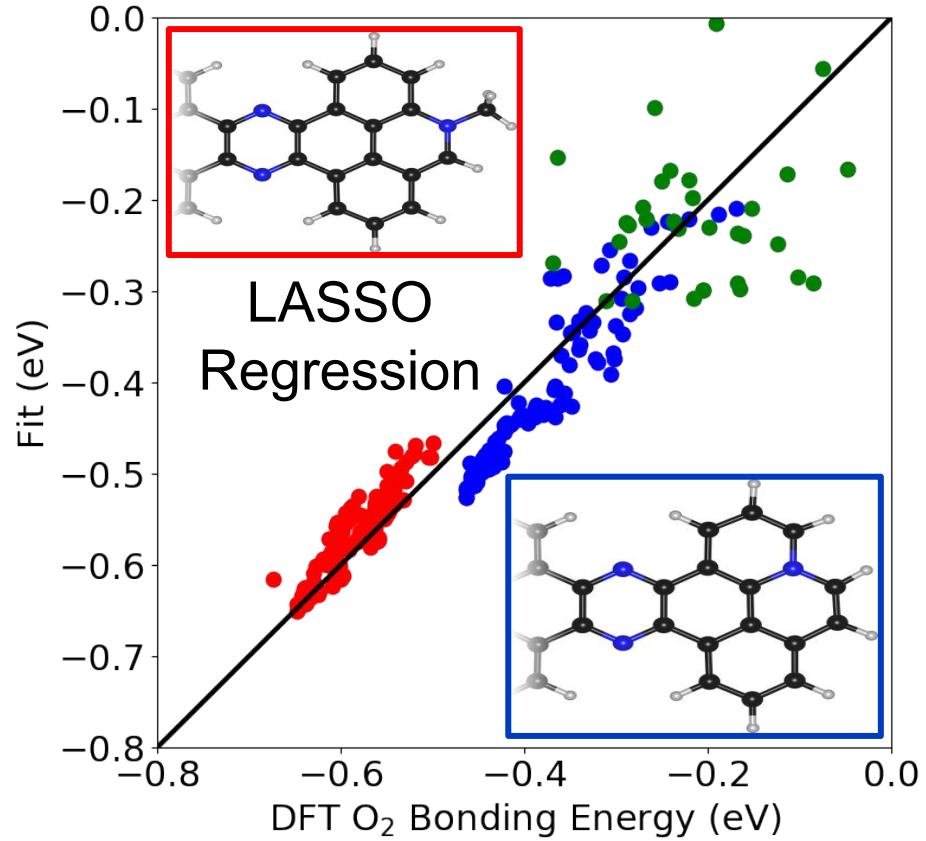
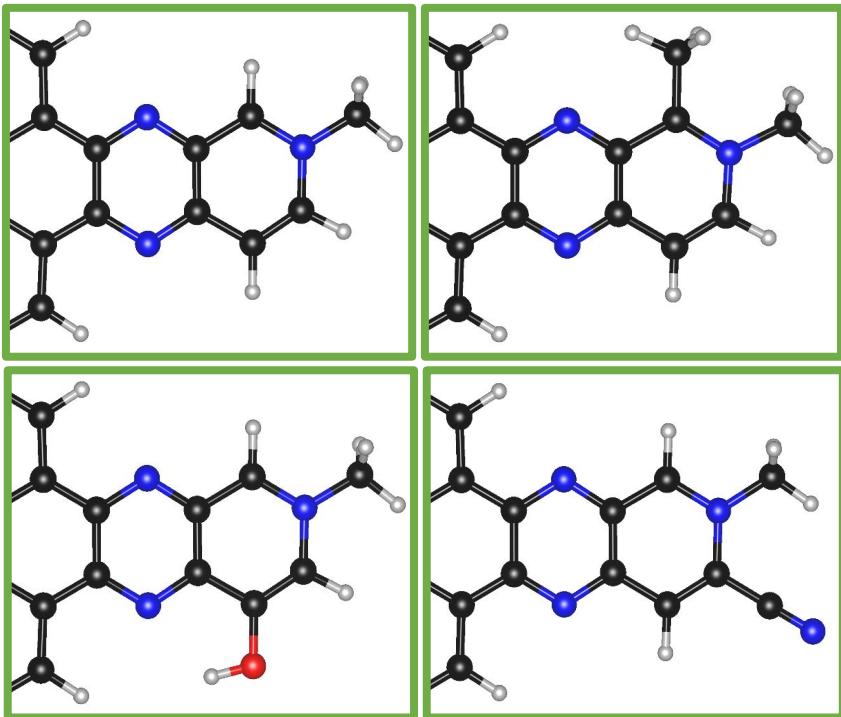


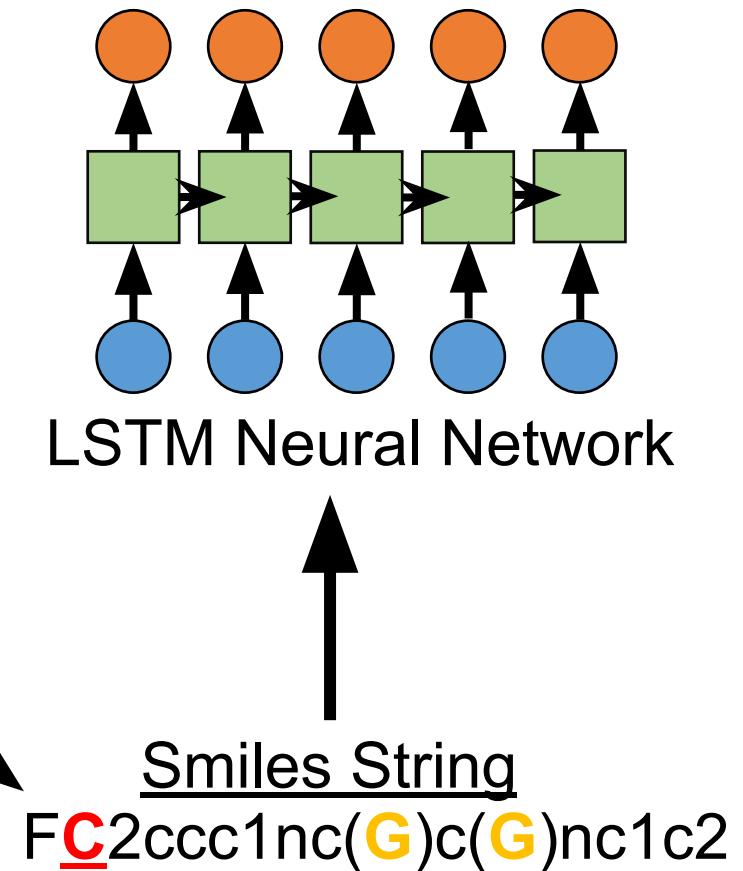
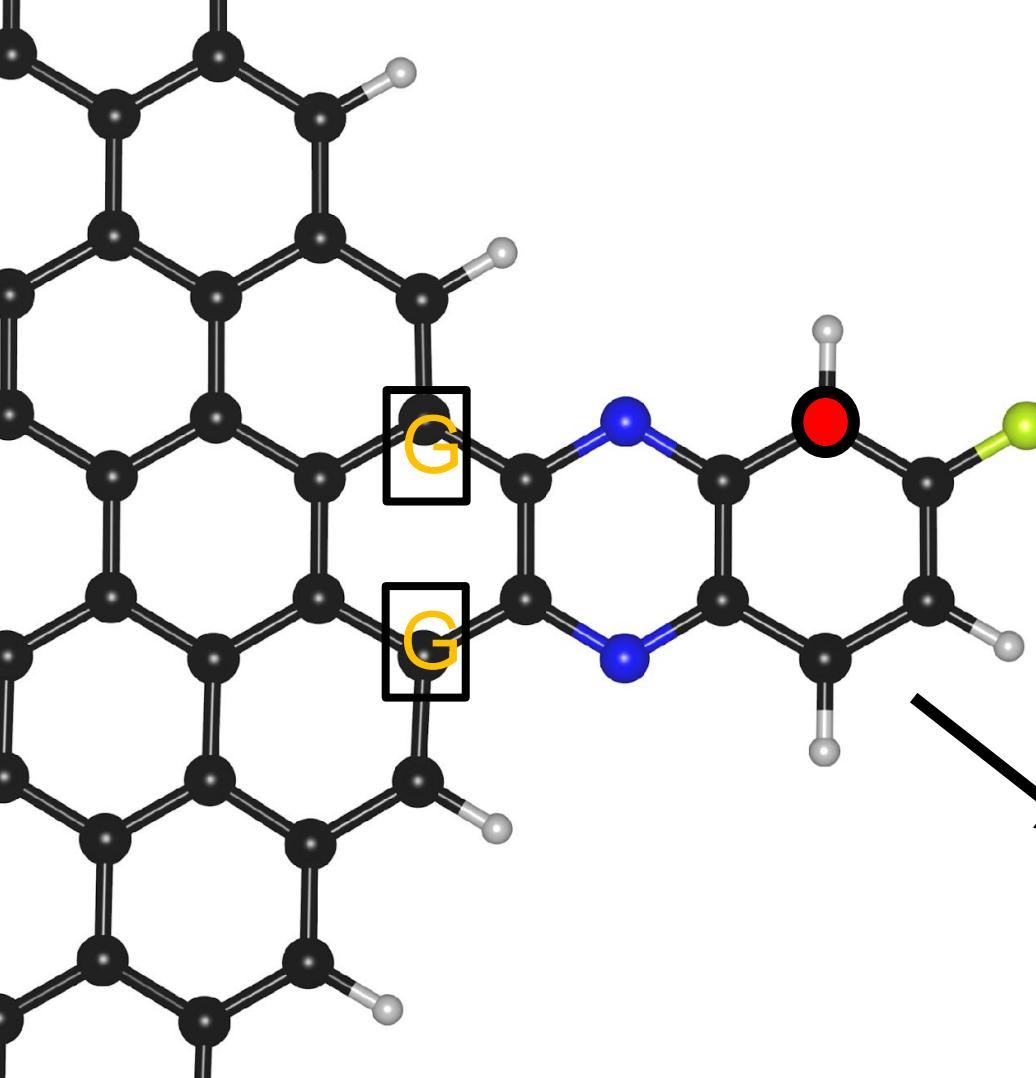
Nathan Ricke and Eric Alt
6.S191
Group 6

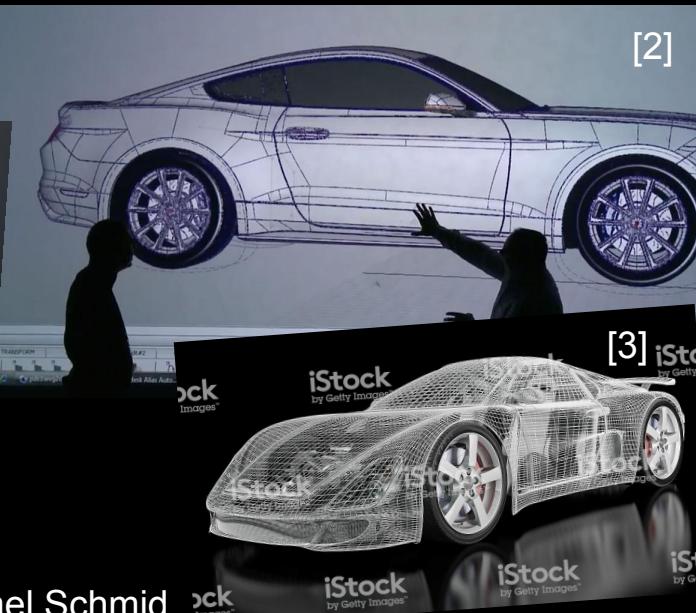
Electrocatalysts for Storing and Recovering Energy



Computationally Generate and Test Catalysts





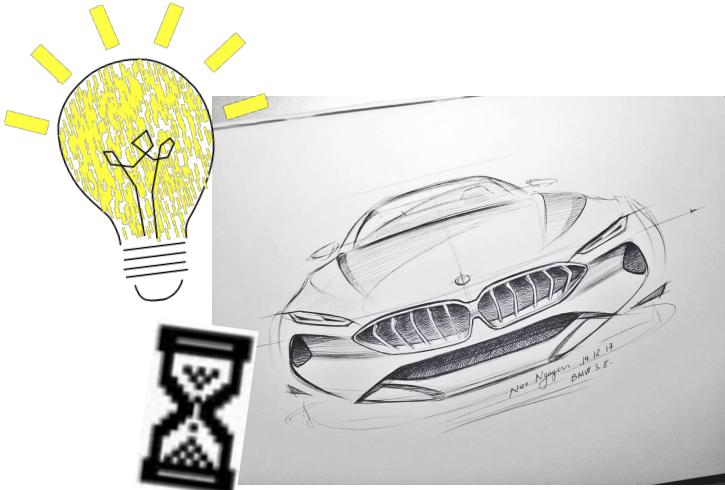


Group 7: Yiwen Huang, Greg Allan, Michael Schmid

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!



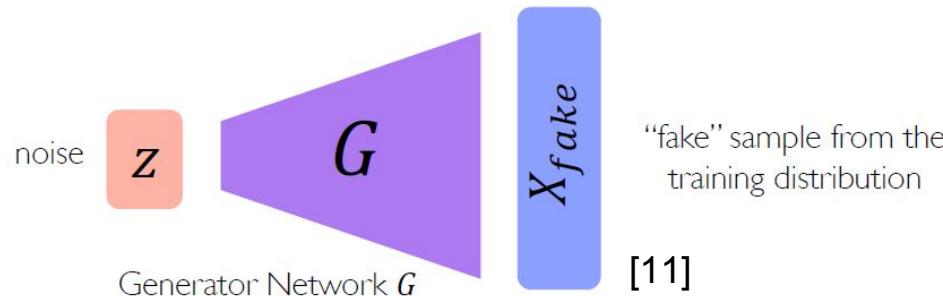
BMW 8 series concept car [5]



BMW 8 series final design [6]

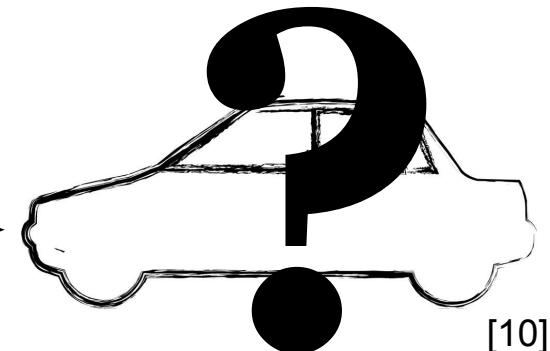
Idea: GANs in Automotive Design

Idea from lecture:
Exploit the creativity of
Generative Networks



Generative Network

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



design suggestions

Thank you for your attention!

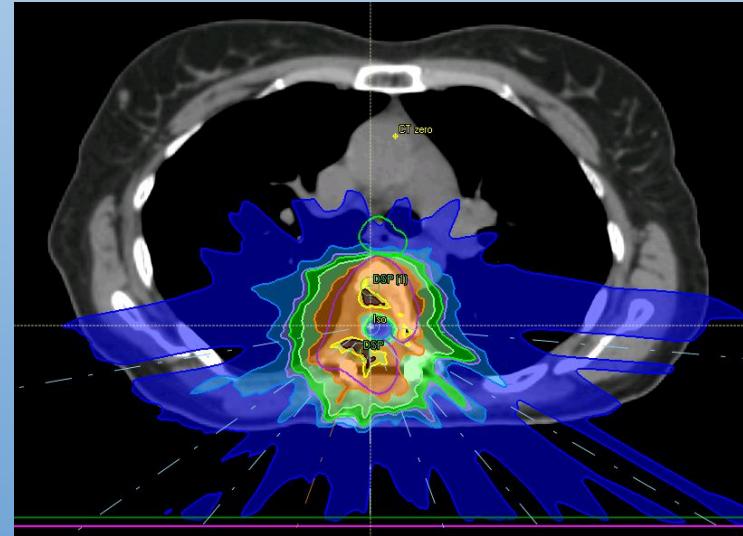


[12]

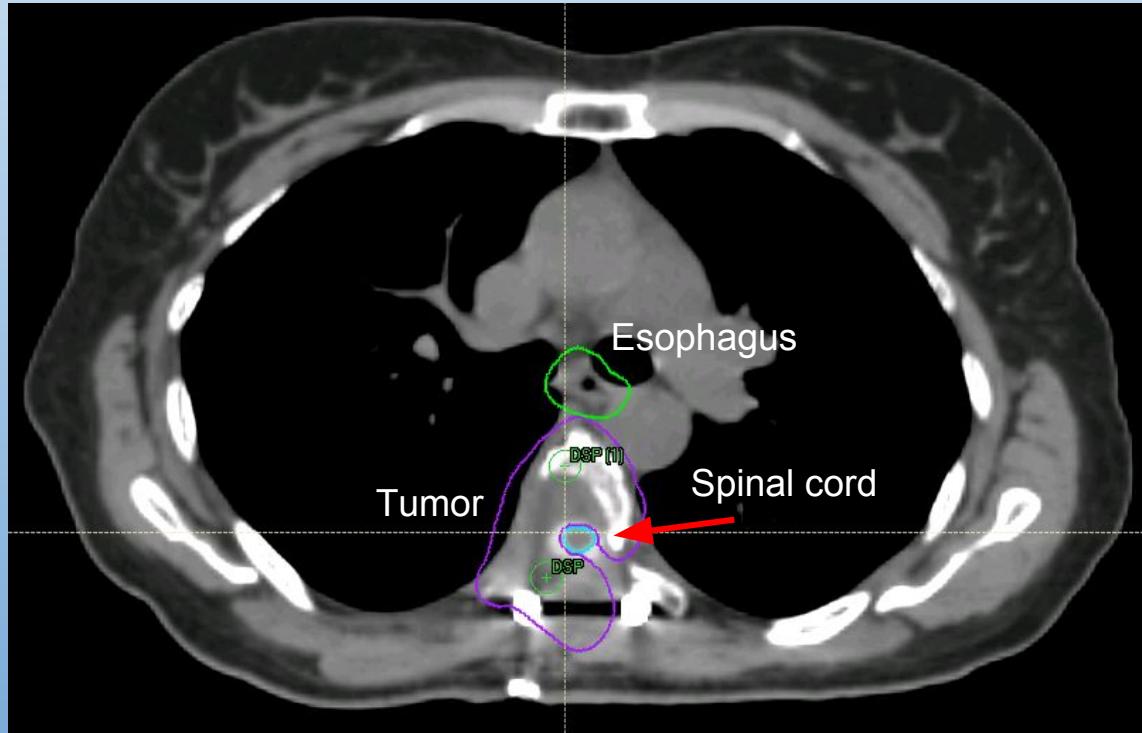
Deep Reinforcement Learning for Radiation Therapy Planning

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

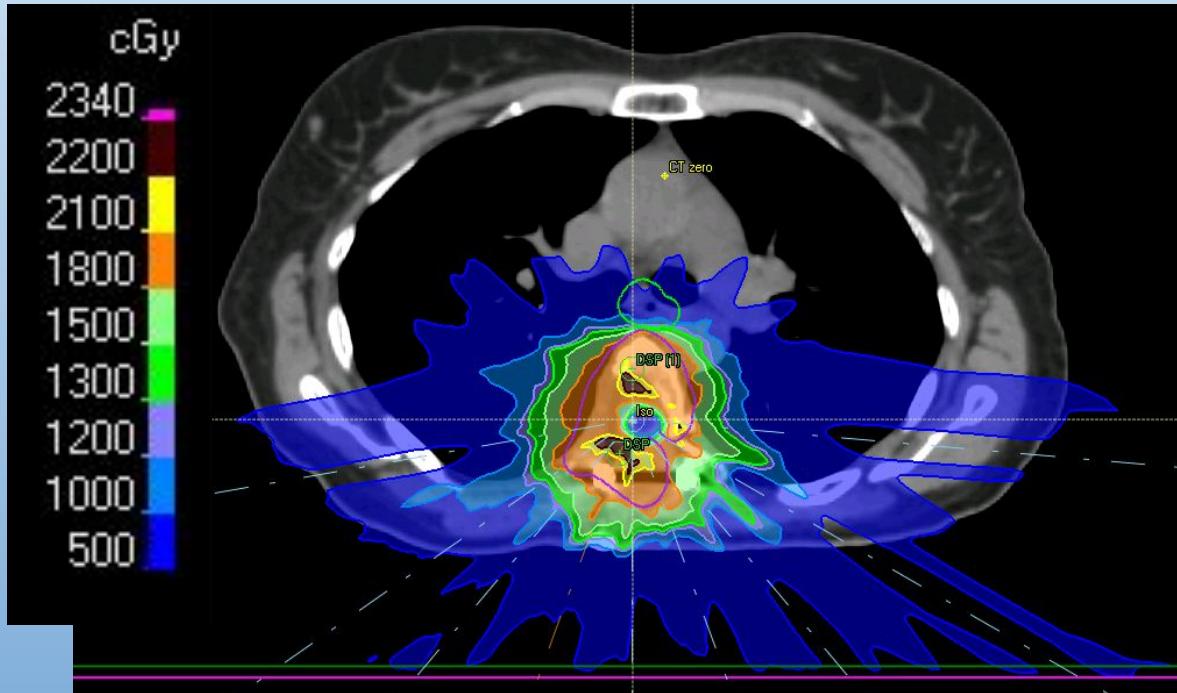
MIT 6.S191 presentation



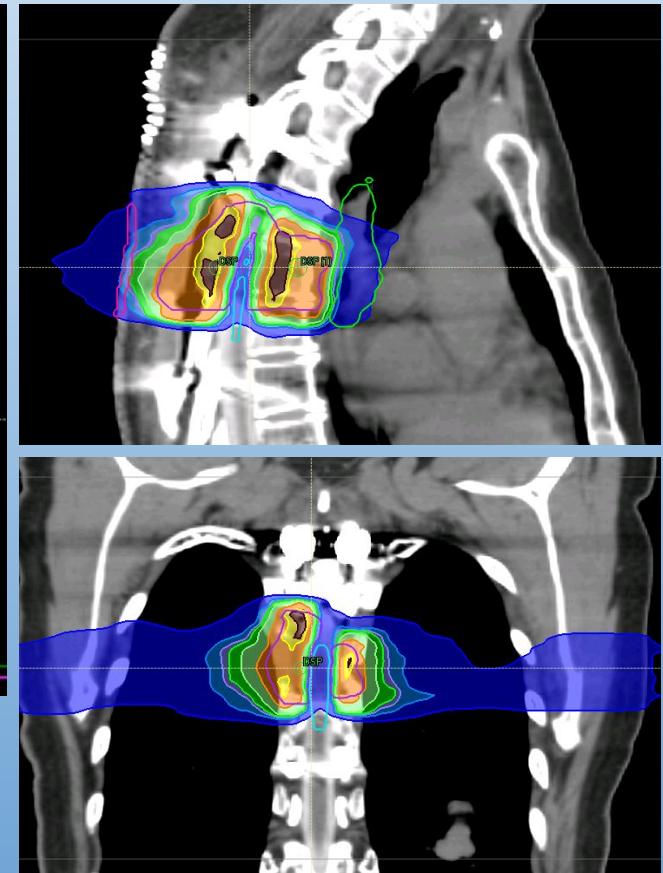
Radiation Treatment Plan: Tumor and Organs-at-risk



Radiation Treatment plan: Dose Distribution



3D distribution of dose in patient shown on CT



Actions

Isocenter [cm]				SSD [cm]		Energy [MV]	Gantry angle [deg]	Coll. angle [deg]	Couch angle [deg]	No. segm	MU/fx	Bolus
Name	R-L	I-S	P-A	To surface	To skin							
● 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

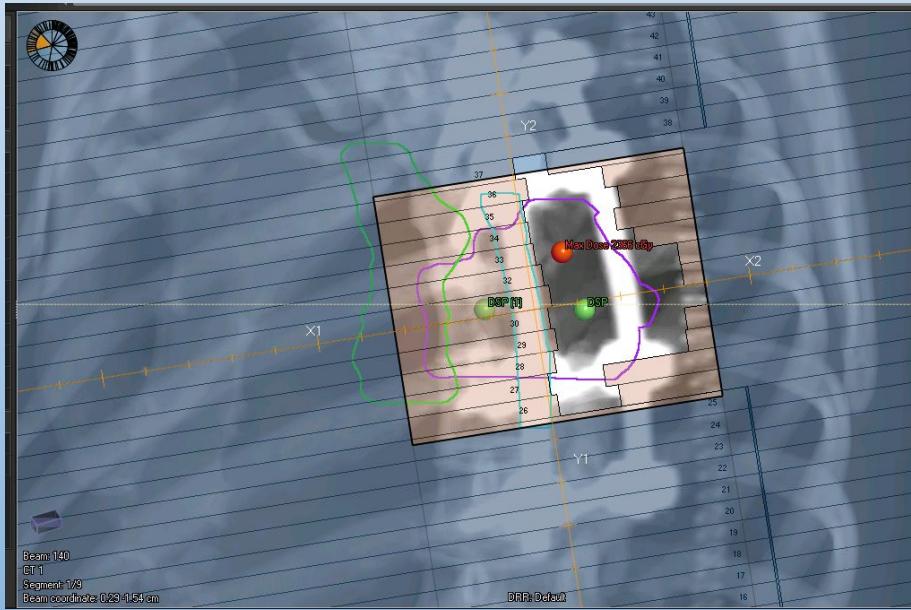
Add Edit Delete

Constraints

Add Edit Delete

ROI	Description	ROI	Description
■ PTV T6	Min DVH 1800 cGy to 100% volume	■ PTV T6	Min DVH 1800 cGy to 94% volume
■ cord + 1 mm	Max DVH 1000 cGy to 9% volume	■ cord + 1 mm	Max Dose 1300 cGy
■ 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 Dose 1500 cGy
■ RingOuter1cmGap1mm	Dose Fall-Off [H]1800 cGy [L]0 cGy, Low dose distance 1.00 cm	■ esophagus + 2 mm	Max DVH 1200 cGy to 30.5% volume
■ RingInner5mm	Min DVH 1800 cGy to 100% 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	<input type="checkbox"/>	<input checked="" type="radio"/>	6.09
2	200	333.31	170	<input type="checkbox"/>	<input checked="" type="radio"/>	5.46
3	220	423.52	145	<input type="checkbox"/>	<input checked="" type="radio"/>	6.94
4	235	468.94	123	<input type="checkbox"/>	<input checked="" type="radio"/>	7.68
5	260	678.92	190	<input type="checkbox"/>	<input checked="" type="radio"/>	11.12
6	95	941.50	55	<input type="checkbox"/>	<input checked="" type="radio"/>	15.42
7	120	1103.28	69	<input type="checkbox"/>	<input checked="" type="radio"/>	18.07
8	140	1068.20	92	<input type="checkbox"/>	<input checked="" type="radio"/>	17.49
9	160	716.37	66	<input type="checkbox"/>	<input checked="" type="radio"/>	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

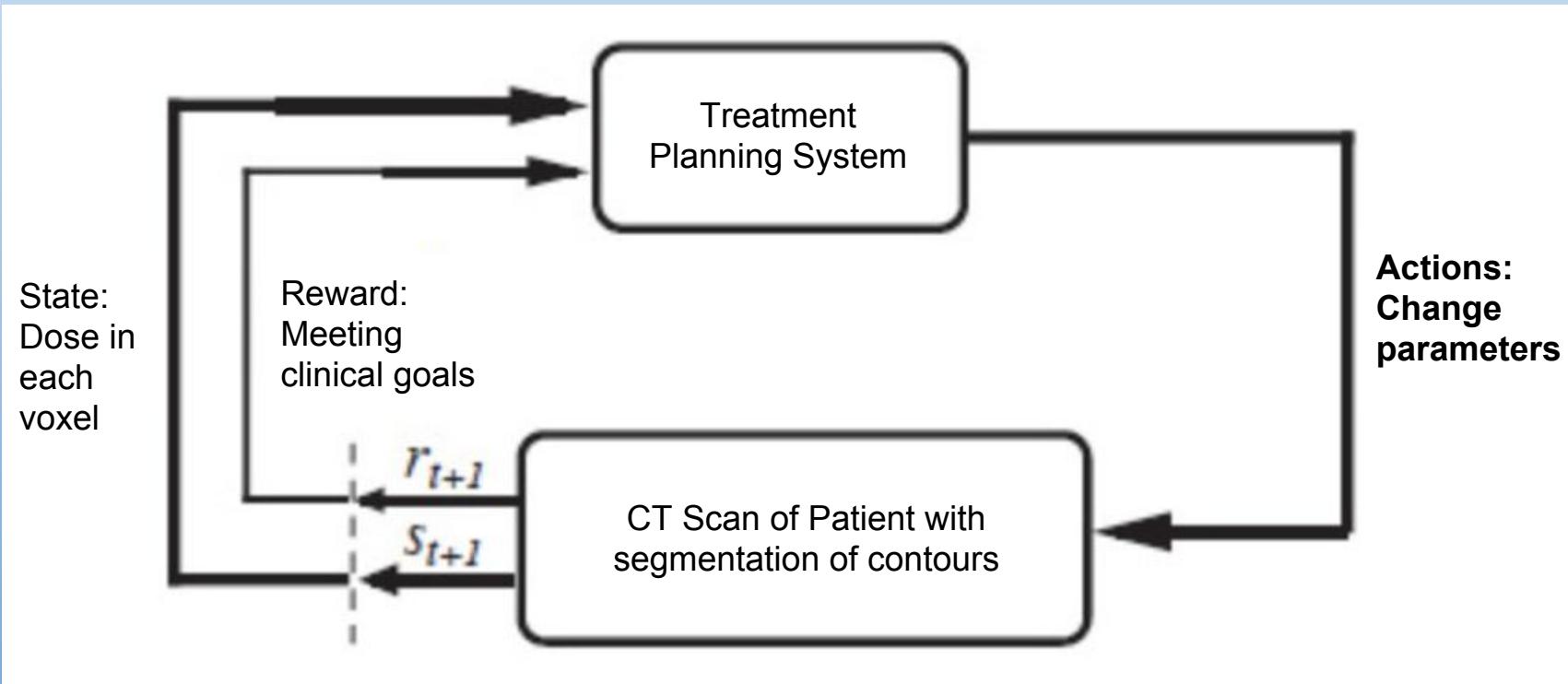


Challenges



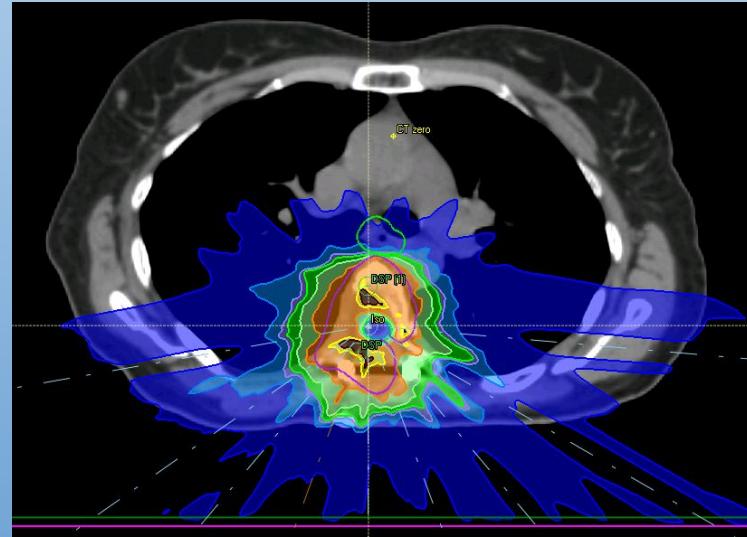
- Requires years of training and experience
- Time consuming
- Never sure if a better plan exists
- Patient needs to be treated as soon as possible

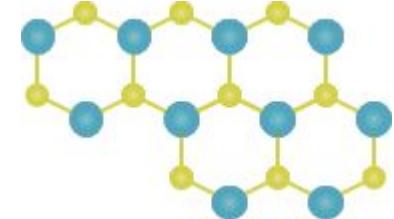
Reinforcement Learning



Thank you!

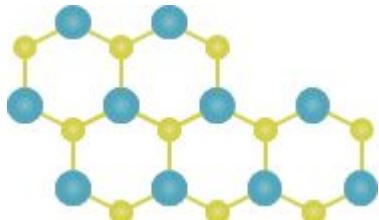
Group 8: Susu Yan (Listener), Michelle Jiang (Credit)





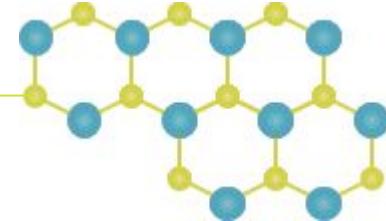
Diagnosing Defects in 2D Materials with Deep Learning

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

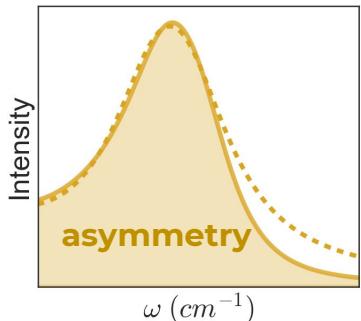
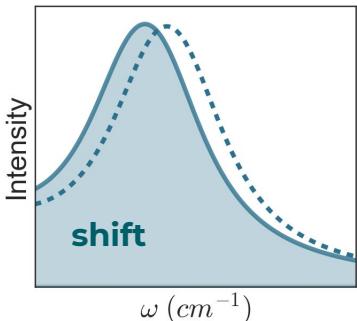
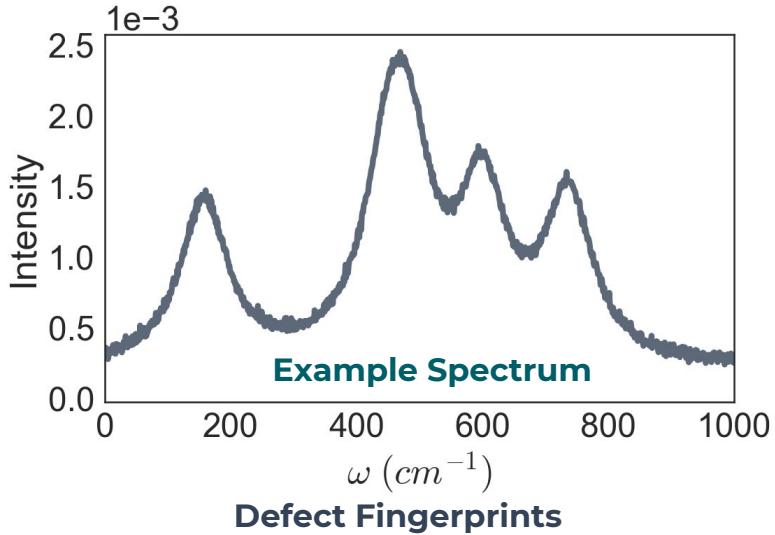
Can unsupervised deep learning **automate the screening of “defect fingerprints”?**

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

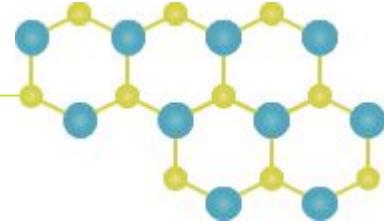
- is **resistant to artifacts** produced by defects
- **distinguishes different materials** in an unsupervised manner



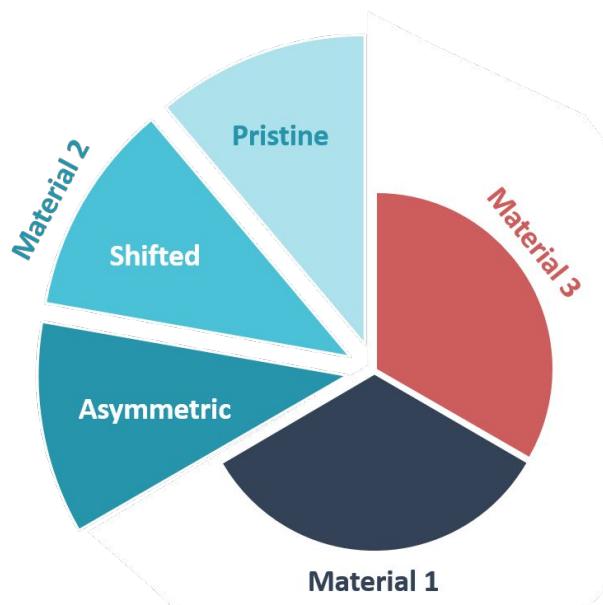
Data Generation



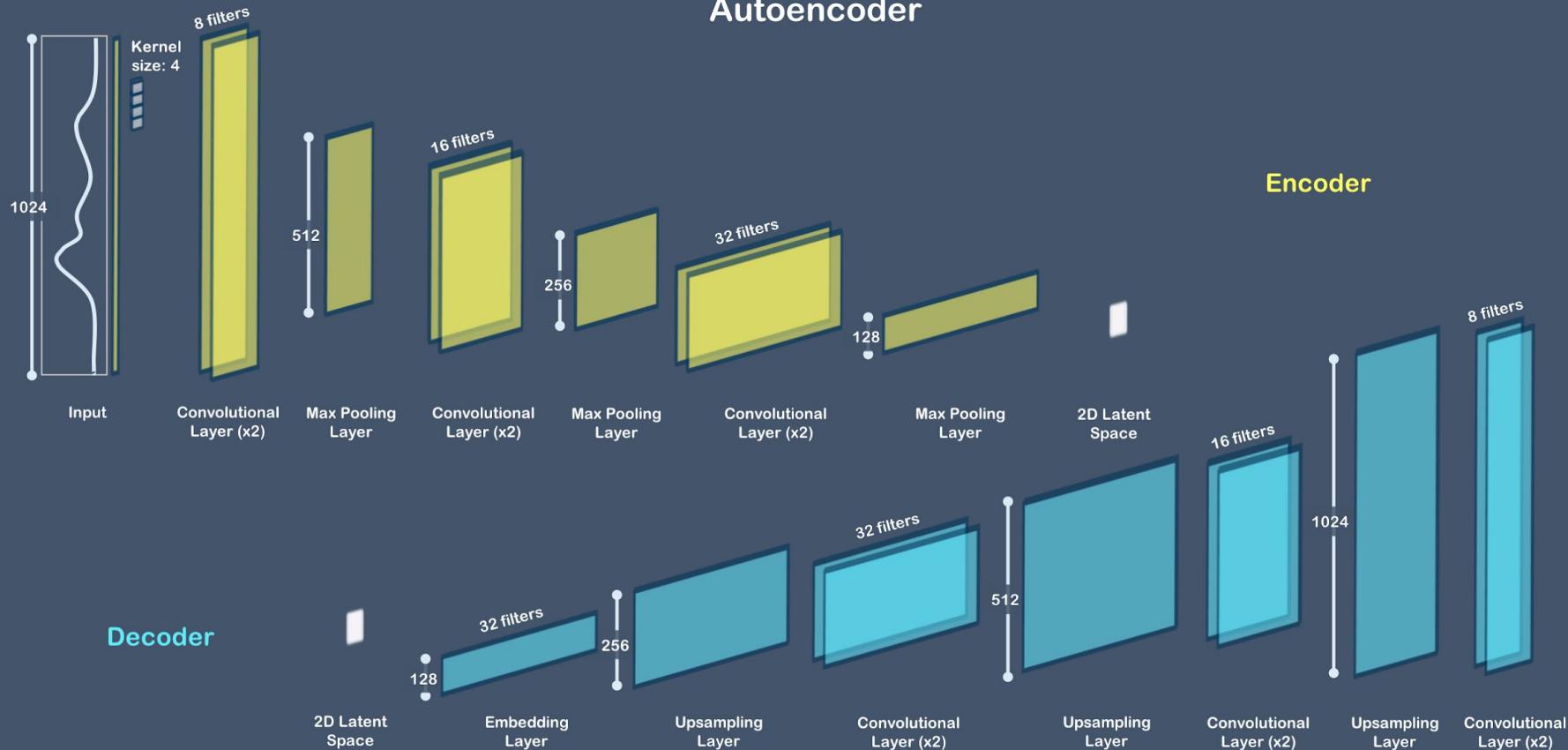
Project Group 9



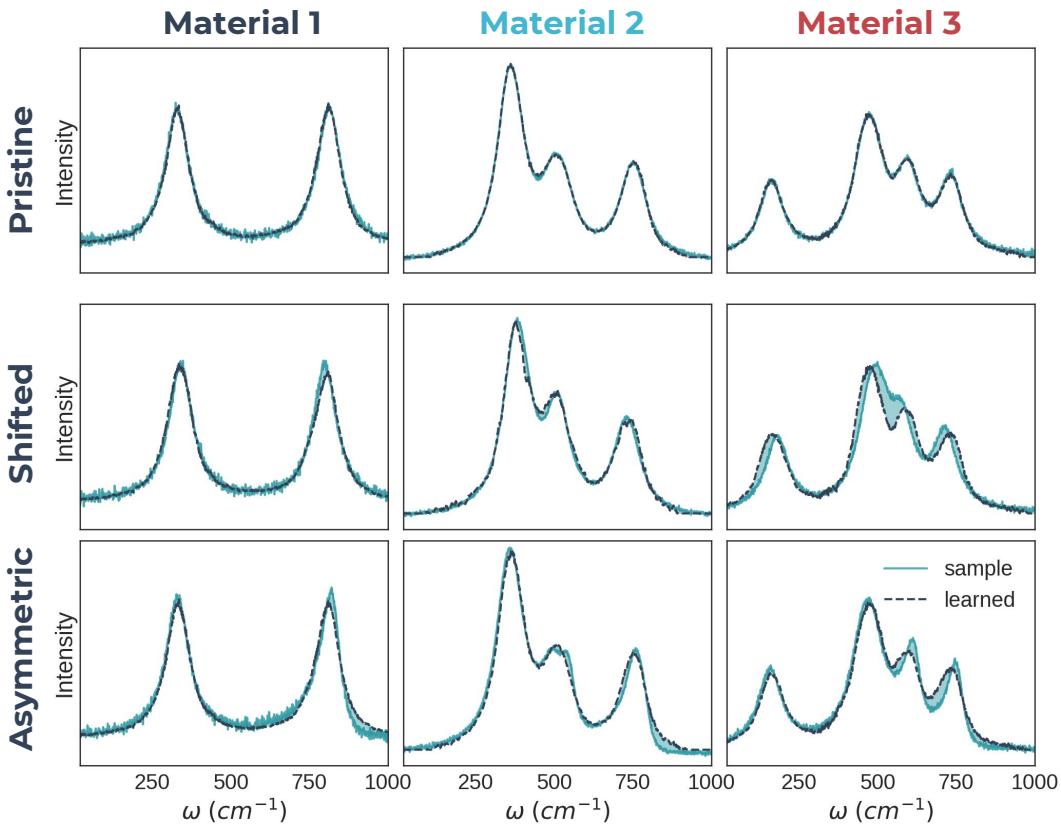
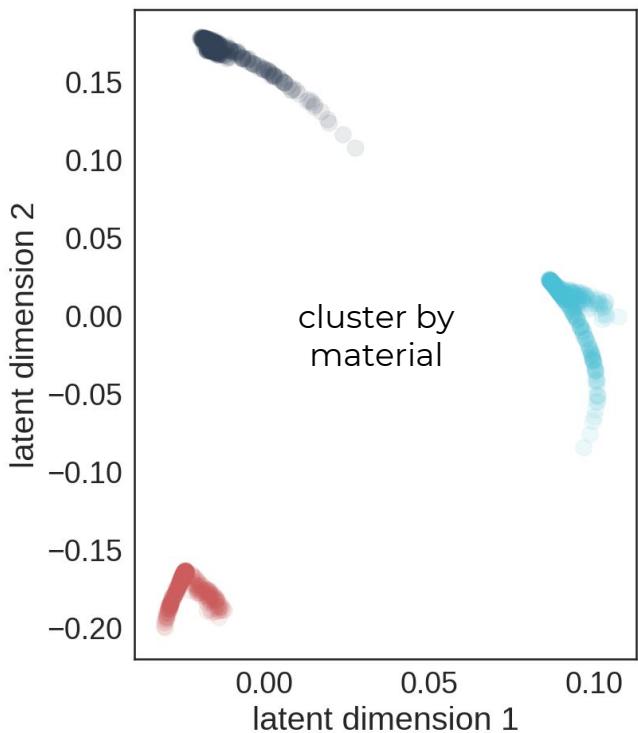
Generate 3 different materials classes with increasing complexity



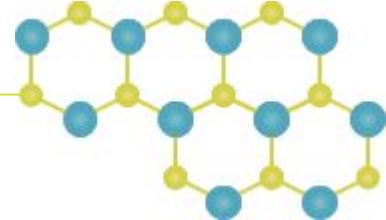
Autoencoder



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

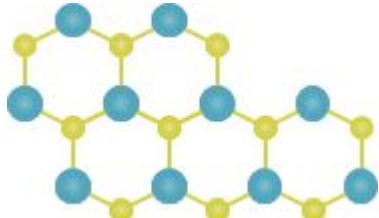
Next steps:

- 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

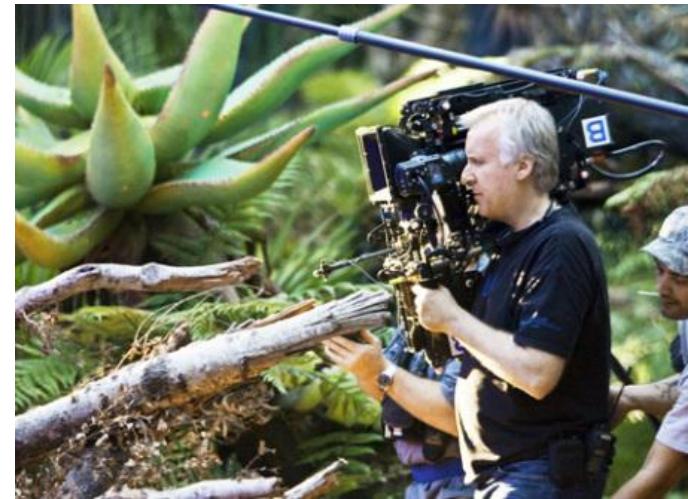
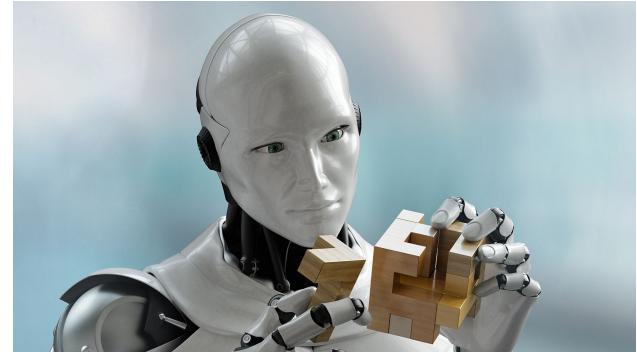


Image courtesy of Imaginarium Studios

Current Uses of Machine Learning in VFX

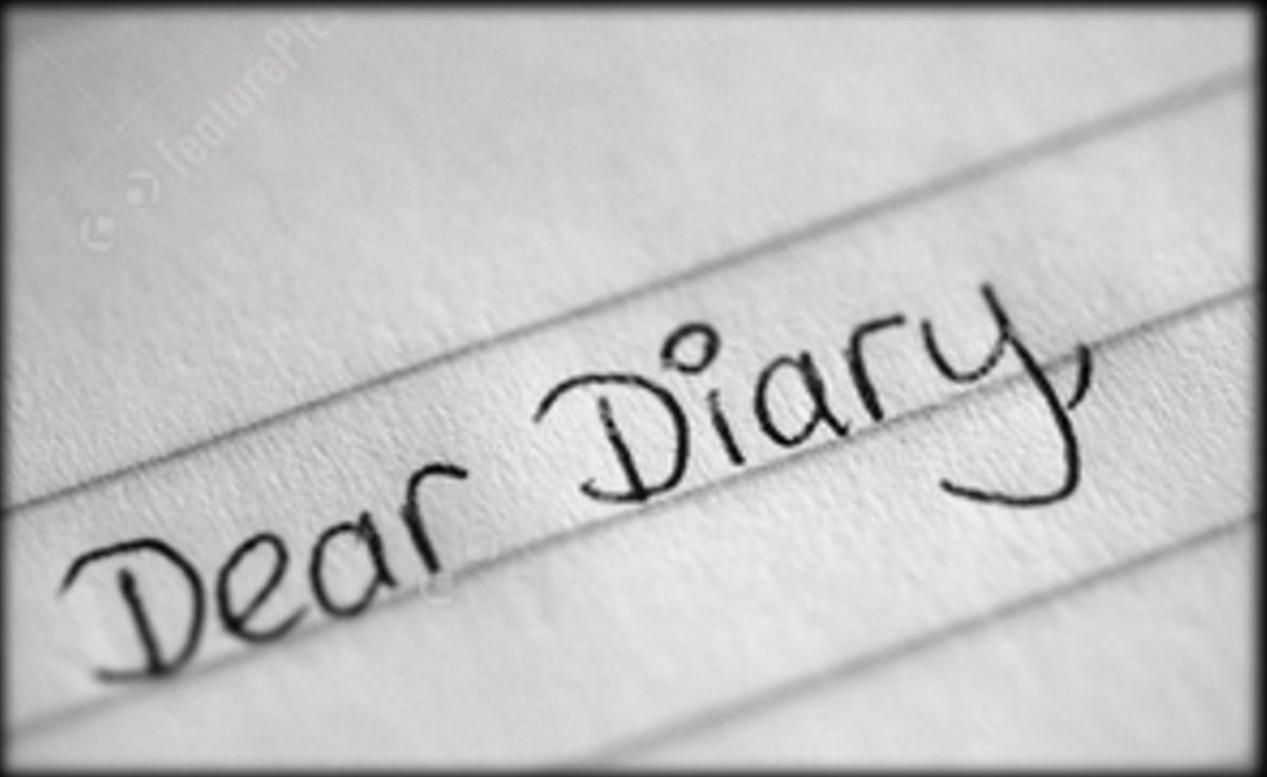
- CGI overlaid on real images
- Wire removal & green screen detection
- Rotoscoping
- Deepfakes
- Human faces created out of nothing
- Already large dataset





My. Inventory. Assistant.

DEEP LEARNING FOR HOUSEHOLD INVENTORY MANAGEMENT



© featurepics.com

Dear Diary

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.



Last Year



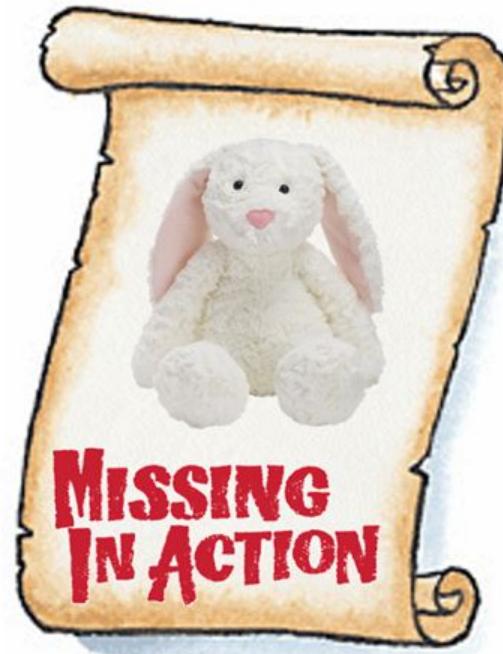
This Year



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.



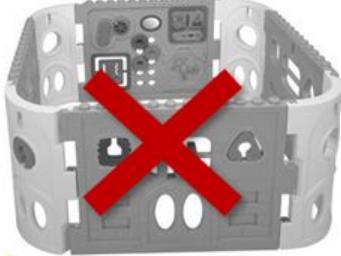
Toy bunny – Where is it?



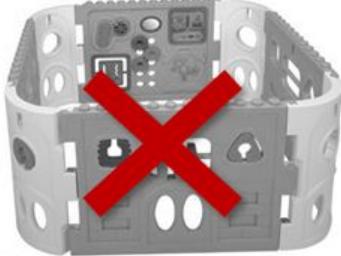
Toy bunny – Where is it?
The cot?



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!



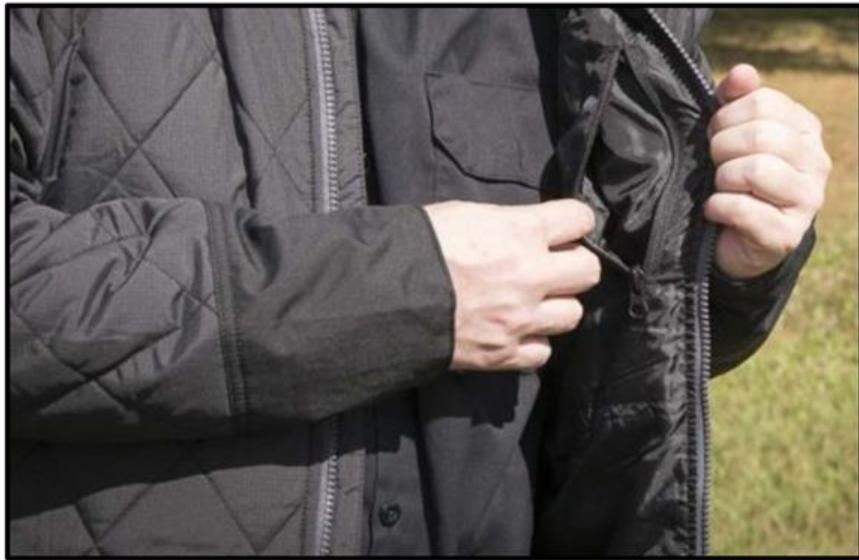
No coffee... A raging baby... A missing bunny...
An upset wife...



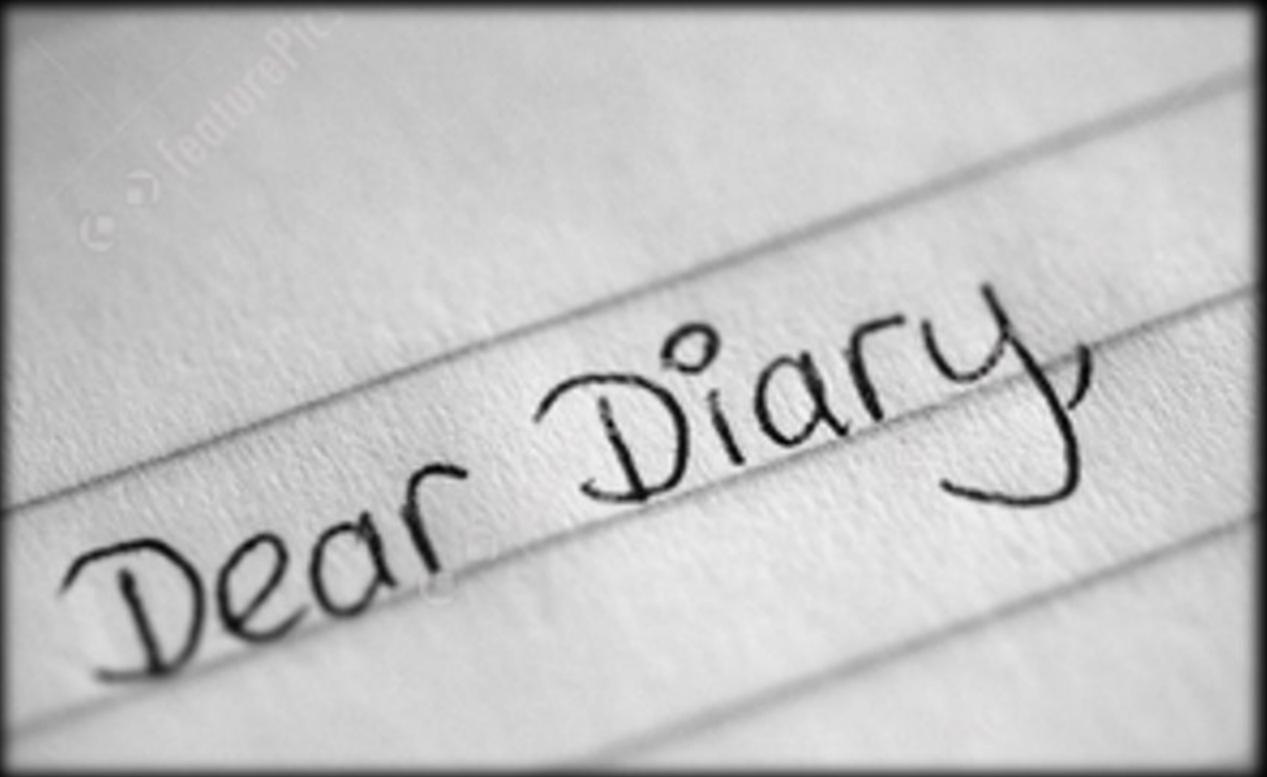
It can only get better right? I consoled myself as I approached my car.



Reaching into my pockets, I panicked...



Where is my car key?!!...



Dear Diary

Entry #2

2019 FEBRUARY						
Sun	Mon	Tue	Wed	Thu	Fri	Sat
27	28	29	30	31	1	2
X 3	X 4	X 5	X 6	X 7	X 8	X 9
X 10	X 11	X 12	X 13	X 14	X 15	16
17	18	19	20	21	22	23
24	25	26	27	28	1	2

It has been two weeks.

2019 FEBRUARY						
Sun	Mon	Tue	Wed	Thu	Fri	Sat
27	28	29	30	31	1	2
X 3	X 4	X 5	X 6	X 7	X 8	X 9
X 10	X 11	X 12	X 13	X 14	X 15	16
17	18	19	20	21	22	23
24	25	26	27	28	1	2



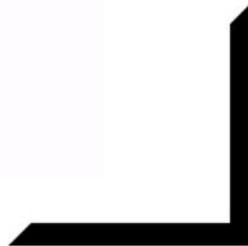
The bunny is still missing, the girl is still screaming, and the wife is still mad.



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.



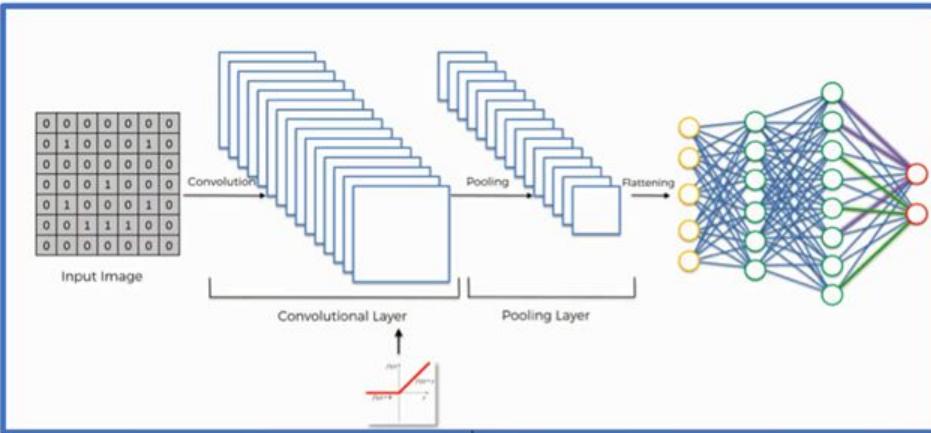
CAPTURED IMAGES



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



CONVOLUTIONAL NEURAL NETWORKS



TRAINING SET:
THE WORLD WIDE WEB IMAGE REPOSITORY



ID: REMOTE



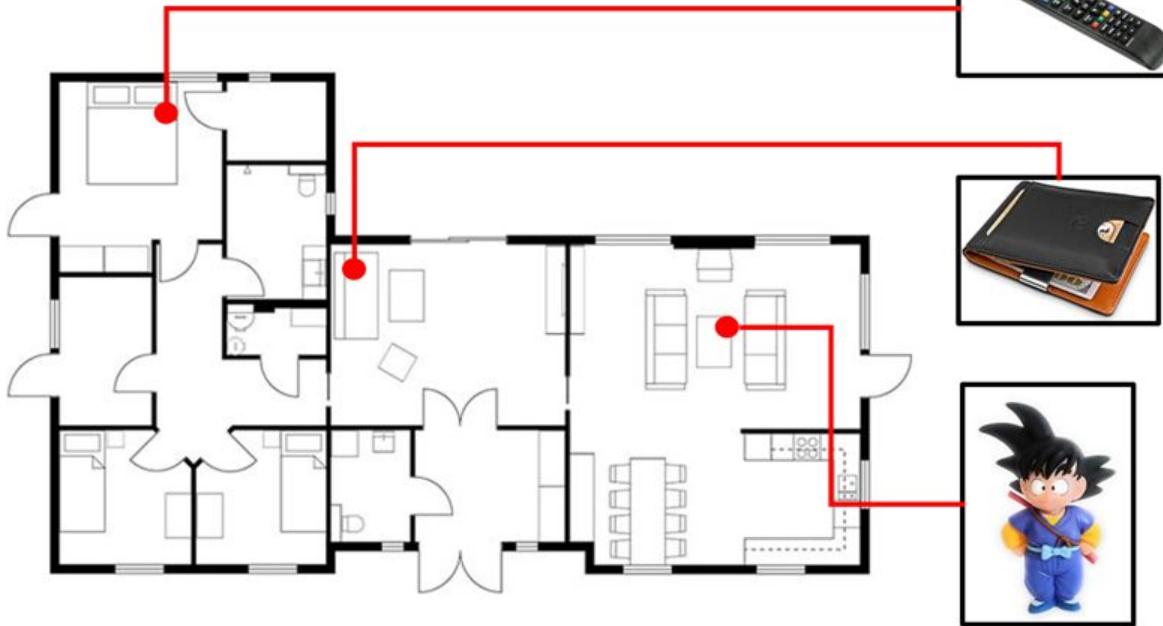
ID: WALLET



ID: GOKU

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

OBJECT LOCATION MAPPING:



... and maps out their location onto a floorplan.



OBJECT LOCATION MAPPING:

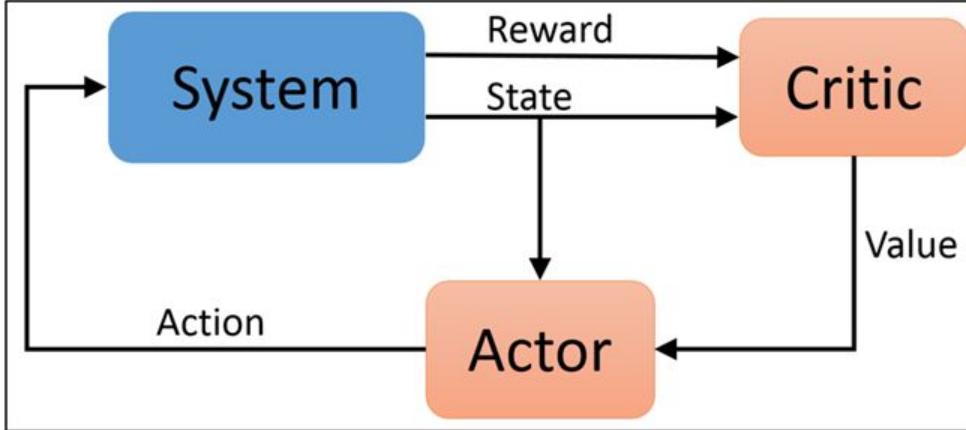


With a click from your device, you will know the quantity and location of the items.



This gadget gets smarter from here.

REINFORCEMENT DEEP LEARNING



State:

Inventory Level for N Items

Action:

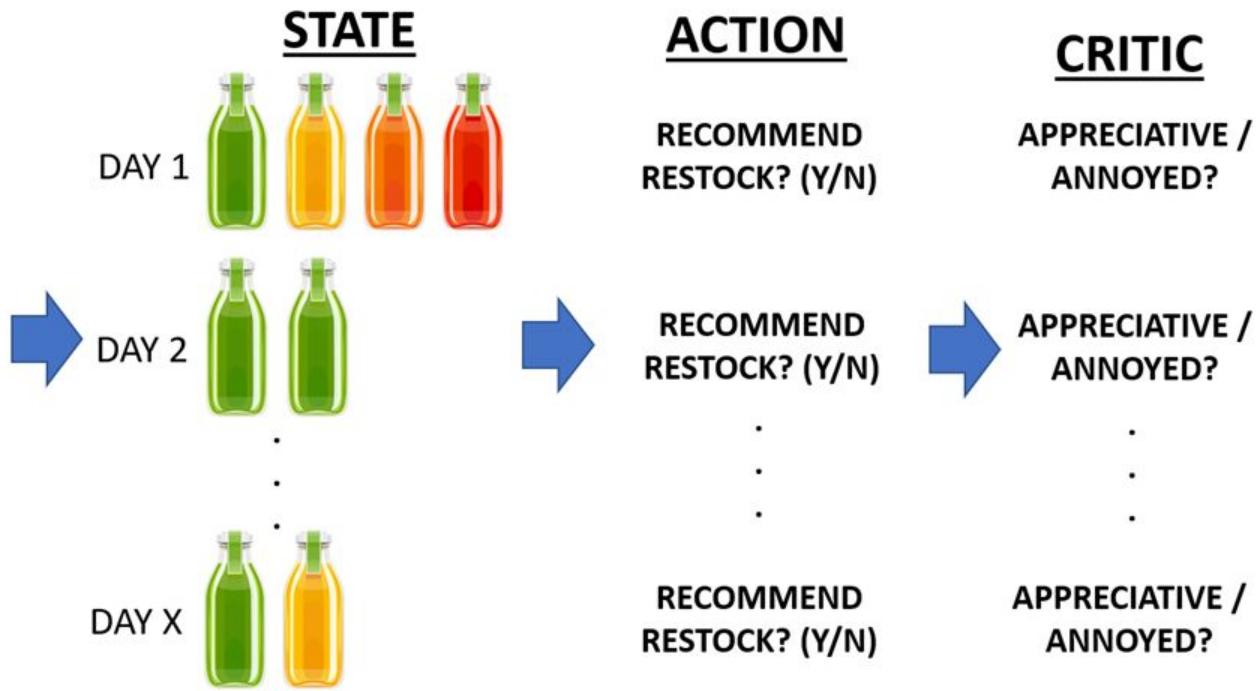
Prompt Restock for Item Category

Reward:

When Shortfall Predicted Correctly

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

IMAGERY ANALYSIS



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

IMAGERY ANALYSIS



STATE

MONTH 1



MONTH 2



MONTH X



ACTION

RECOMMEND
PURCHASE? (Y/N)

CRITIC

APPRECIATIVE /
ANNNOYED?

RECOMMEND
PURCHASE? (Y/N)

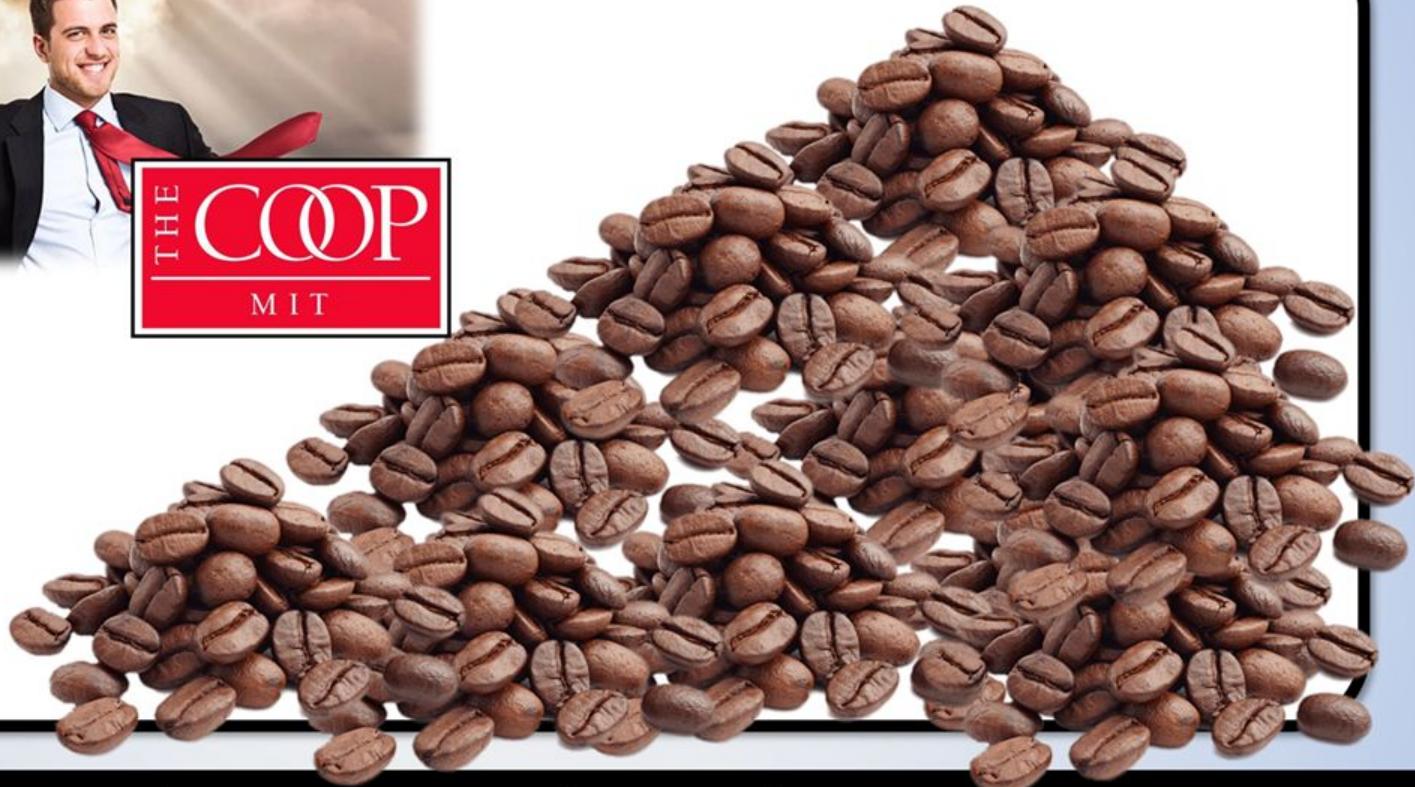
APPRECIATIVE /
ANNNOYED?

.
. .
. .

RECOMMEND
PURCHASE? (Y/N)

APPRECIATIVE /
ANNNOYED?

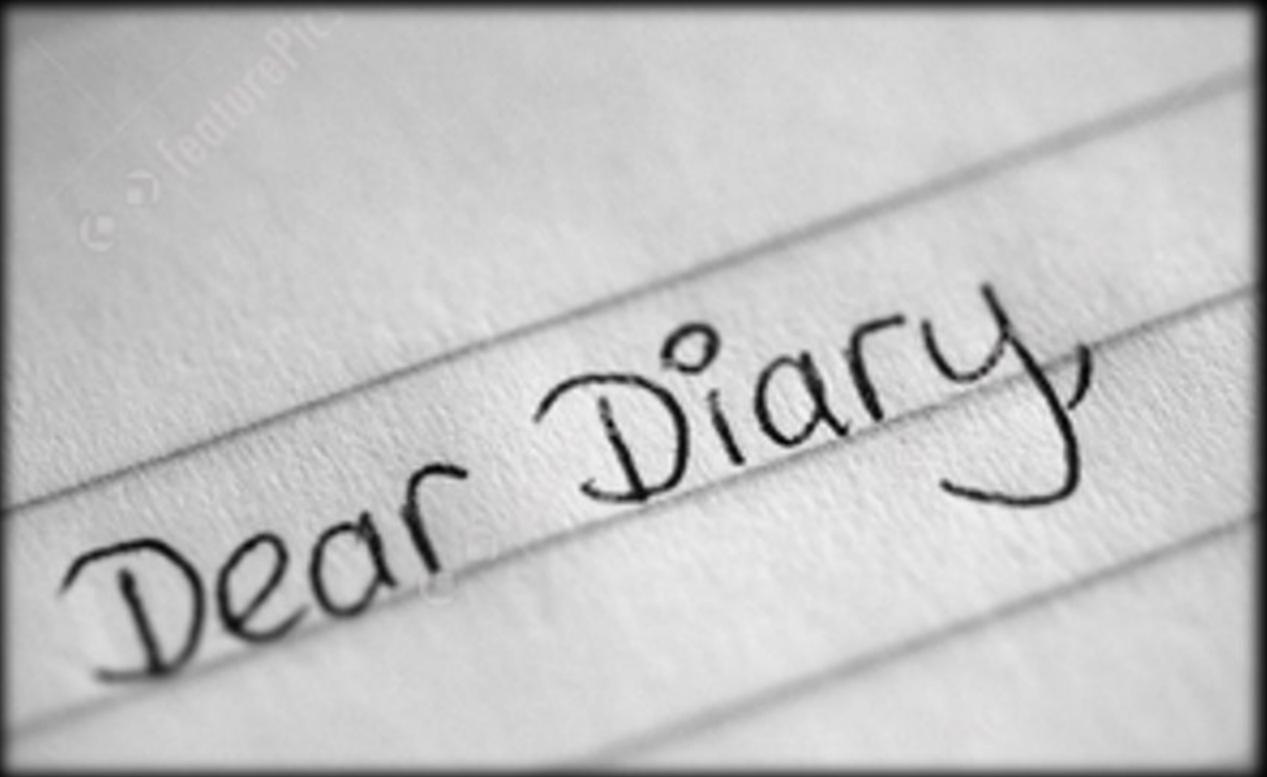
It also profiles your wardrobe based on their color, style, and quantity.



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



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



featurePic
©

Dear Diary

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.



SEARCH RESULTS FOR HANDBAGS:



X 2

SINCERELY, M.I.A.

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



LOW QUANTITY WARNING:



Coffee Beans x 1

SINCERELY, M.I.A.

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.

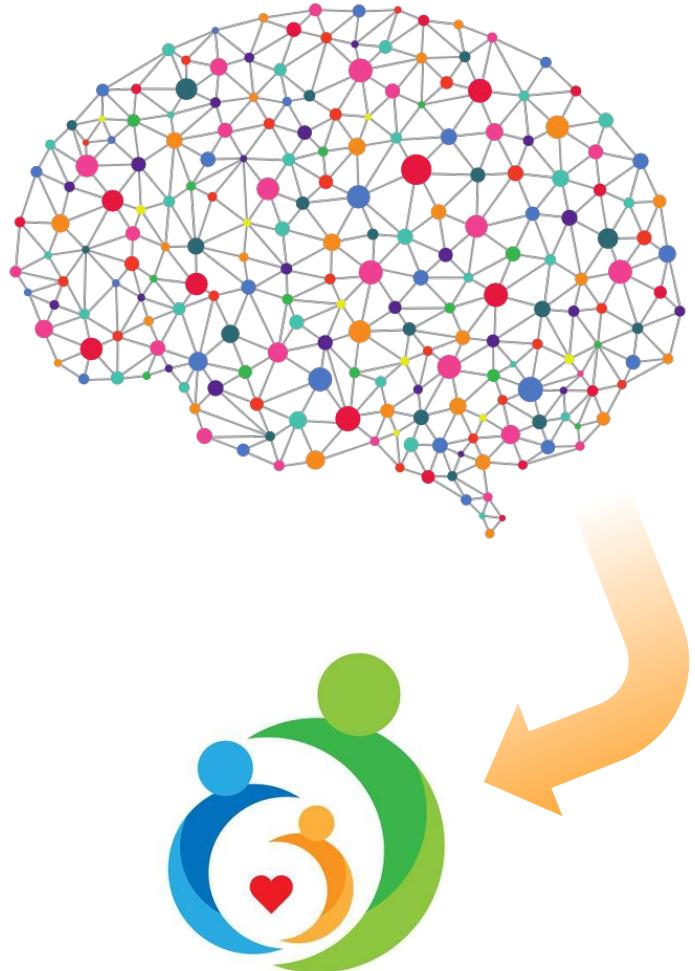
“My Inventory Assistant has my back.”



My. Inventory. Assistant.

DEEP LEARNING FOR HOUSEHOLD INVENTORY MANAGEMENT

THANKS FOR LISTENING!



AI-assisted parenting

Zhenhua (Ray) Rui
&
Kai Jin

Group 12

parenting is a sophisticated job



Kids development

Language
Motor skills
Mental
Habits

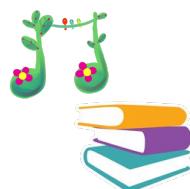
...

learn how kids learn and suggest the next move

“en”, “a”, ...



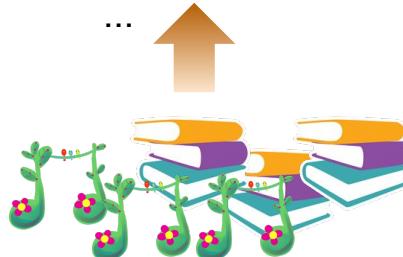
“en”, “a”, “mama”
dance
“car”



“en”, “a”, “mama”
dance
tempo

“car”,
“pickup truck”

choose books



6 month

12 month

18 month

24 month

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?

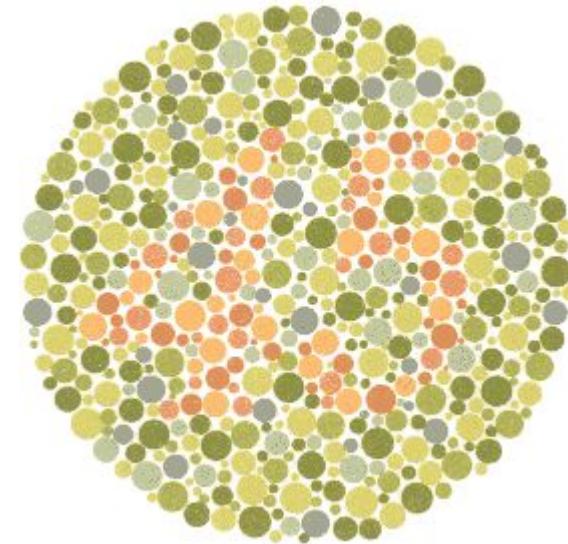
Proposed solution

Potential applications

What is Color blindness, and why it matters?

8% of men are colorblind^[1]

1 in every 200 women is colorblind^[1]

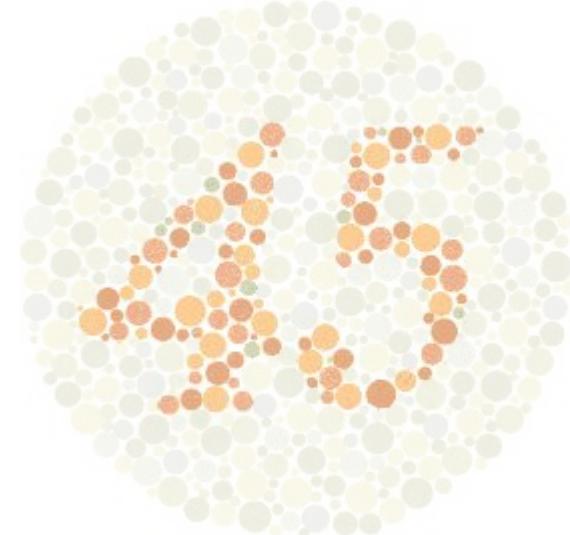


What number do you see?

What is Color blindness, and why it matters?

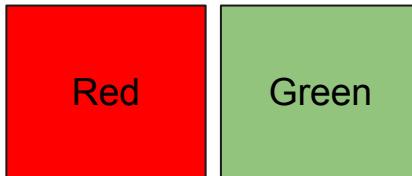
8% of men are colorblind^[1]

1 in every 200 women is colorblind^[1]

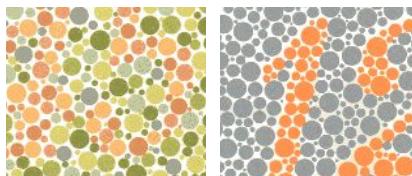


The problem

Colorblind people usually can distinguish standalone colors



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



Do EnChroma glasses improve color vision for colorblind subjects?
L. Gómez-Robledo, E. M. Valero, R. Huertas, M. A. Martínez-Domínguez, 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>

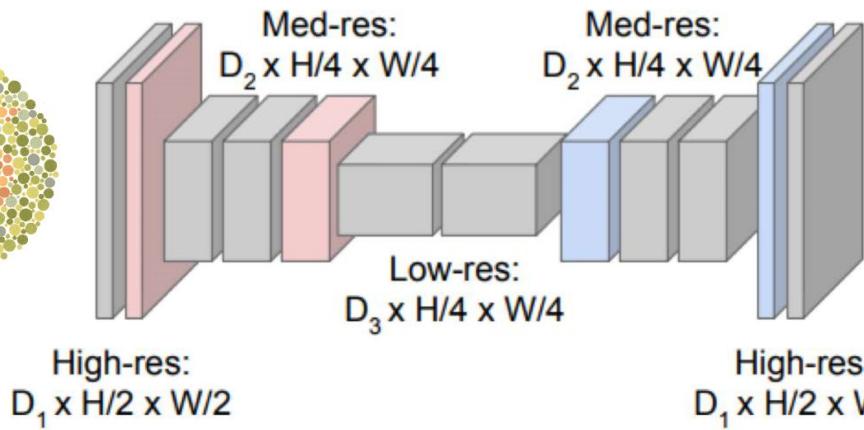
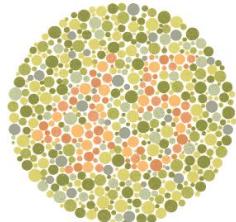
[2] Jimmi Lee, Wellington P. dos Santos. An Adaptive Fuzzy-Based System to Simulate, Quantify and Compensate Color Blindness

[3] Gajo Petrovic, Hamido Fujita. Deep Correct: Deep Learning color correction for color blindness

The model/system

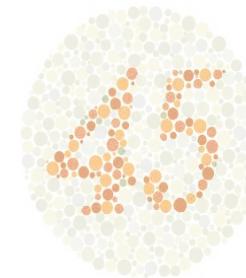
[Illustrative]

Input image



CNN

Output image



*Using colors within
the domain of
visualization for
colorblind people*

**Loss-function
dependent on:**

Interpretability by
colorblind people
*Assessed by mathematical
transformation and field
tests (feedback)*

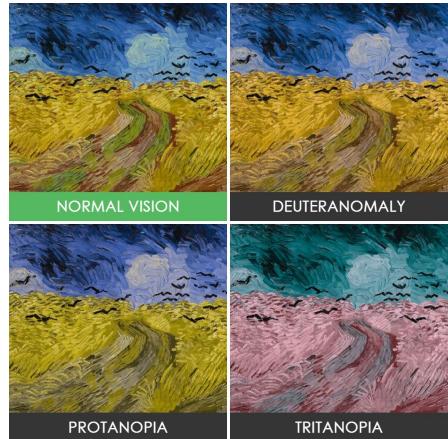
↑ max

Distortion from
original image

↓ min

Potential applications

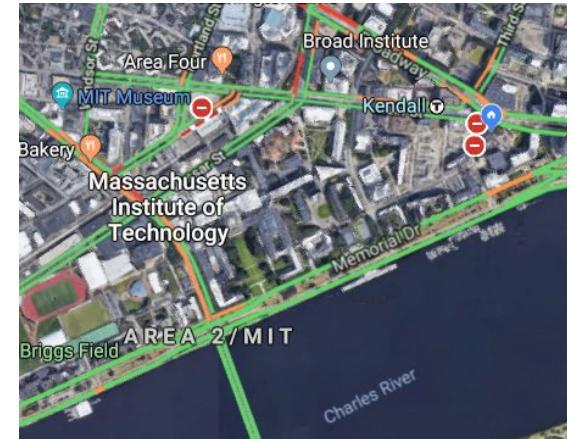
Improve accessibility to digital content



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

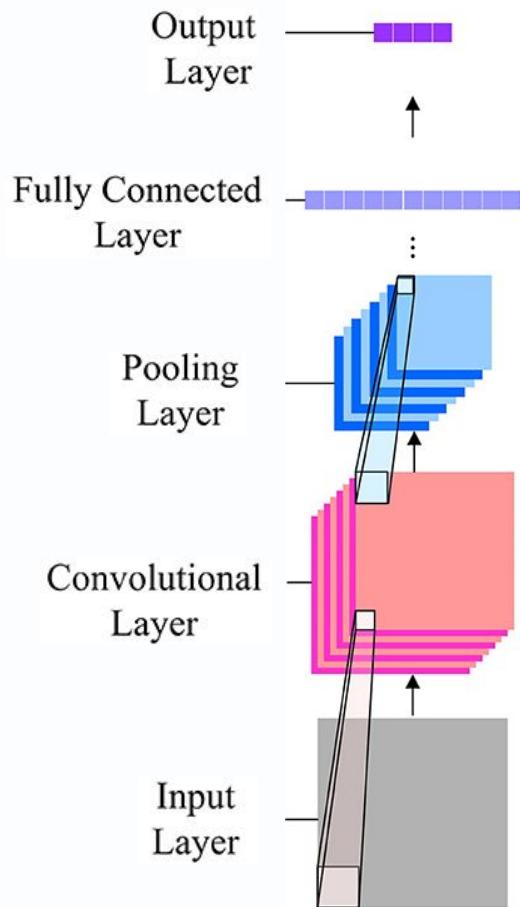
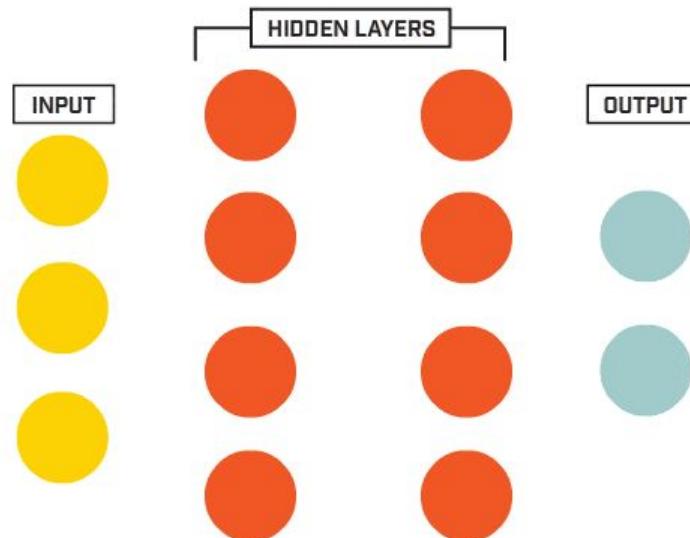
training a set of Classifiers

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



Massachusetts Institute of Technology

Background

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



Customized interior design using generative models

Group 18: Keran Rong ; Mia Hong



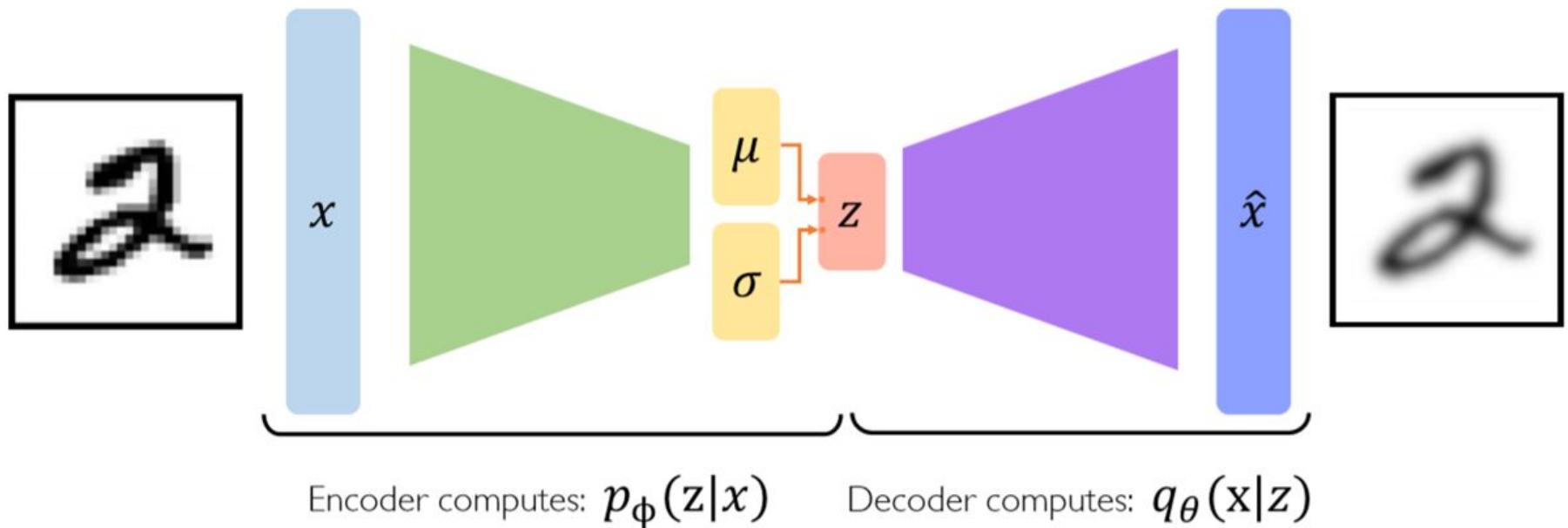
Customized interior design using generative models

Interior design Current situation:

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

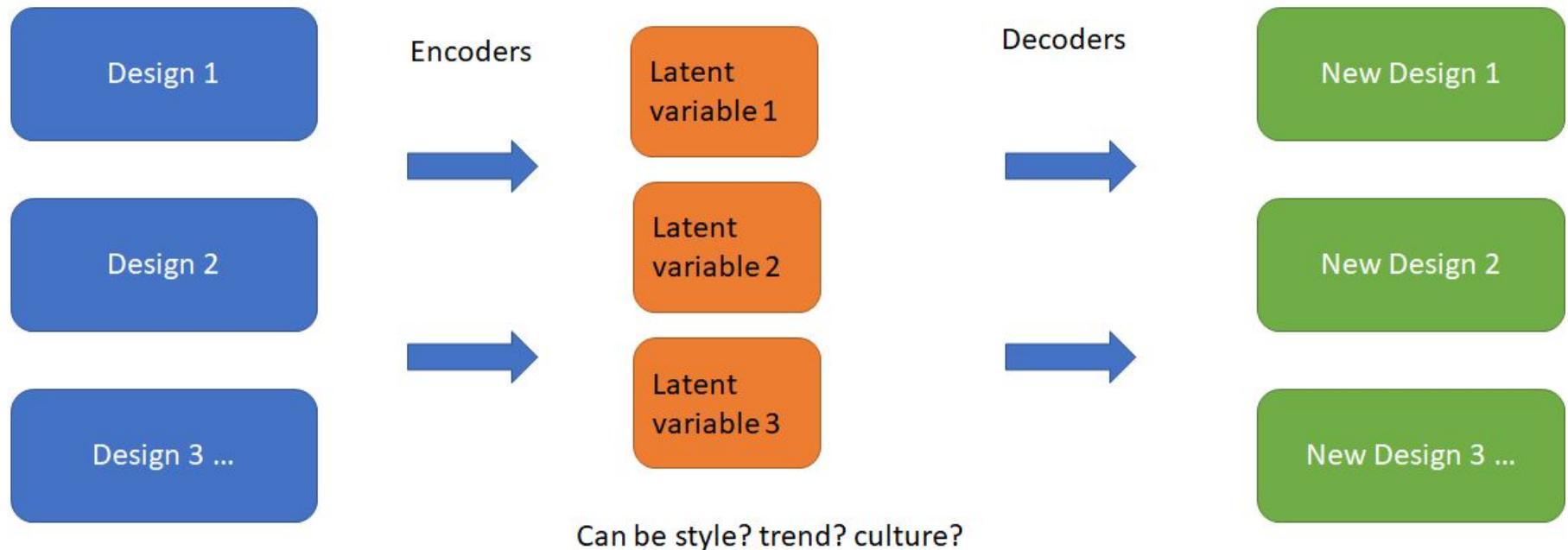


VAE optimization



Customized interior design using generative models

Previous high rate design



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



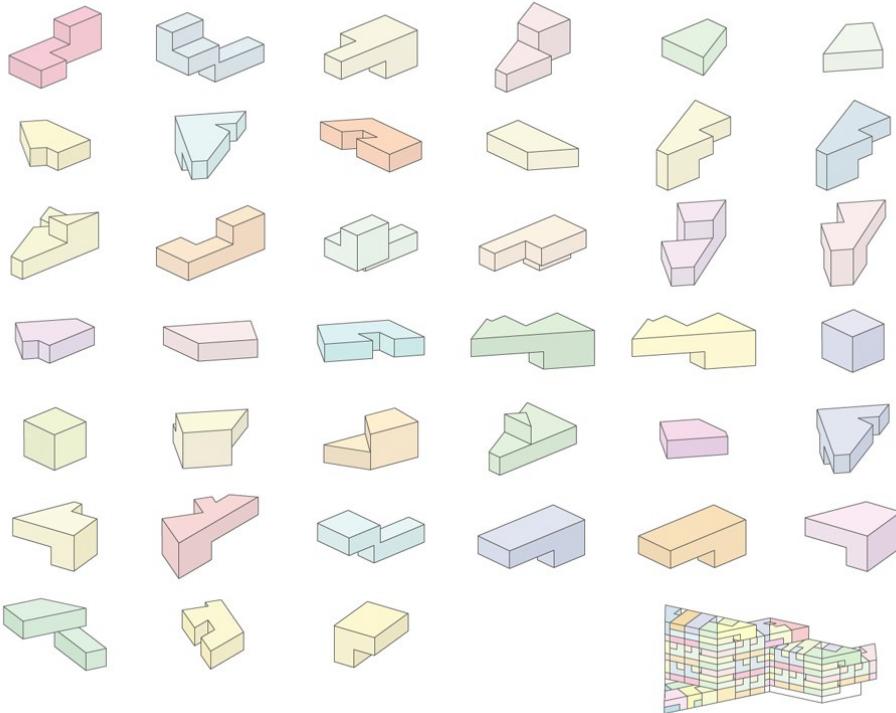
CARBON EMISSIONS

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



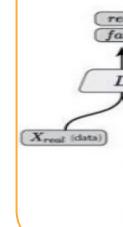
(Low) material wastage



B Design and develop GAN model

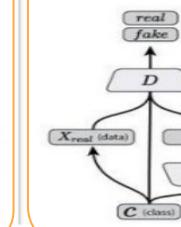
Vanilla GAN

Vanilla GAN
(Goodfellow, et al., 2014)



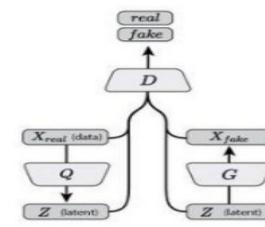
Discriminator Looks at Latent Variables

Conditional GAN
(Mirza & Osindero, 2014)



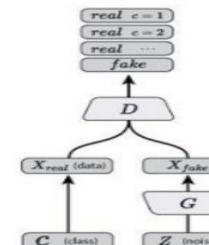
Bidirectional GAN

(Donahue, et al., 2016; Dumoulin, et al., 2016)

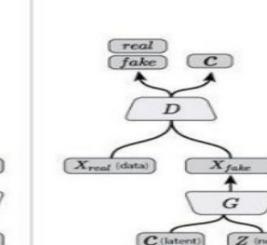


Discriminator Predicts Latent Variables

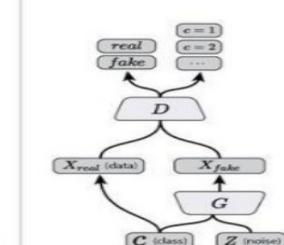
Semi-Supervised GAN
(Odena, 2016; Salimans, et al., 2016)



InfoGAN
(Chen, et al., 2016)



Auxiliary Classifier GAN
(Odena, et al., 2016)

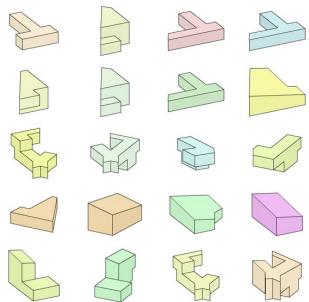


PROPOSED APPLICATION

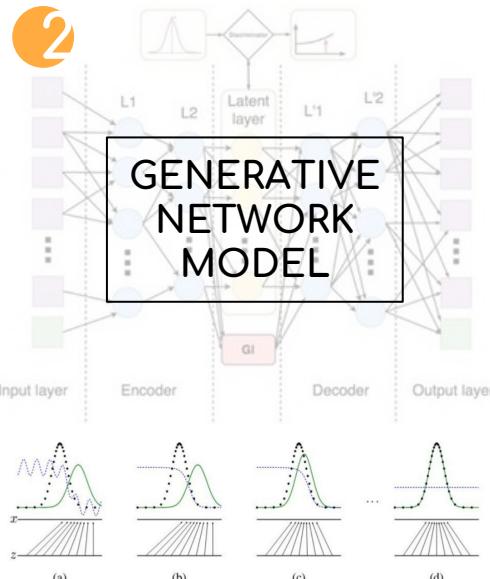
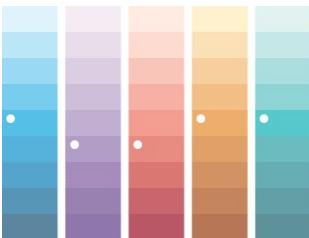
GENERATIVE ADVERSARIAL NETWORKS (GAN)

1 Data | Samples

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



Latent Space



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





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



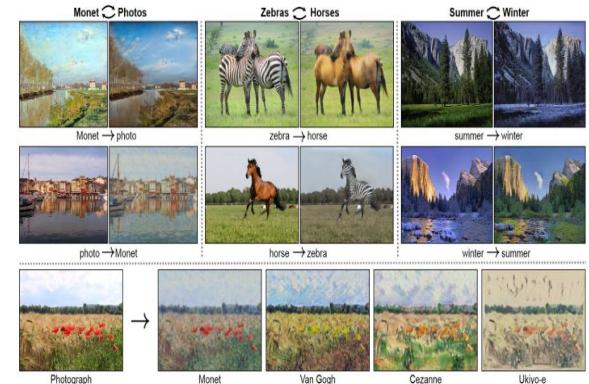
Jin et al (2017)
(Fudan & Carnegie Mellon)

2 Generating Pose-guided Apparel



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

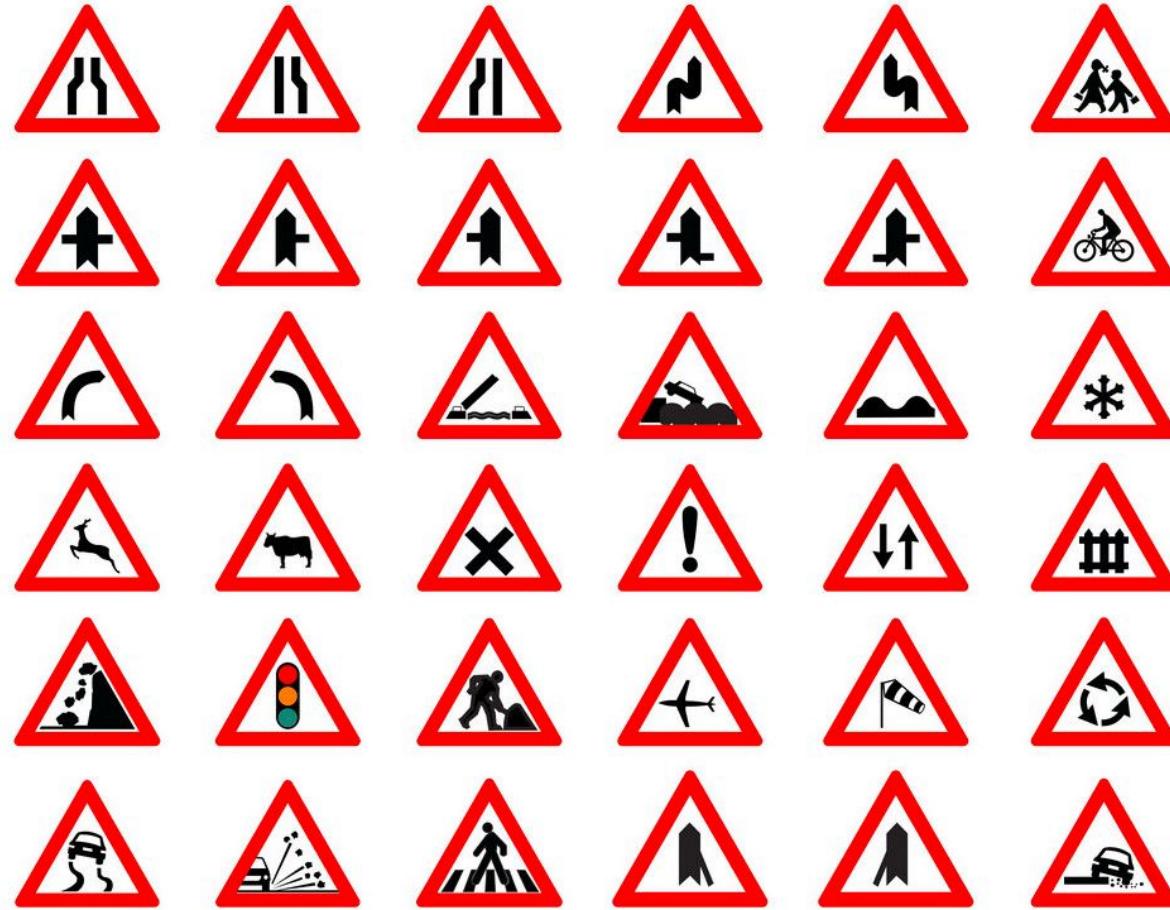
3 CycleGAN: Generating photos from paintings etc



Zhu et al (2017)
(UC Berkeley)



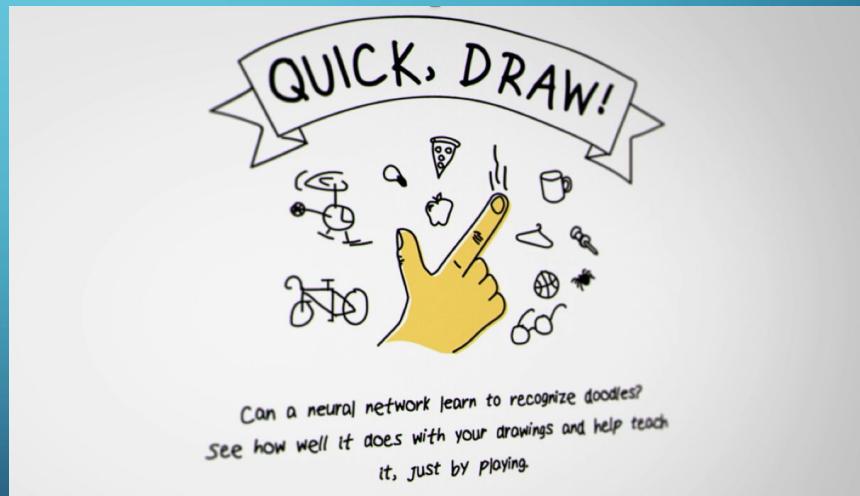
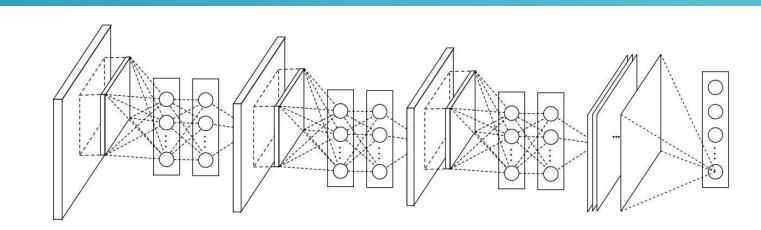
THANK YOU

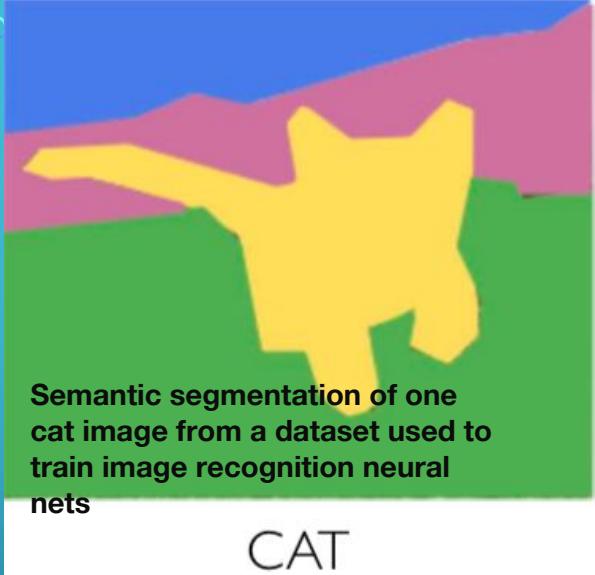


DEEP DOODLE

DEEP LEARNING METHODS TO GENERATE SKETCHES FROM LABELS

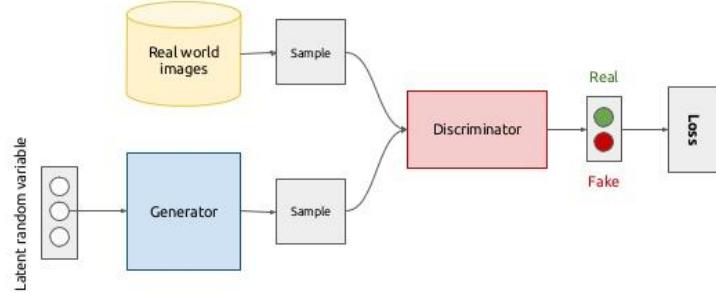
WHAT DEEP LEARNING CONCEPTS ARE WE USING?



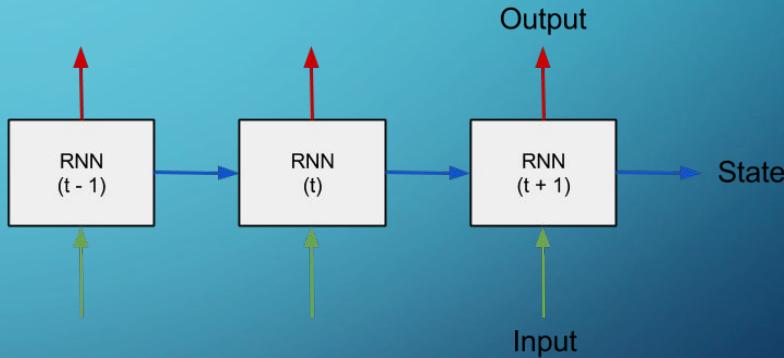


WHAT DEEP LEARNING CONCEPTS ARE WE USING?

Generative adversarial networks (conceptual)

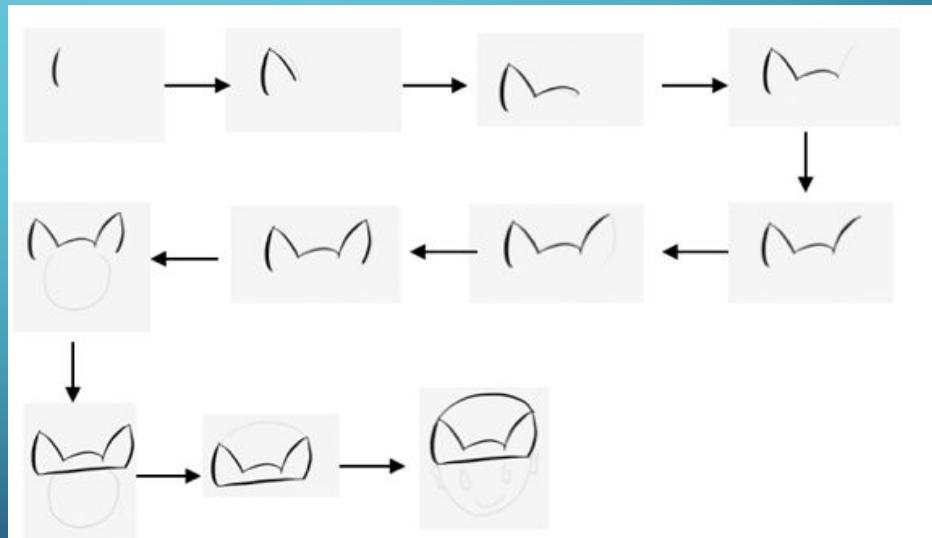


5



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?



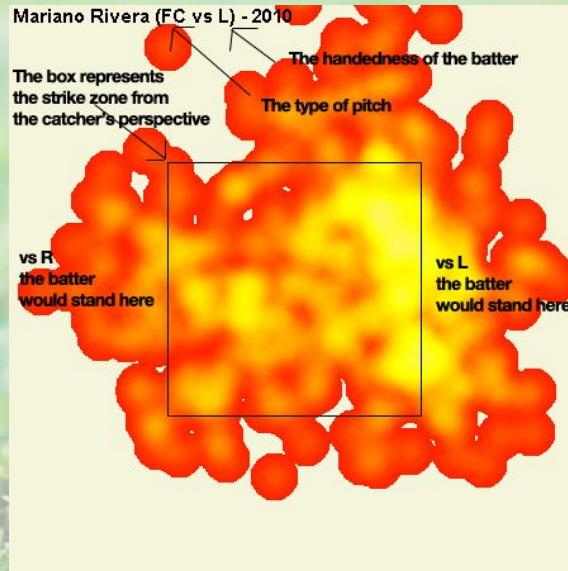
Why not just pick the top hitters in the MLB?

- 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

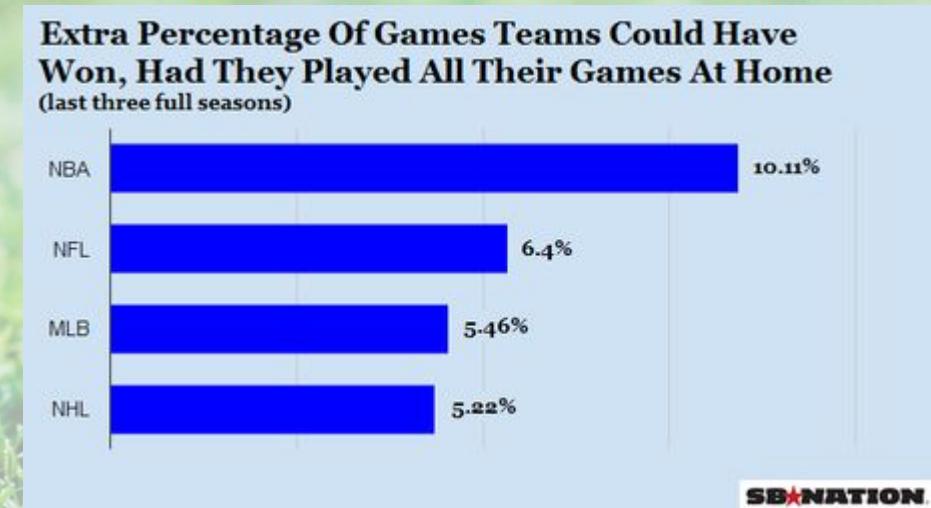
Why not just pick the top hitters in the MLB?

- 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

```
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

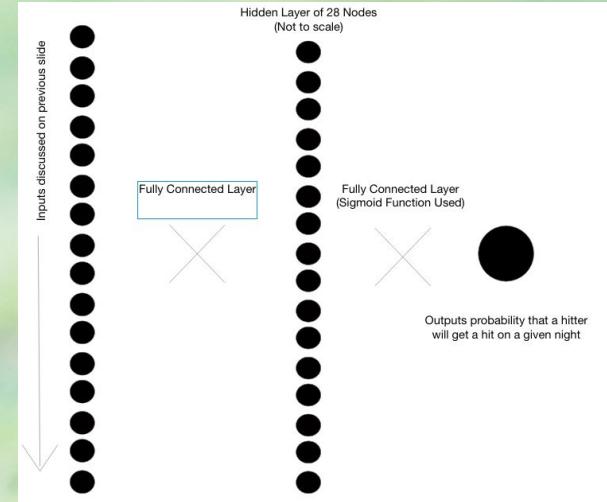
        got_hit = False
        for ab in player['atbats'][0]['ab']:
            if 'Single' or 'Double' or 'Triple' or 'Home Run' in ab['event']:
                got_hit = True

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

```
        ],
        "vs_LHP": [
        {
            "avg": ".263",
            "ab": "95",
            "h": "25",
            "bb": "10",
            "so": "16",
            "rb": "9",
            "sb": "2",
            "cs": "0",
            "hr": "0",
            "rbi": "6",
            "ops": ".667"
        }
    ],
    "vs_RHP": [
    {
        "avg": ".238",
        "ab": "143",
        "h": "34",
        "bb": "20",
        "so": "37",
        "rb": "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 = 16
hidden_num_units = 32
output_num_units = 1

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

# set remaining variables
epochs = 5
batch_size = 128
learning_rate = 0.01

### 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 neural 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

A close-up photograph of a baseball resting on a vibrant green lawn. The ball is positioned on the left side of the frame, showing its white cover and red stitching. The background is a soft-focus view of the same green grass, creating a sense of depth.

Thank you!

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Final Project Presentations

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