GRADUATE FELLOW FAST FORWARD

Bill Dally, Chief Scientist and SVP Research, NVIDIA

Thursday, March 21, 2019

GRADUATE FELLOWSHIP PROGRAM

Funding for Ph.D. students revolutionizing disciplines with the GPU

Engage:

- Build mindshare
- Facilitate recruiting

Learn:

- Keep a finger on the pulse of leading academic research
- Keep up with all the applications that are powered by GPUs

Leverage:

- Track relevant research
- Help to guide researchers working on relevant problems

GRADUATE FELLOWSHIP PROGRAM

165 Graduate Fellowships awarded -- $4.9M since program inception in 2002

Eligibility/Application Process:

- Ph.D. candidates in at least their 2nd year
- Nomination(s) by Professor(s)/Advisor
- 1-2 page research proposal

Selection Process:

- Committee of NVIDIA scientists and engineers review applications
- Applications evaluated for originality, potential, and relevance

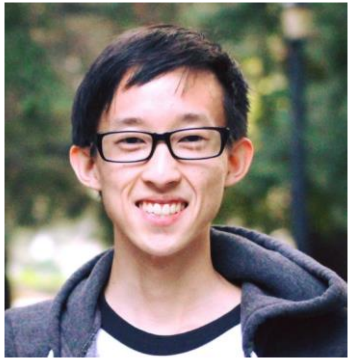
CURRENT 2018-2019 GRAD FELLOWS

Abhishek Badki, UCSB

Adam Stooke, UCB

Aishwarya Agrawal, Georgia Tech

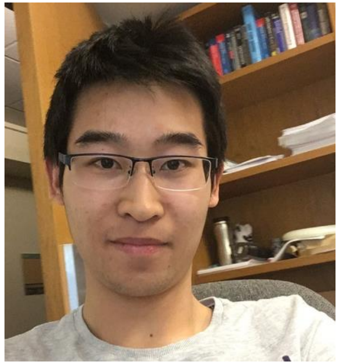
Ana Serrano, Universidad de Zaragoza



Andy Zeng, Princeton

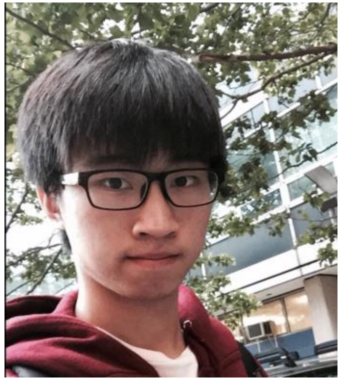
Daniel George, UIUC

CURRENT 2018-2019 GRAD FELLOWS



Huizi Mao, Stanford

Philippe Tillet, Harvard



Xun Huang, Cornell

Zhilin Yang, CMU

William Yuan, Harvard
NVIDIA Foundation Fellow

CURRENT 2018-2019 GRAD FELLOW FINALISTS

- Chenxi Liu, Johns Hopkins University
- Jake Zhao, New York University
- Mario Drummond, EPFL
- Mark Buckler, Cornell University
- Steve Bako, UC Santa Barbara

AGENDA

- Grad Fellow Fast Forward Talks, 3 mins each:
  - Aishwarya Agrawal, Georgia Tech
  - Abhishek Badki, UC Santa Barbara
  - Daniel George, Univ of Illinois Urbana-Champaign
  - Xun Huang, Cornell
  - Huizi Mao, Stanford
  - Ana Serrano, Univ de Zaragoza
  - Philippe Tillet, Harvard
  - Zhilin Yang, CMU
  - William Yuan, Harvard
- Certificates/Photographs
- NVIDIA Foundation Overview
- Announcement of the 2019-2020 Fellows & Finalists

AISHWARYA AGRAWAL, GEORGIA TECH

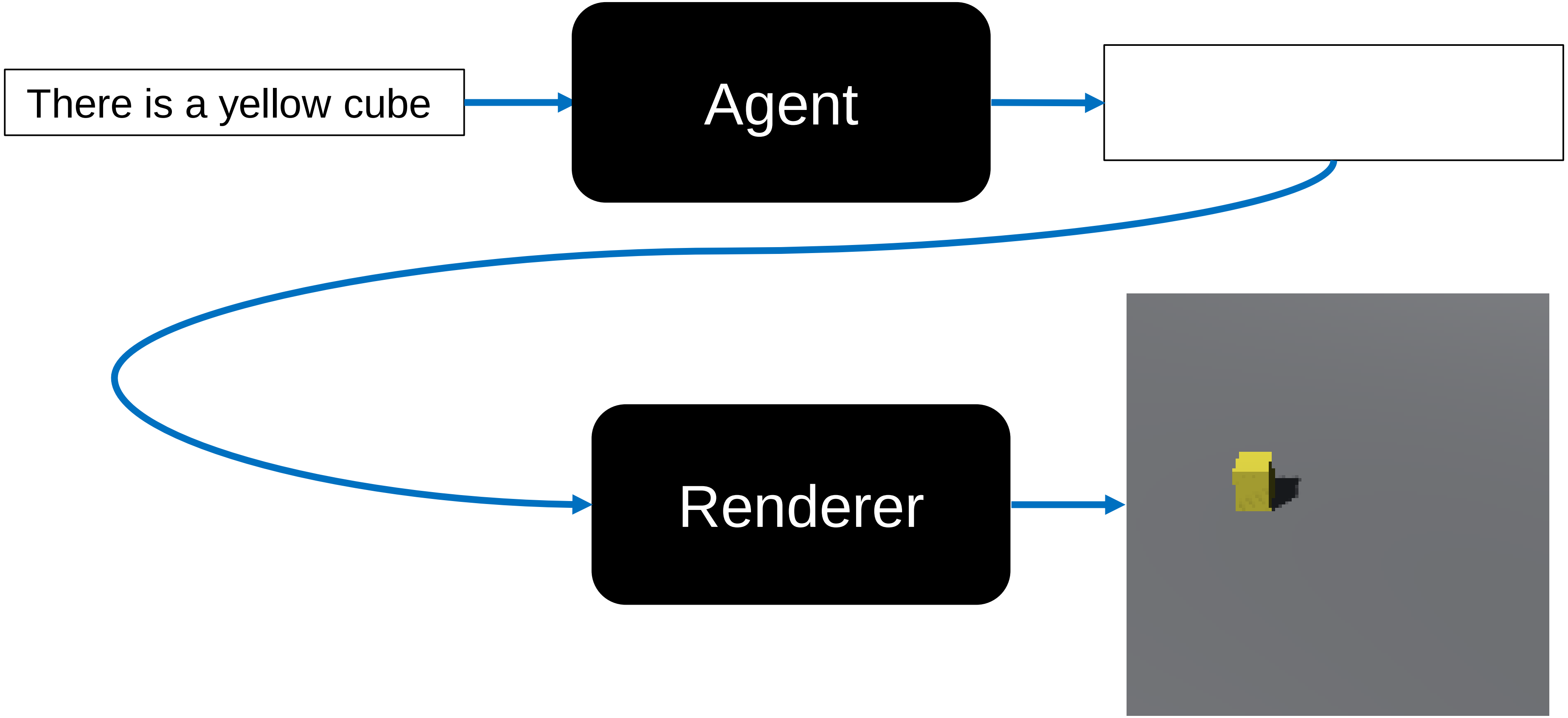
NVIDIA

GENERATING DIVERSE PROGRAMS WITH INSTRUCTION CONDITIONED REINFORCED ADVERSARIAL LEARNING

Aishwarya Agrawal, Georgia Tech

March 21, 2019

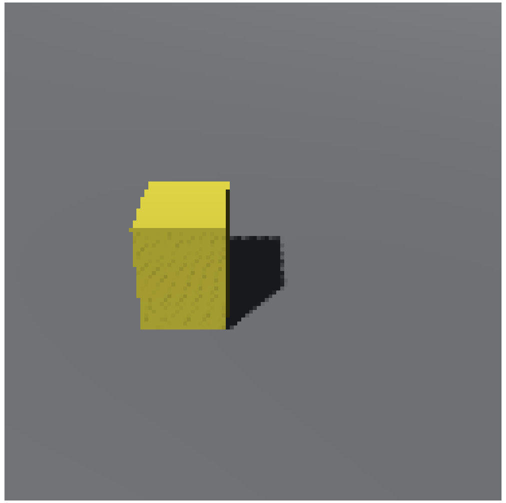
TASK

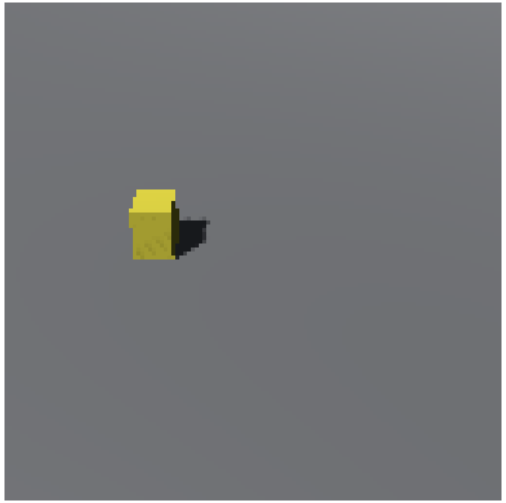


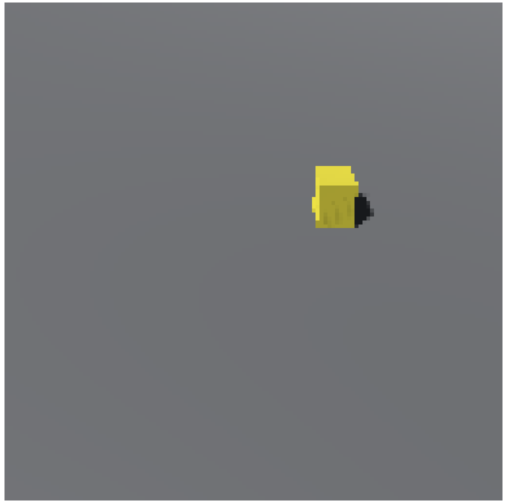
TASK

There is a yellow cube. → Agent →

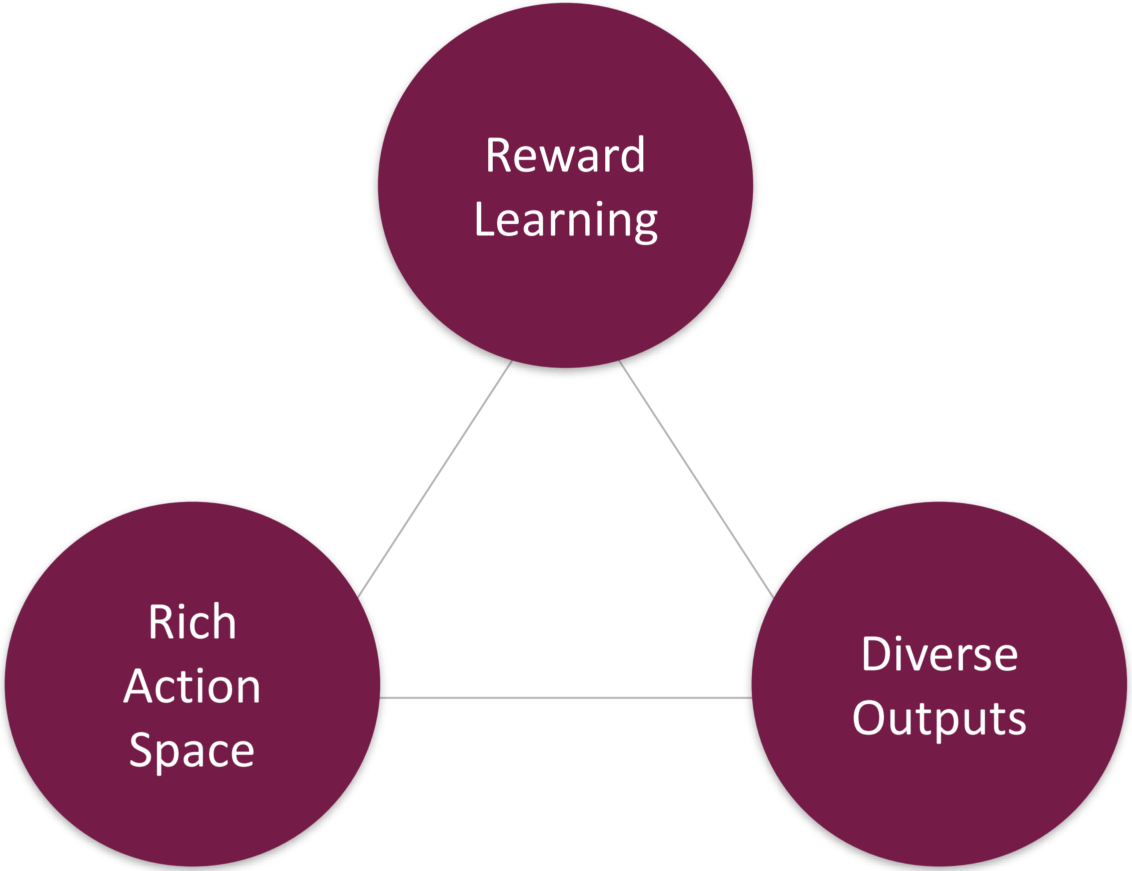
- add object, cube, yellow, large, at (12,17)
- add object, cube, yellow, small, at (8,14)
- add object, cube, yellow, small, at (22,12)







TECHNICAL CHALLENGES



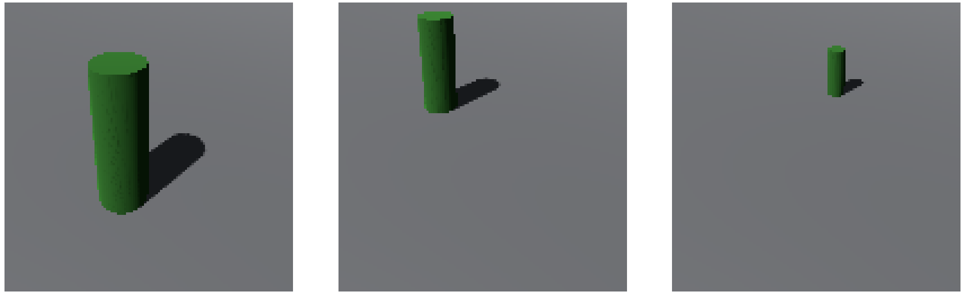
DOMAIN 1: MNIST DIGIT PAINTING

Draw 9.

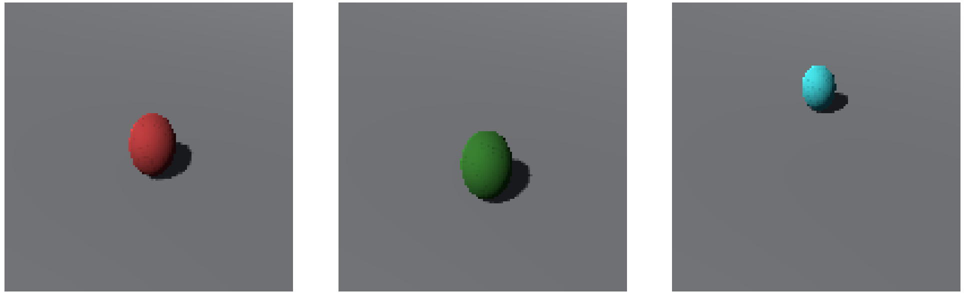
Paint five.

DOMAIN 2: 3D SCENE CONSTRUCTION

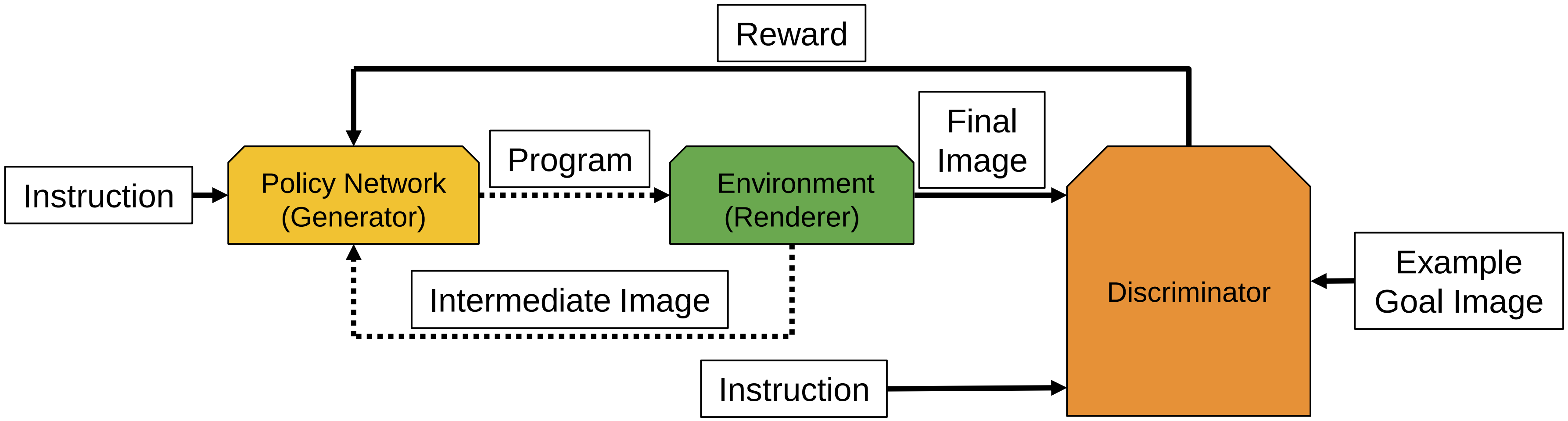
There is a green cylinder.



There is a large sphere.

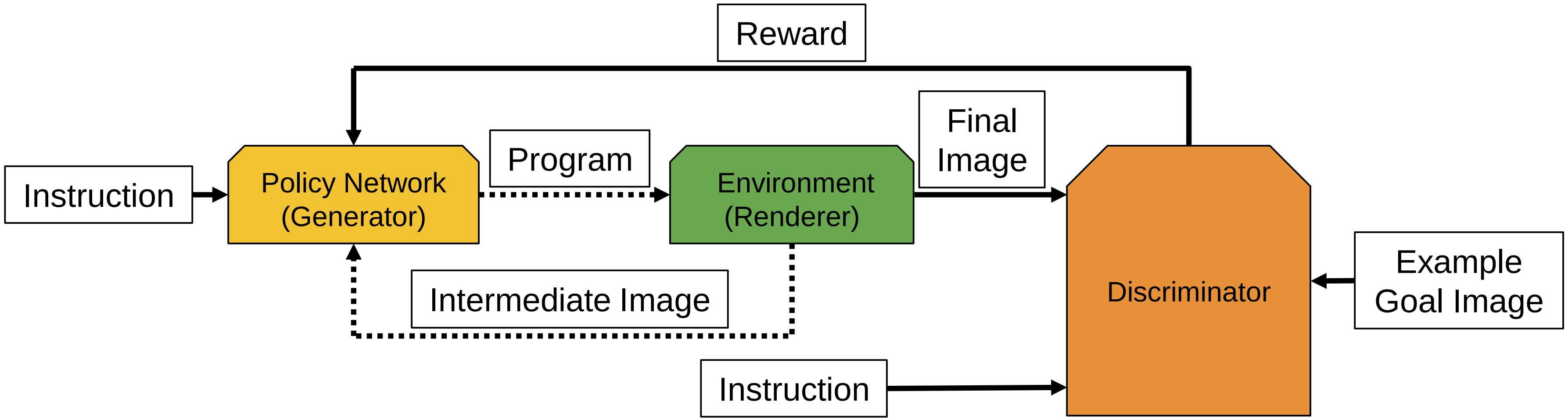


APPROACH



Extending *Ganin et al., ICML18*

APPROACH



All of the model training uses GPUs!

Extending *Ganin et al., ICML18*

DOMAIN 1: MNIST DIGIT PAINTING

Create zero

Put 1

Paint two

Draw 3

Add four

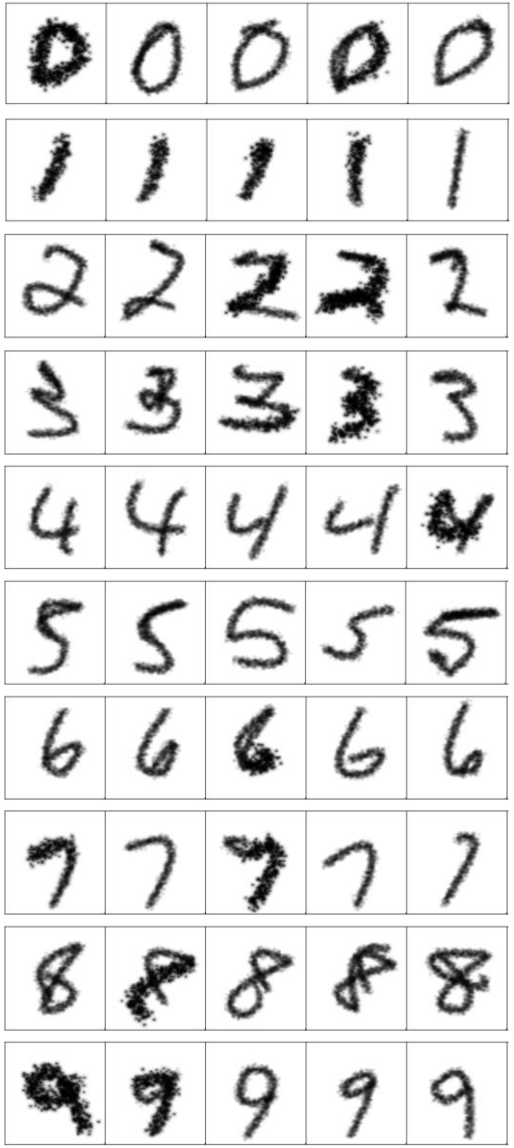
Draw 5

Paint six

Put 7

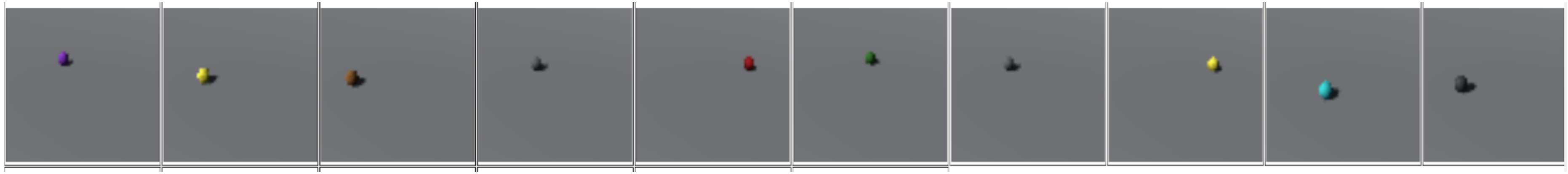
Create eight

Add 9



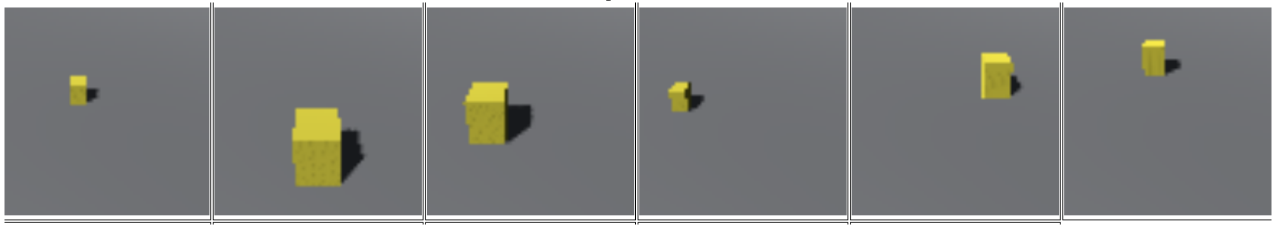
DOMAIN 2: 3D SCENE CONSTRUCTION

There is a small sphere.



There is a large cylinder.

There is a yellow cube.



THANKS!

COME TO OUR POSTER!

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ABHISHEK BADKI, UC SANTA BARBARA

COMPUTATIONAL ZOOM: A FRAMEWORK FOR POST-CAPTURE IMAGE COMPOSITION

Abhishek Badki, University of California, Santa Barbara

March 21, 2019

IMAGE COMPOSITION

16 mm, close

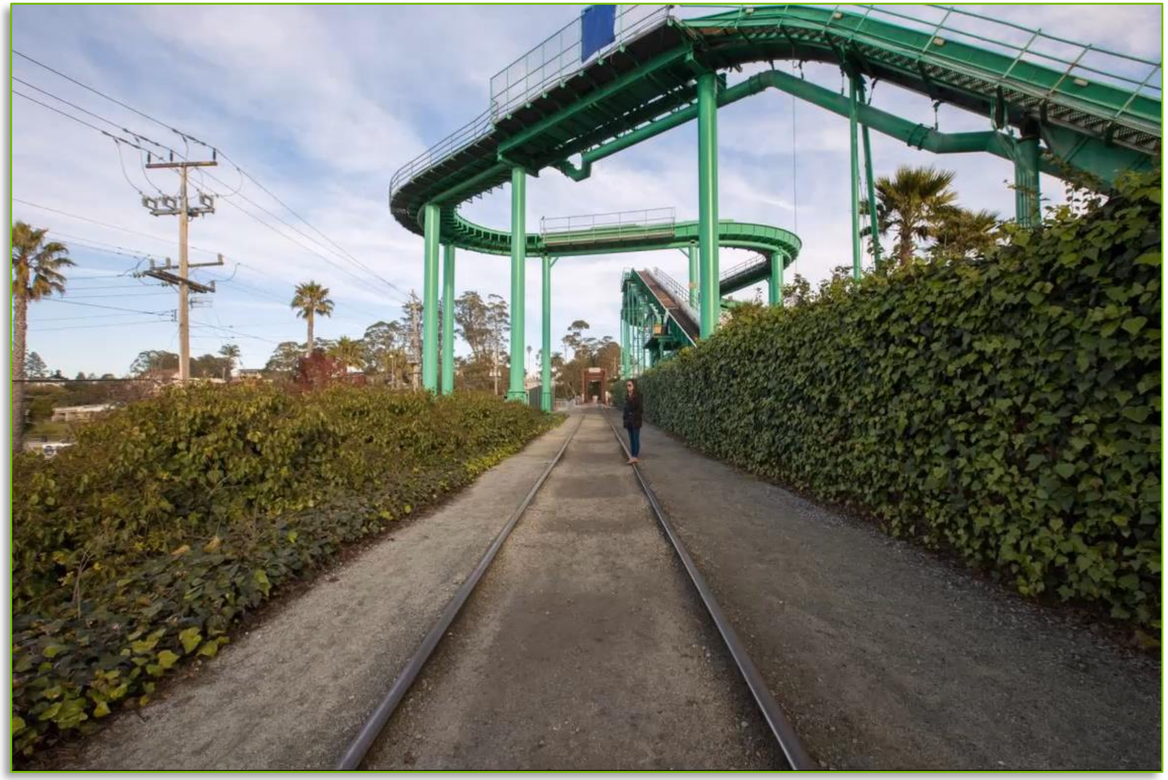
35 mm, far

105 mm, farthest

IMAGE COMPOSITION

OUR GOAL

Post-Capture Image Composition

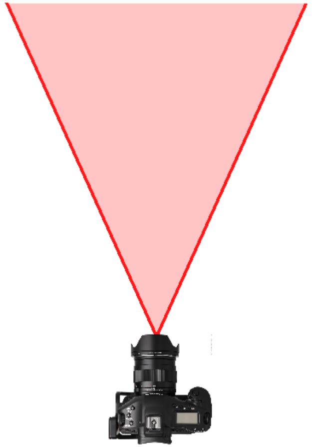


Input image stack/video

OUR GOAL

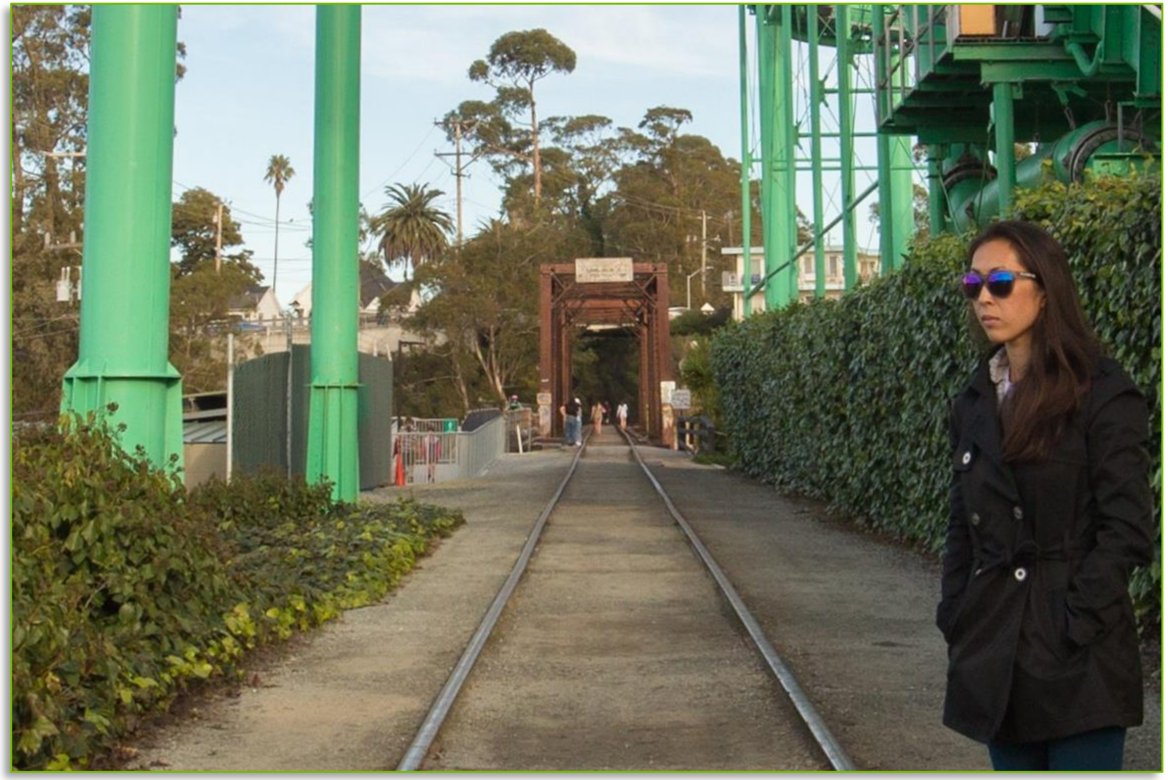
Post-Capture Image Composition

Computational zoom results

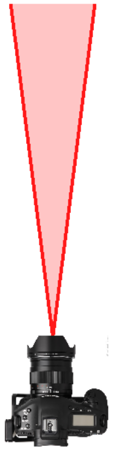


OUR GOAL

Post-Capture Image Composition



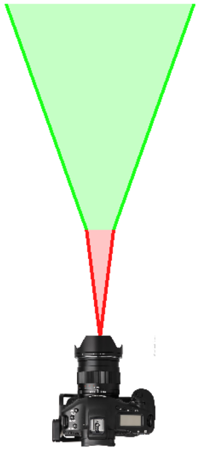
Computational zoom results



OUR GOAL

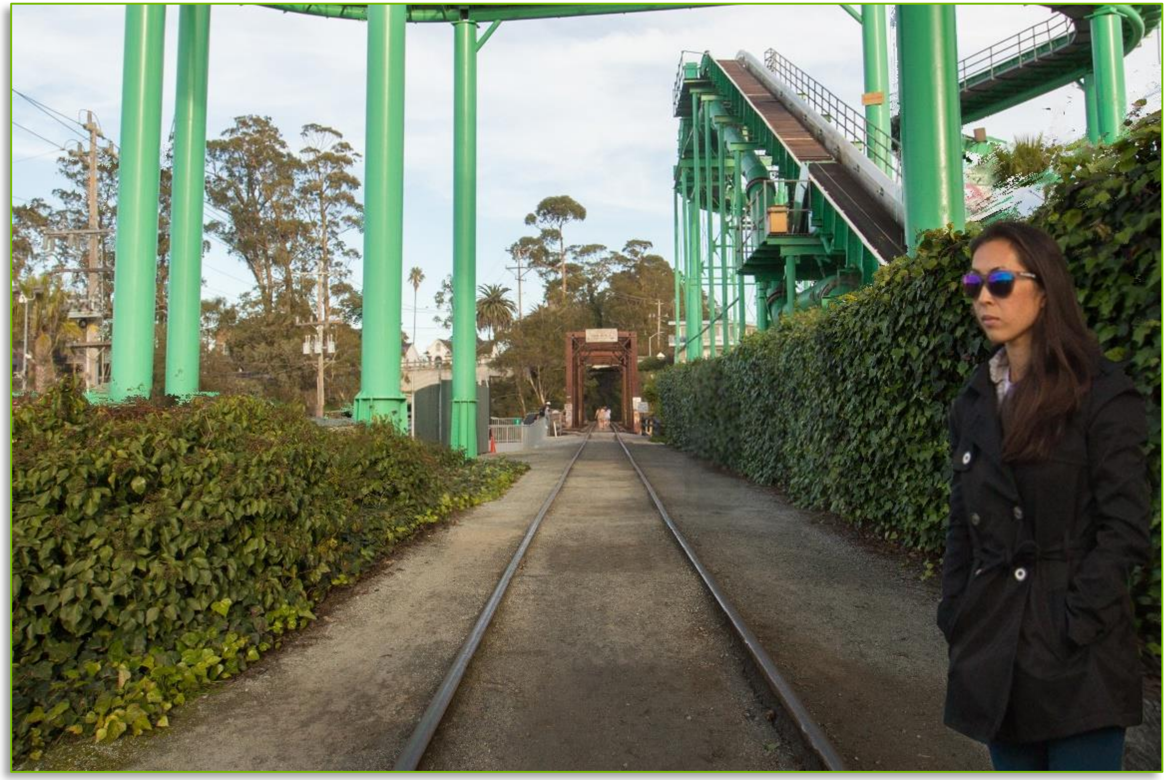
Post-Capture Image Composition

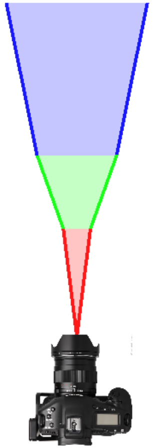
Computational zoom results



OUR GOAL

Post-Capture Image Composition

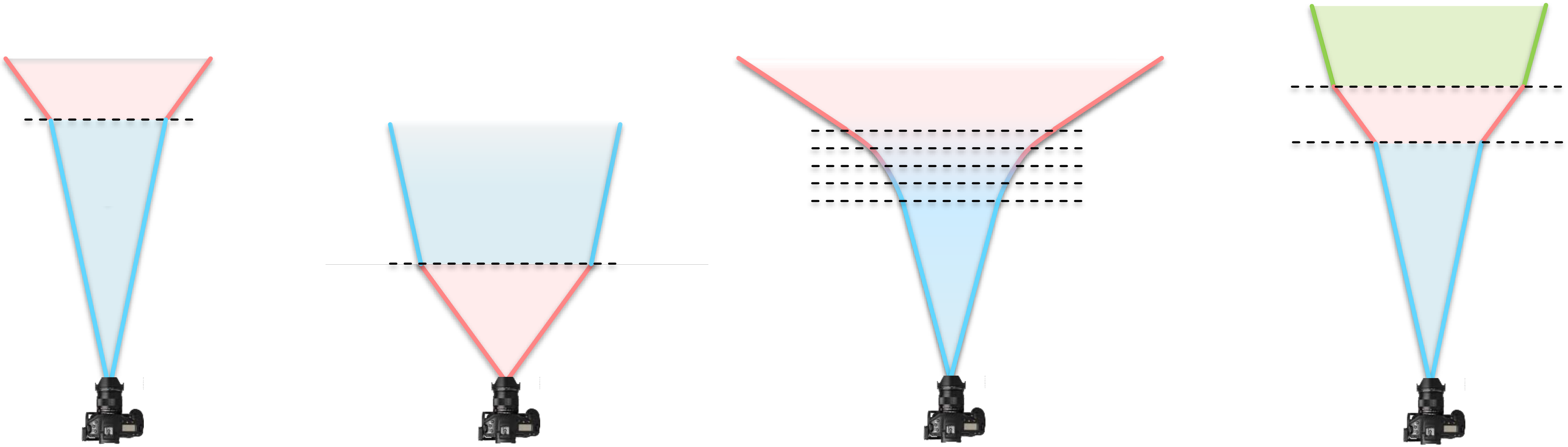




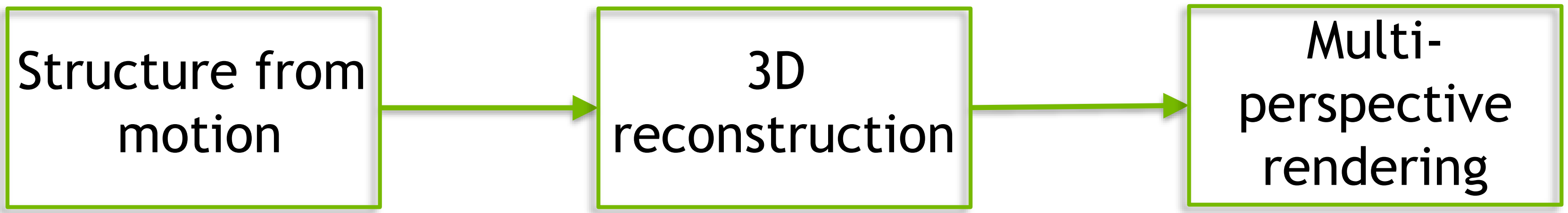
Computational zoom results

MULTI-PERSPECTIVE CAMERA MODELS

Allow novel image compositions of the scene

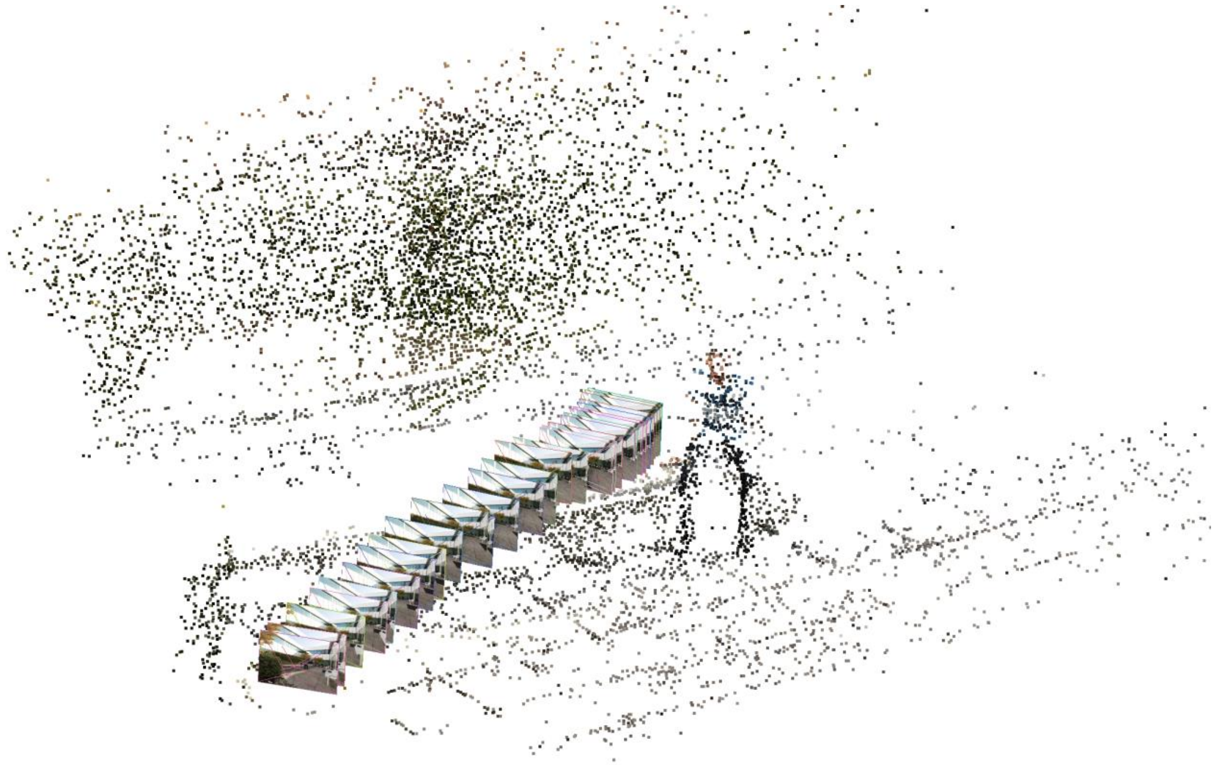


MULTI-PERSPECTIVE IMAGE SYNTHESIS



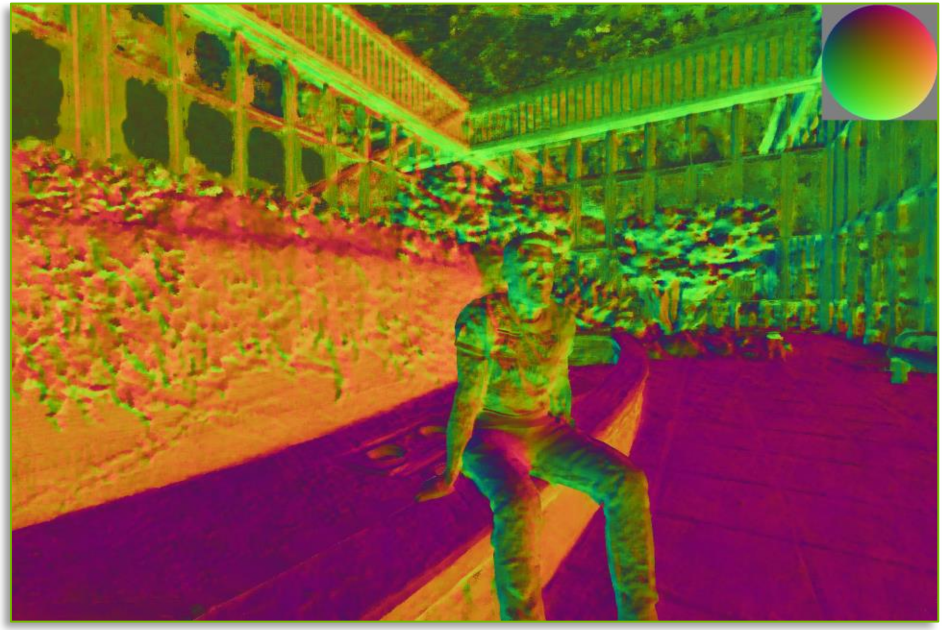
MULTI-PERSPECTIVE IMAGE SYNTHESIS

Structure from motion → 3D reconstruction → Multi-perspective rendering



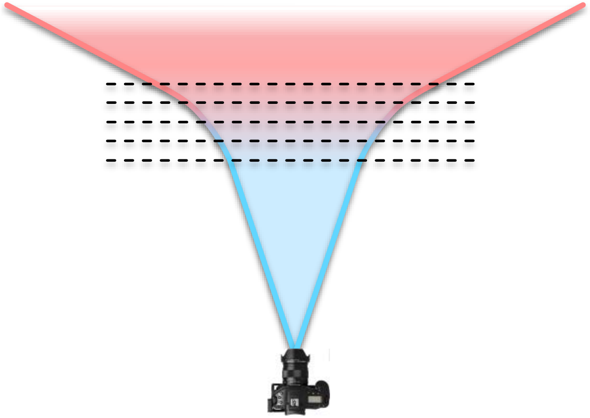
MULTI-PERSPECTIVE IMAGE SYNTHESIS

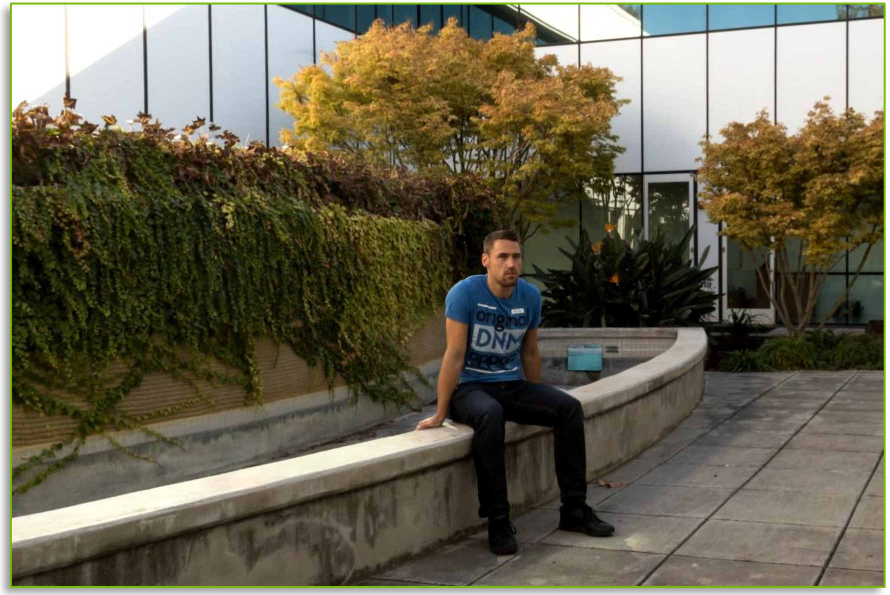
Structure from motion → 3D reconstruction → Multi-perspective rendering



MULTI-PERSPECTIVE IMAGE SYNTHESIS

Structure from motion → 3D reconstruction → Multi-perspective rendering





our result with different image compositions


NVIDIA

DANIEL GEORGE, UIUC

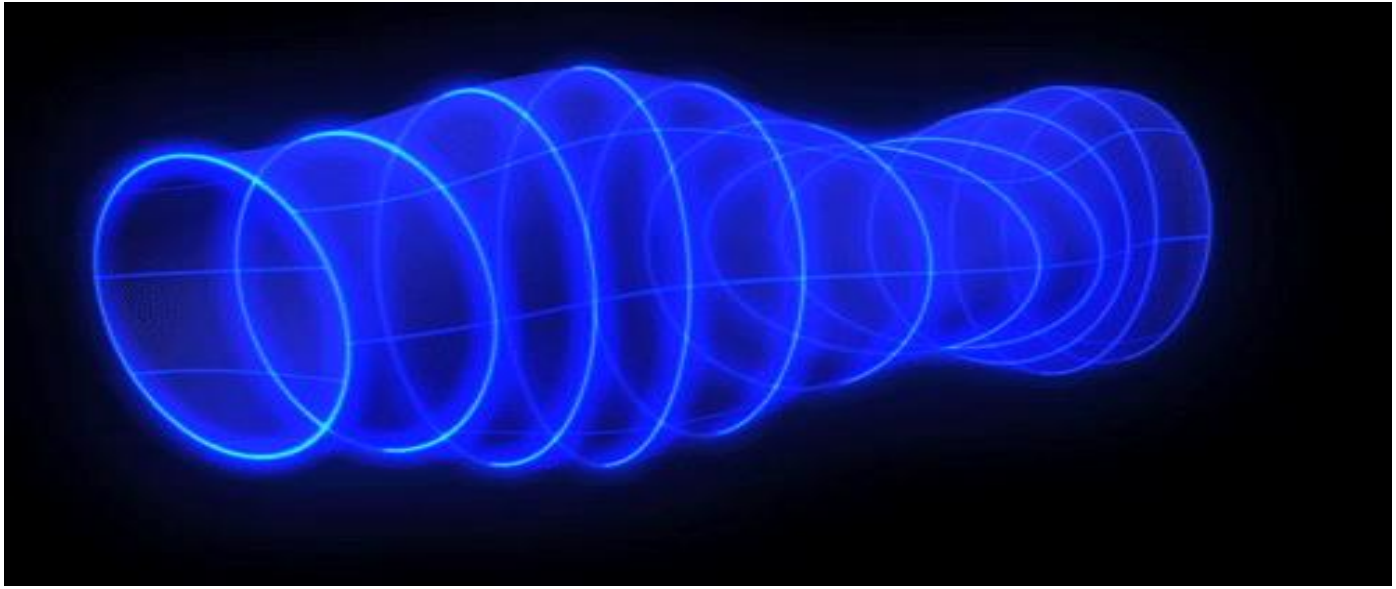
Link to full slides: **tiny.cc/phd-defense**

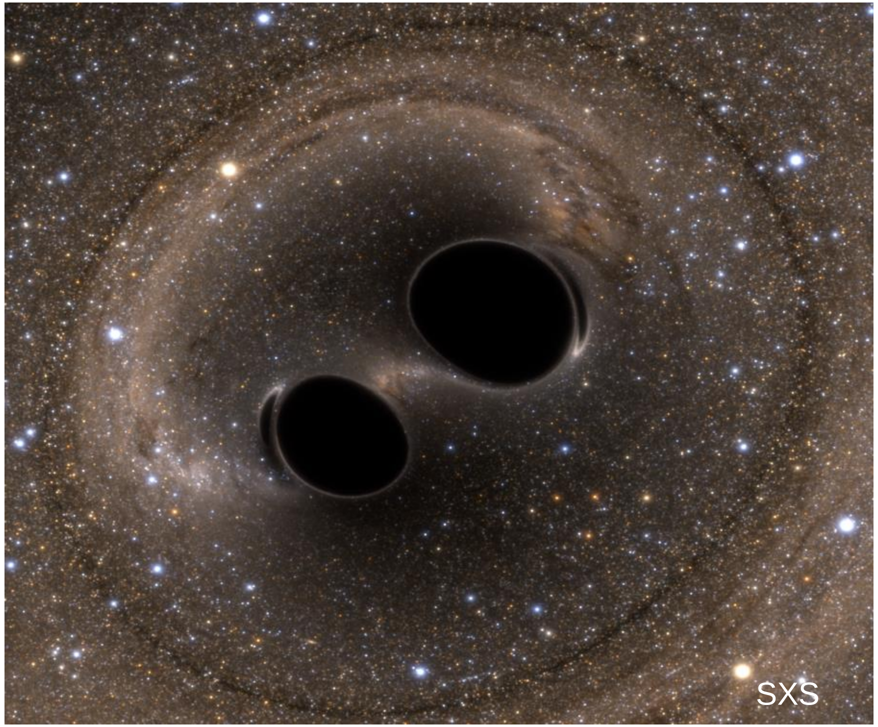
Deep Learning for Gravitational Wave and Multimessenger Astrophysics

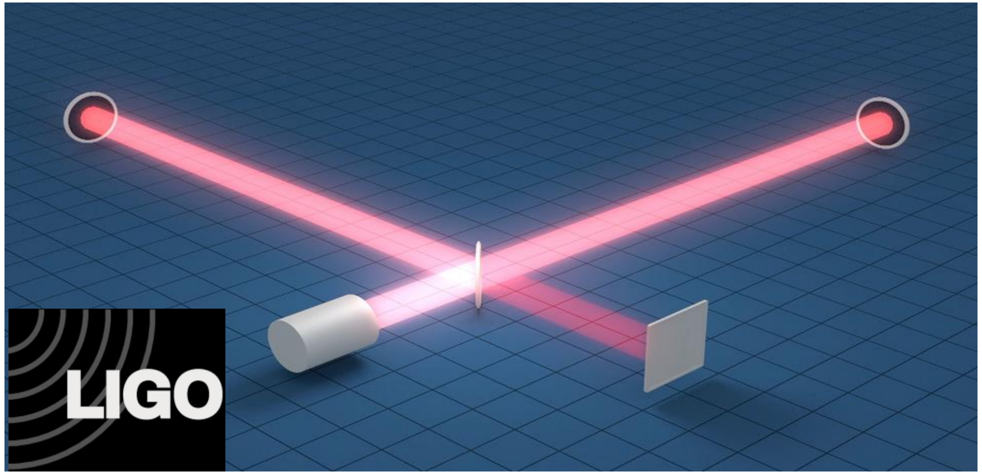
Daniel George, Google X / University of Illinois at Urbana-Champaign

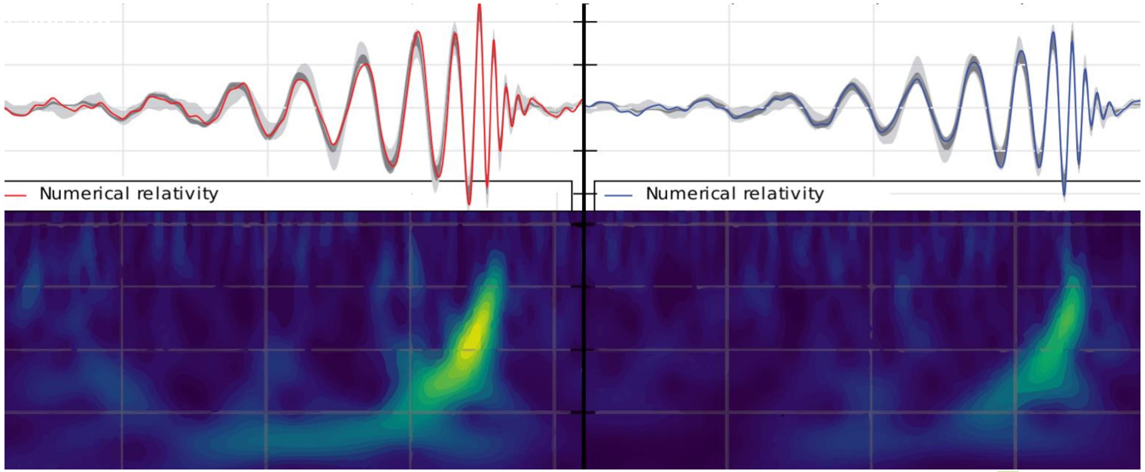
March 21, 2019

GRAVITATIONAL WAVES

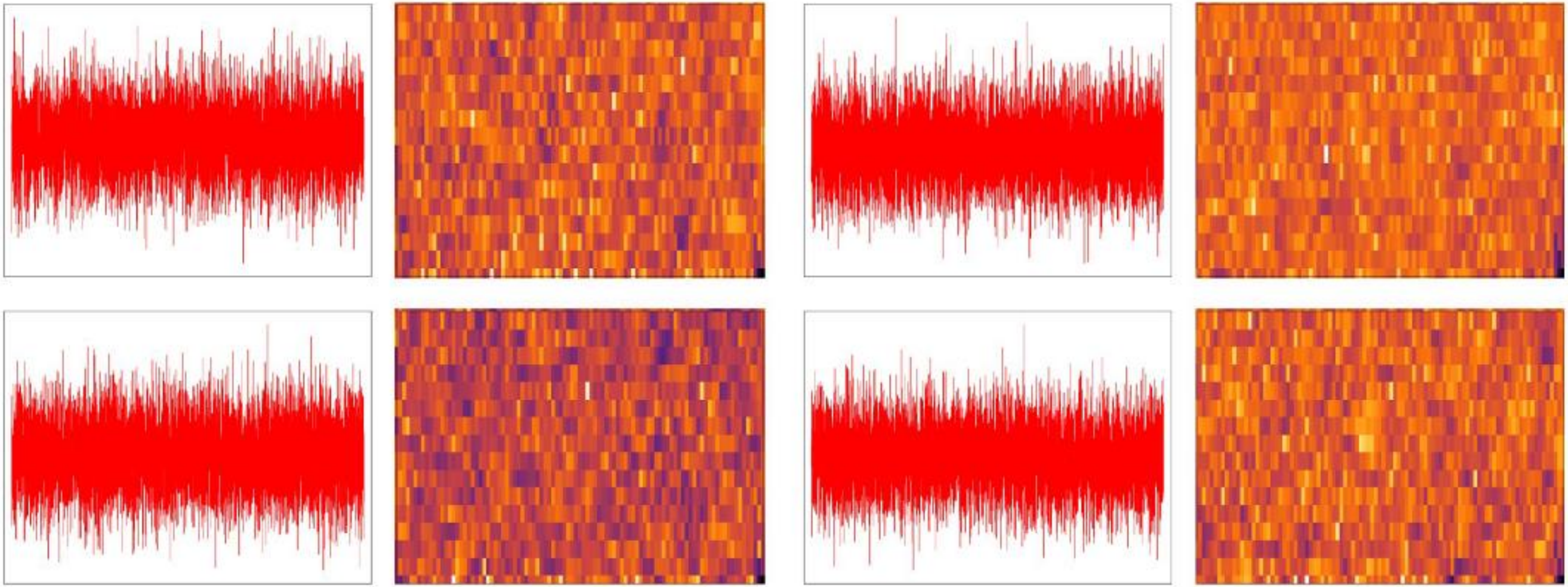


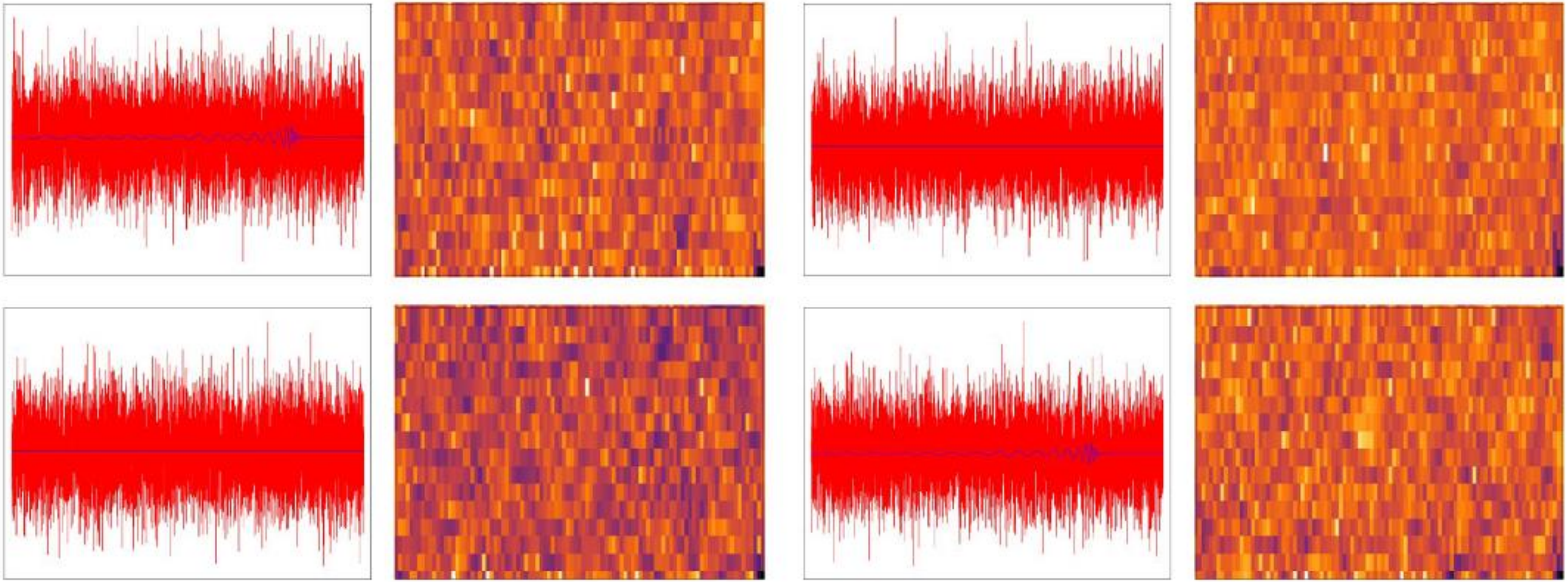






Challenge





Applying Deep Learning

Use convolutional neural nets with time-series inputs (1 x n image)

Train using signal injections

Test on real data

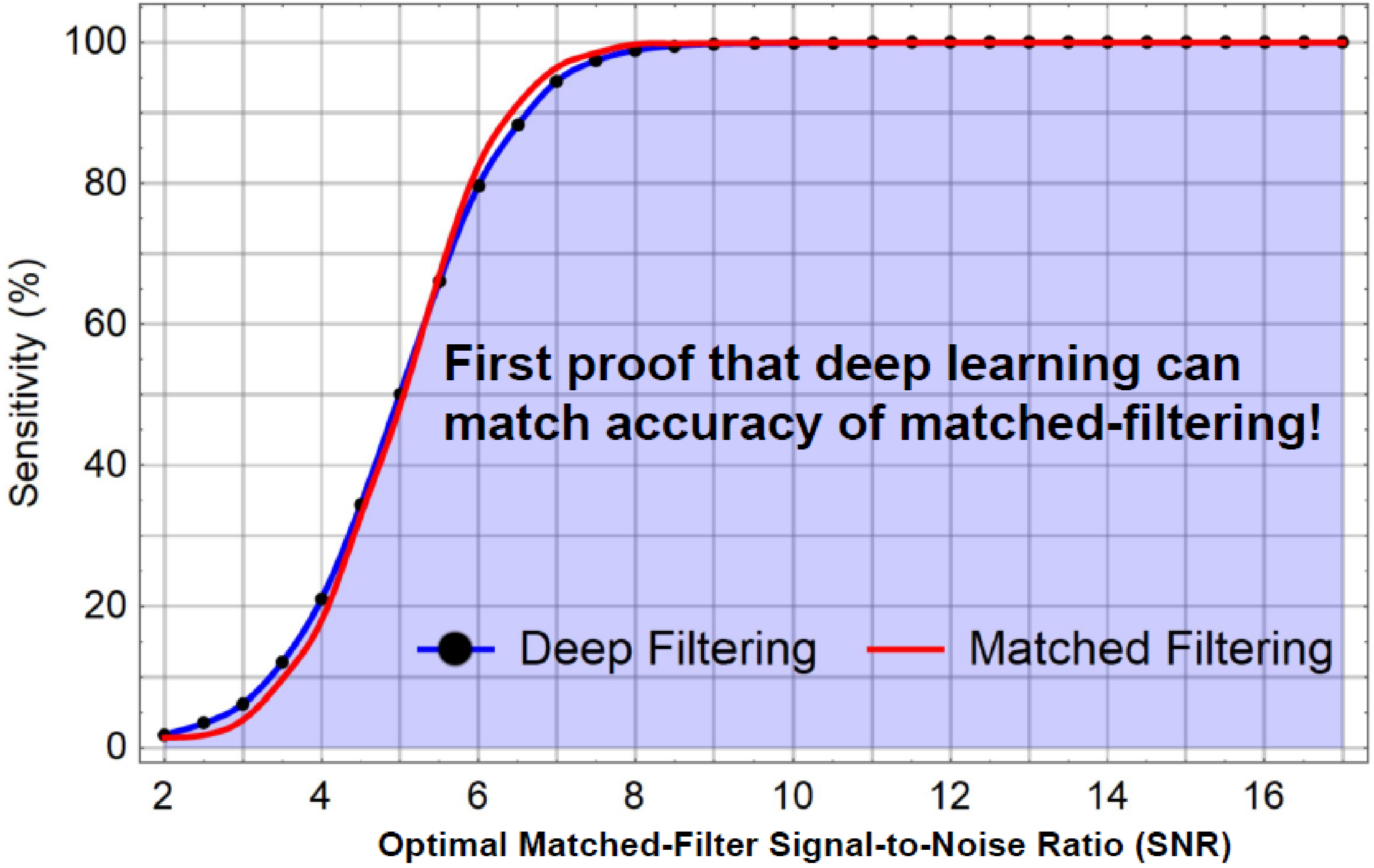
2 networks (shared weights):

Classifier for detecting signals

Predictor for parameter estimation

	Input (1s, 8192Hz)	vector (size: 8192)
1	Reshape Layer	tensor (size: 1 × 1 × 8192)
2	Convolution Layer	tensor (size: 16 × 1 × 8177)
3	Pooling Layer	tensor (size: 16 × 1 × 2045)
4	Ramp	tensor (size: 16 × 1 × 2045)
5	Convolution Layer	tensor (size: 32 × 1 × 2017)
6	Pooling Layer	tensor (size: 32 × 1 × 505)
7	Ramp	tensor (size: 32 × 1 × 505)
8	Convolution Layer	tensor (size: 64 × 1 × 477)
9	Pooling Layer	tensor (size: 64 × 1 × 120)
10	Ramp	tensor (size: 64 × 1 × 120)
11	Flatten Layer	vector (size: 7680)
12	Linear Layer	vector (size: 64)
13	Ramp	vector (size: 64)
14	Linear Layer	vector (size: 2)
15	Softmax Layer	vector (size: 2)
	Output	vector (size: 2)

Accuracy of Detecting Signals

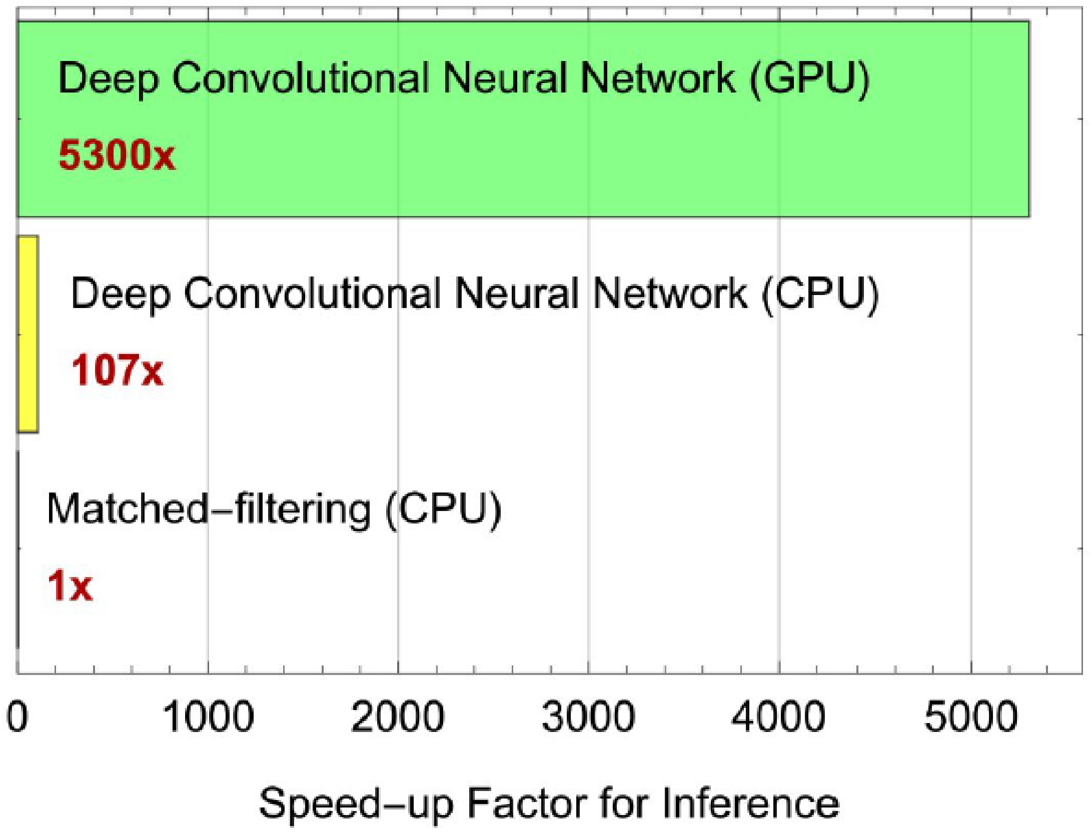


100% Sensitivity for SNR > 10

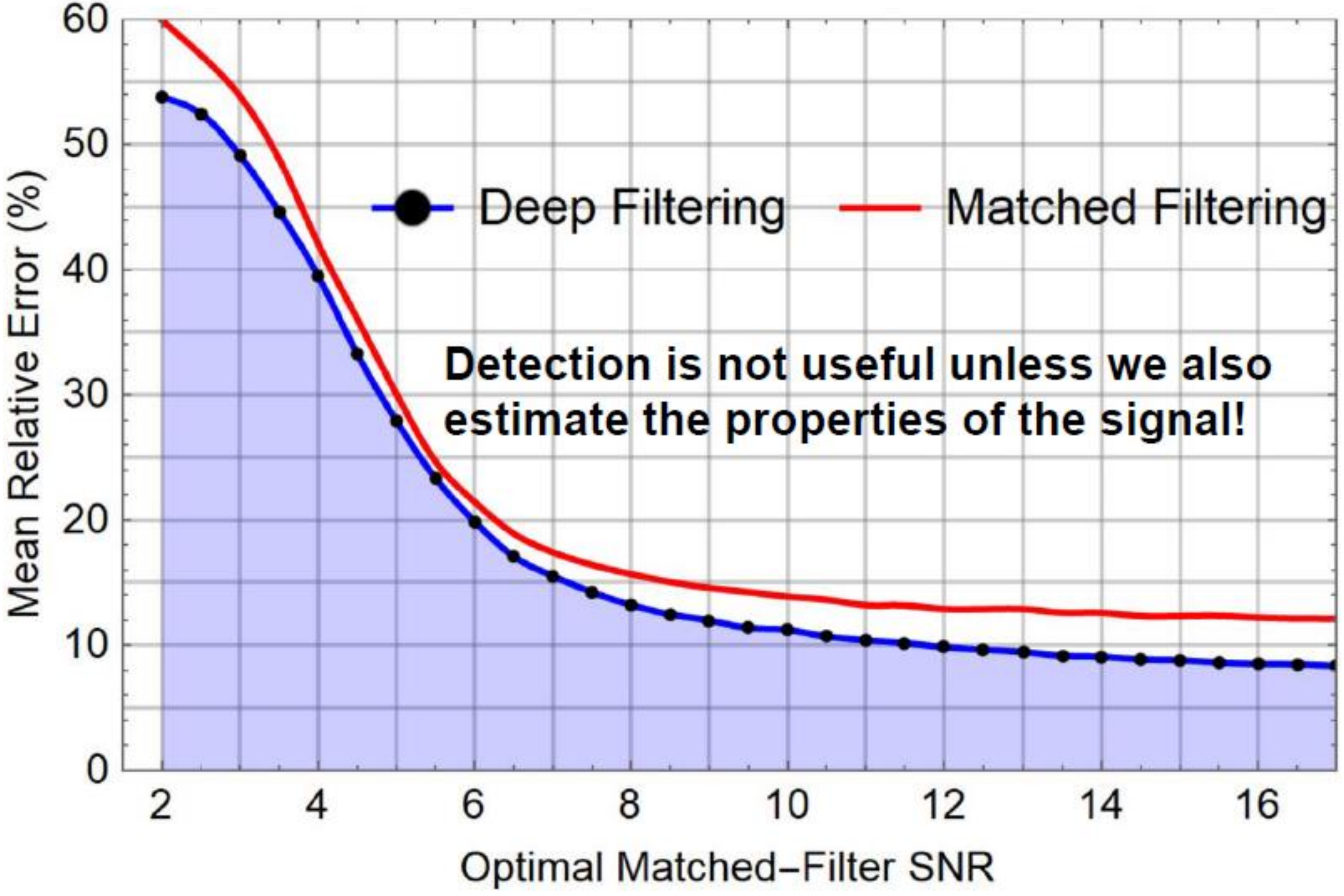
False Alarm Rate < 0.6%

Orders of Magnitude Faster!

- Real-time analysis (milliseconds)
- 1s to analyze 4096s of data
- Constant time regardless of number of templates, after training once.
- Thousands of inputs can be processed at once on a cheap GPU.
- Dedicated inference engines can offer more speed-up with low-latency



Error in Predicting Masses (Regression)



CNN error < 5% for SNR>50

Can interpolate between templates!

Matched-Filtering error with same template bank is always > 11%

Deep learning overcomes the limitations!

1) **Very fast!** Enables real-time analysis with a single CPU/GPU. Enable follow-up!

2) **Predict more signal properties**! Scalable to full range of signals since the one-time training process can be carried out with billions of templates on supercomputers

3) **Can find new sources!** Can automatically detect new types of events from spinning and/or eccentric black hole mergers without any extra training. Works for supernovae

4) **Resilient to anomalous noise and bad data quality**! Can learn and adapt to the characteristics of real noise in LIGO and thus outperform matched-filtering

5) **Interpretable!** Validate with matched-filtering with single predicted template, i.e., accelerate existing pipelines. Can constrain search space of templates

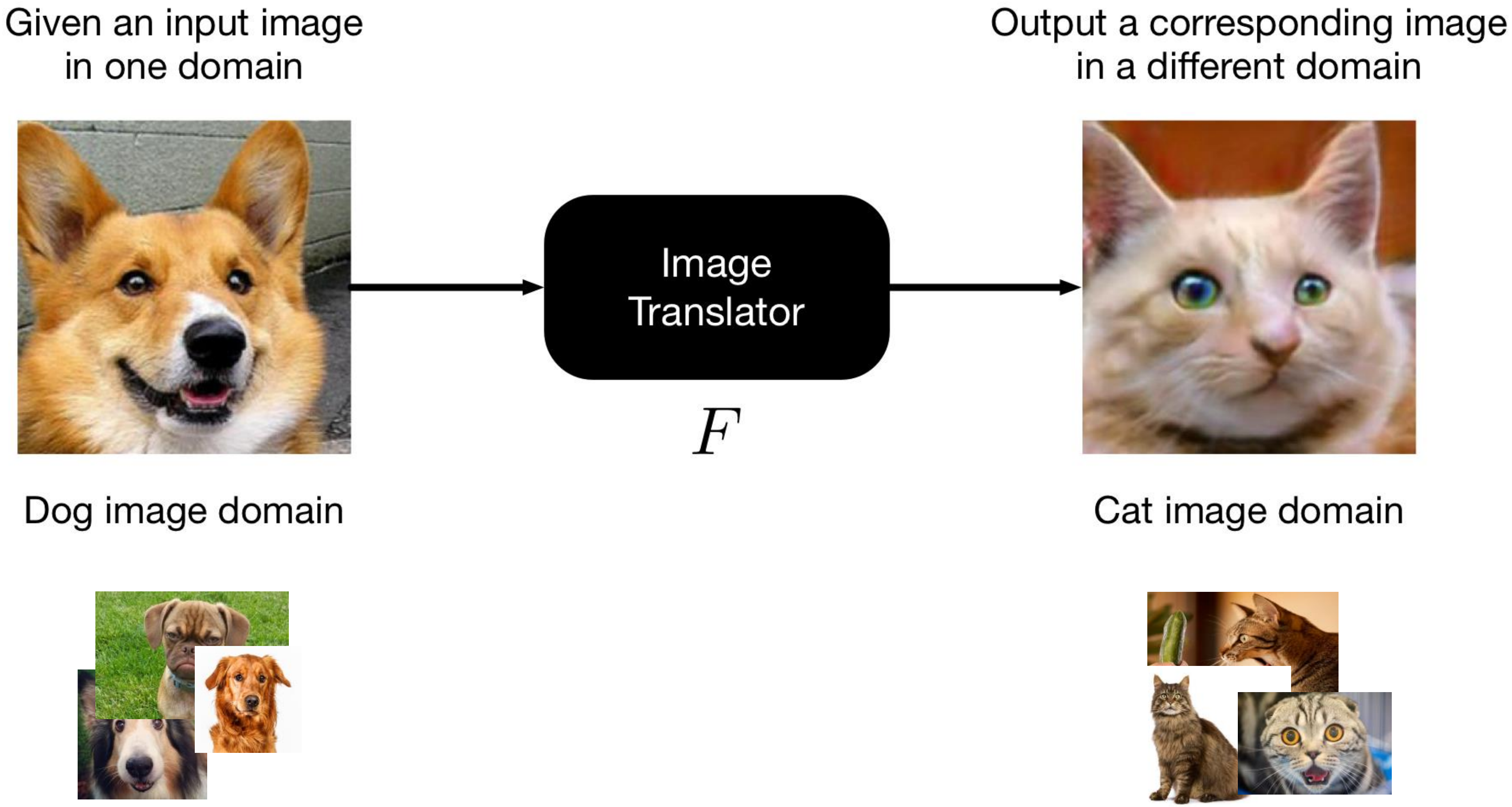
Link to full slides: **tiny.cc/phd-defense**

XUN HUANG, CORNELL

MULTIMODAL UNSUPERVISED IMAGE-TO-IMAGE TRANSLATION

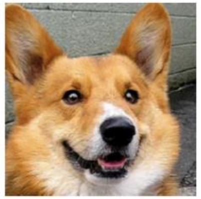
Xun Huang, Cornell University
March 21, 2019

UNSUPERVISED IMAGE-TO-IMAGE TRANSLATION

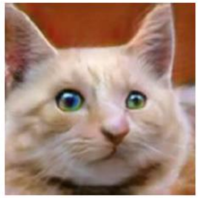


UNIMODAL OR MULTIMODAL

- Unimodal

$F($  $) =$ 

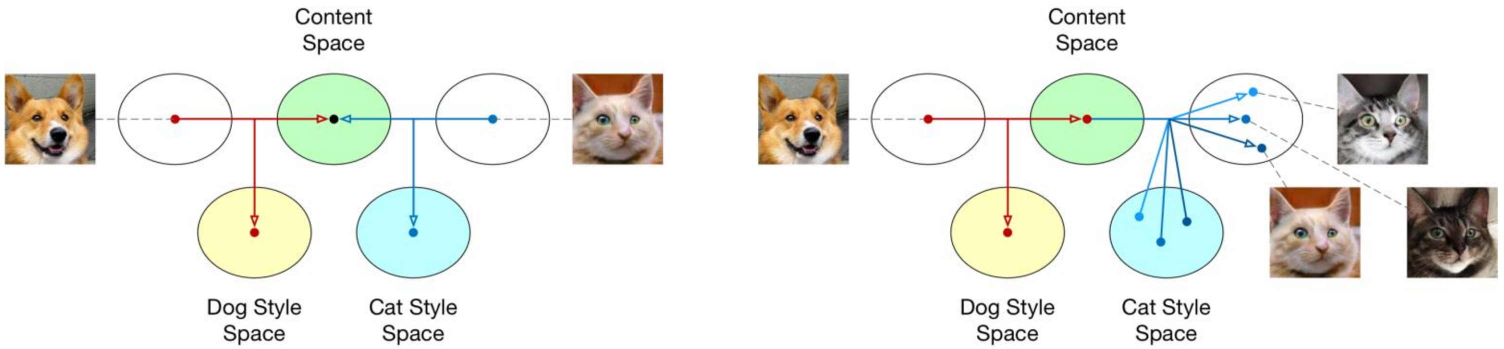
- Multimodal

$F($  $) =$    ......

TOWARDS MULTIMODALITY

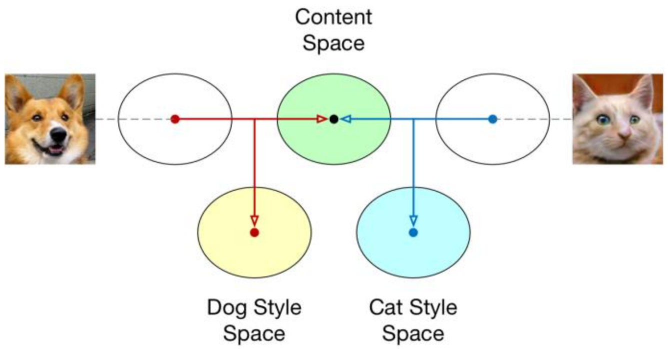
Unsupervised Learning of Disentangled Latent Space

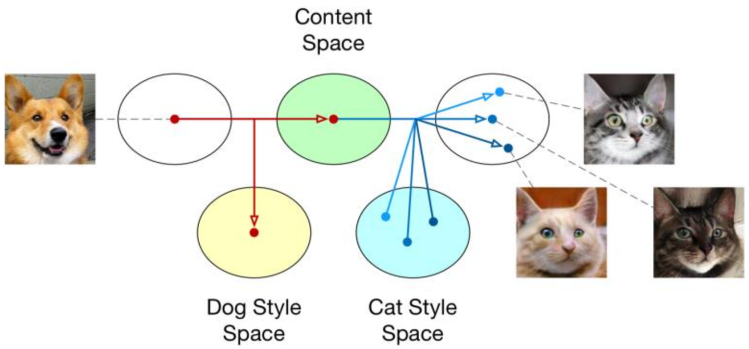
- We assume the image representation space can be disentangled into:
  - The **content** space that are shared by both domains.
  - The **style** space that are specific for each domain.
- To sample a diverse set of outputs, we keep the content code of the input and randomly sample style codes from the target style space.



METHODS

- We use auto-encoders to encode an image into its latent code and reconstruct the image from the latent code.
- We employ Generative Adversarial Networks (GANs) to ensure the translated images are realistic.
- Each model is trained on a NVIDIA Tesla V100 GPU with 16GB memory.



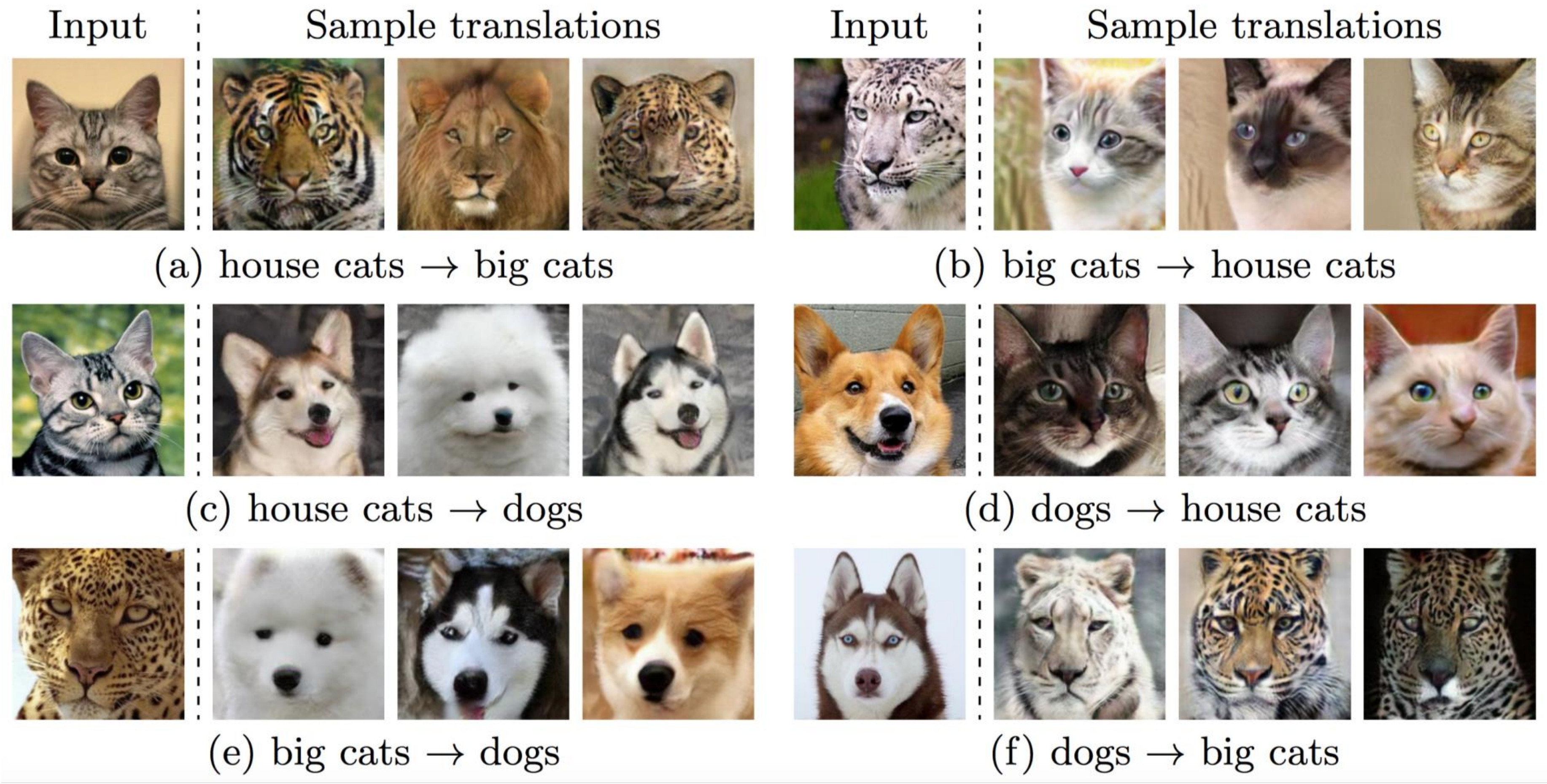


RESULTS (SKETCHES <-> PHOTO)

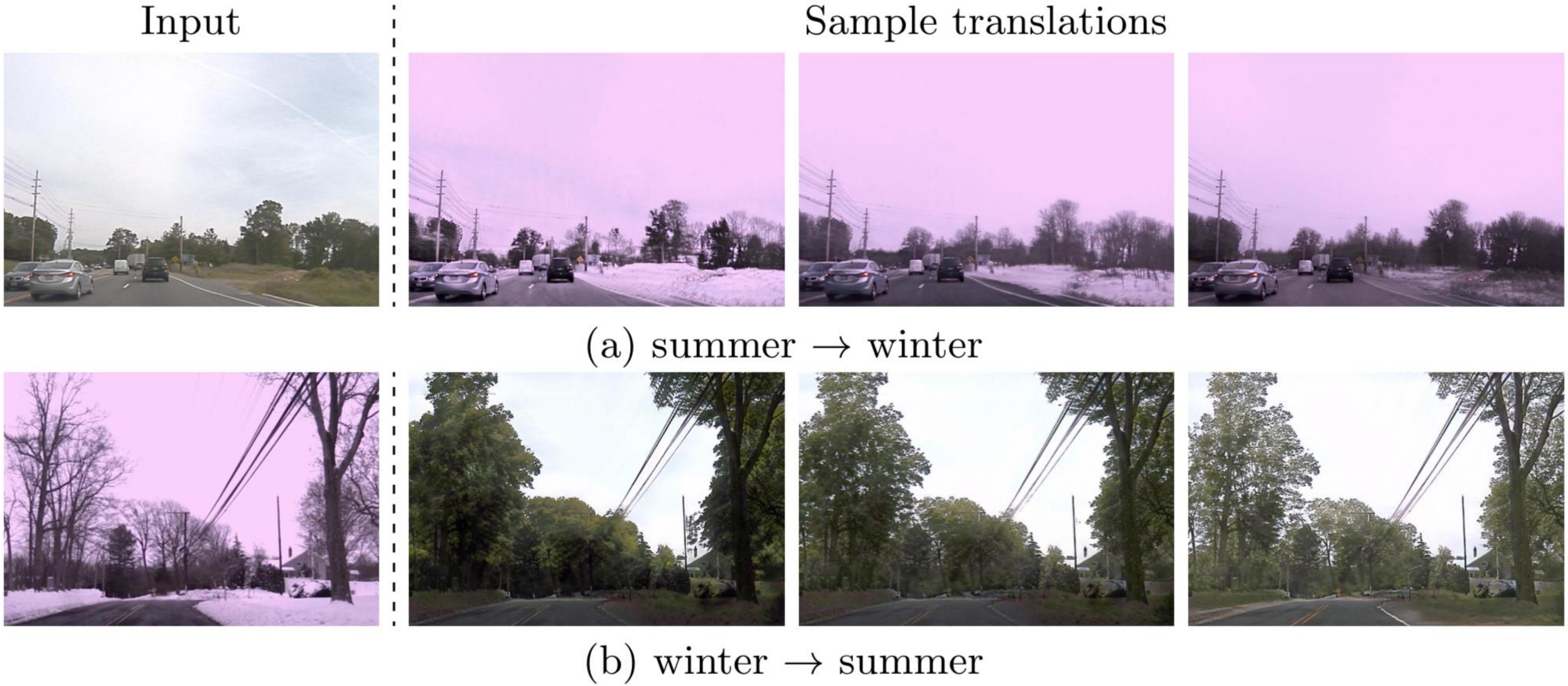
(a) edges $\leftrightarrow$ shoes

(b) edges $\leftrightarrow$ handbags

RESULTS (ANIMALS)



RESULTS (SUMMER <-> WINTER)



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HUIZI MAO, STANFORD

CATDET: AN EFFICIENT VIDEO OBJECT DETECTION SYSTEM

Huizi Mao, Stanford University

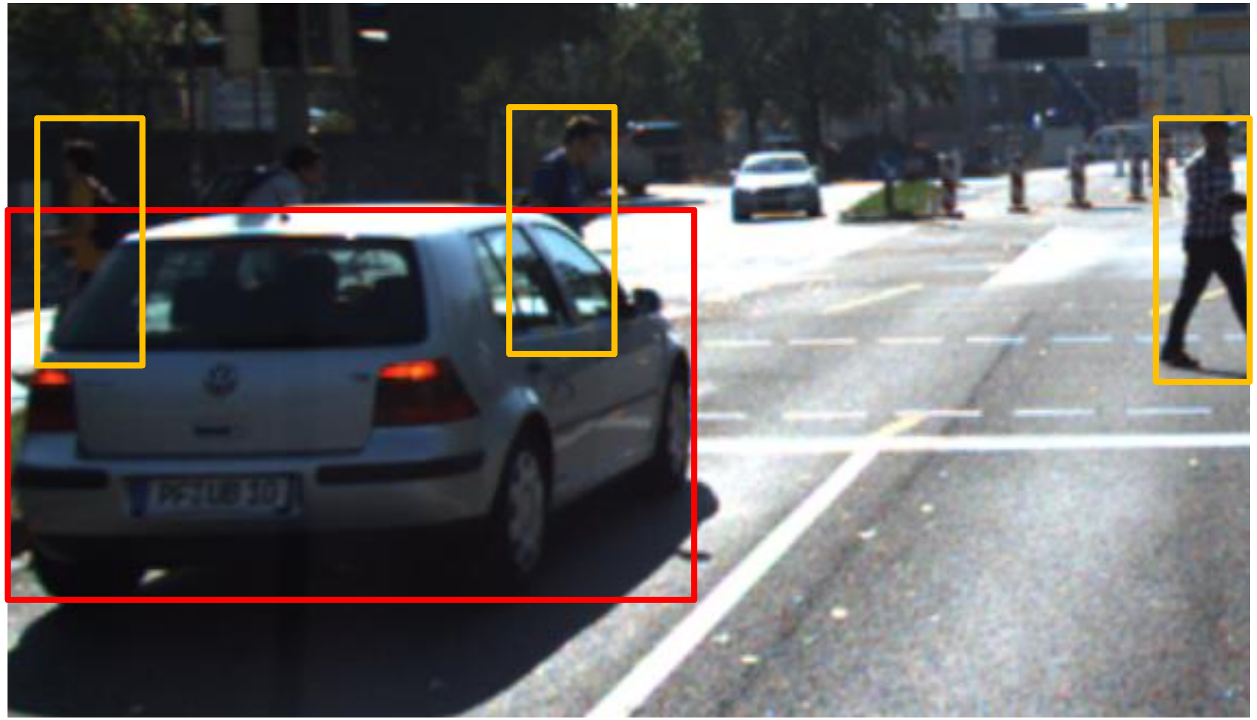
March 21, 2019

To appear on SysML 2019

OBJECT DETECTION FROM VIDEO

Goal: to locate and classify objects in a video stream

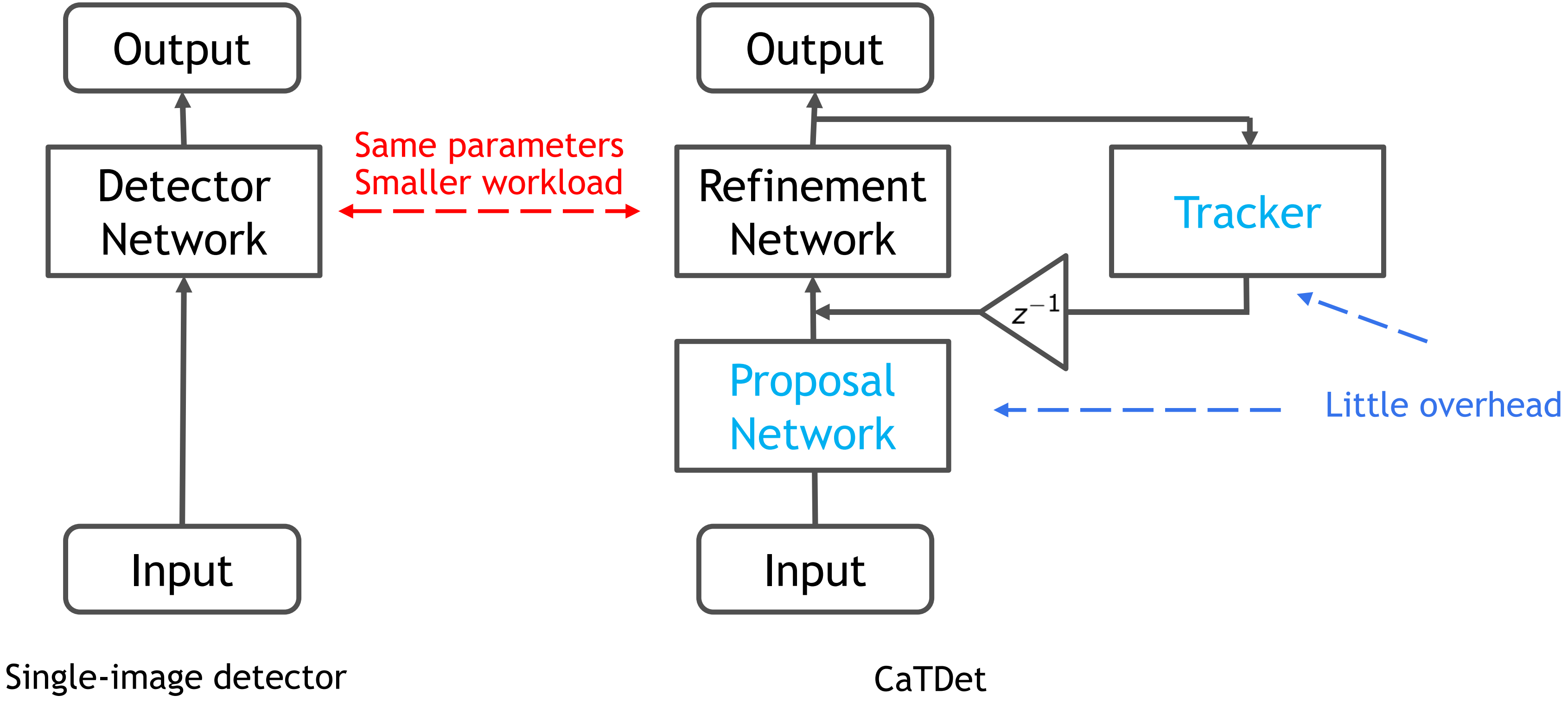
Difficulty: frame-by-frame detection is compute-intensive



CATDET: CASCADED TRACKED DETECTOR

CaTDet is a system to save computations of CNN-based detectors

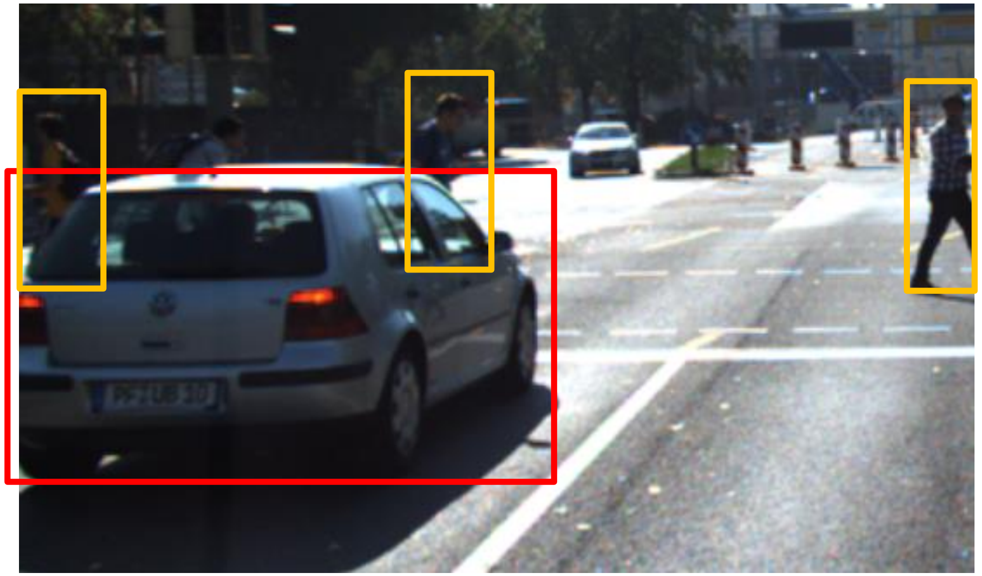
Goal: run large CNN models only on selected regions



EXAMPLE

Come back to the previous example:

We only run the refinement network (the expensive one) on selected regions



Frame N

Frame N+1

RESULTS

Maintain the same mAP on KITTI dataset

Reduce the number of arithmetic operations by 5.2x

Reduce GPU time by 3.8x (Maxwell TITAN X)

Method	mAP	Ops(G)	GPU time(s)
Faster R-CNN Frame-by-frame	0.740	254.3	0.159
CaTDet	0.740	49.3 (5.2x)	0.042 (3.8x)

More results on the SysML 2019 paper: http://www.sysml.cc/doc/2019/111.pdf

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ANA SERRANO, UNIV DE ZARAGOZA

MOTION PARALLAX FOR VR VIDEOS

Ana Serrano, Universidad de Zaragoza
March 21, 2019

EXPERIENCES IN VIRTUAL REALITY

Real-world recorded content vs. CG content

Miyubi
Felix & Paul Studios

SuperHOT VR
SUPERHOT Team

RECORDING CONTENT FOR VR

Commercially available VR cameras

Kandao Obsidian

Yi Halo

Facebook Surround360

Nokia Ozo

VIDEO RECORDED FROM A FIXED CAMERA

How to render the scene from different head positions?

Scene recorded from a fixed camera position

New camera view to show to the user

OUR APPROACH: LAYERED VIDEO

Enabling motion parallax for VR video

Close-up

VR view (stereo)

OUR APPROACH: LAYERED VIDEO

Enabling motion parallax for VR video

- [Serrano et al. 2019] Motion parallax for 360 RGBD video
- Optimized for **real-time GPU rendering** of novel camera views
- **Layered video representation** for storing additional scene information
- Independent of a specific hardware, or camera setup
- User studies confirm a more compelling viewing experience


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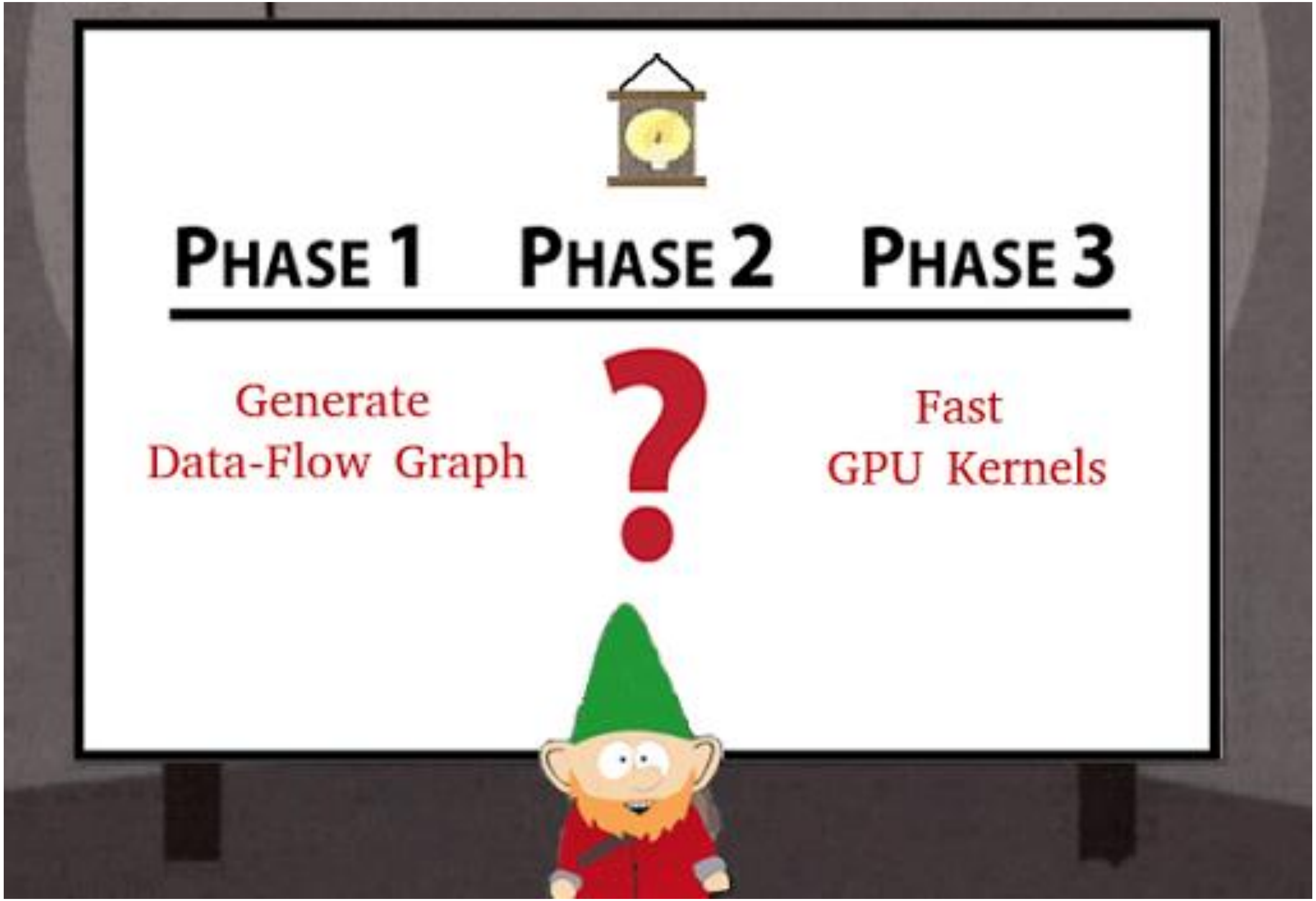
PHILIPPE TILLET, HARVARD

Triton: An Imperative Array Language and Compiler for Efficient Tiled Computations in Machine Learning Workloads

Philippe Tillet, Harvard University

March 21, 2019

MOTIVATIONS



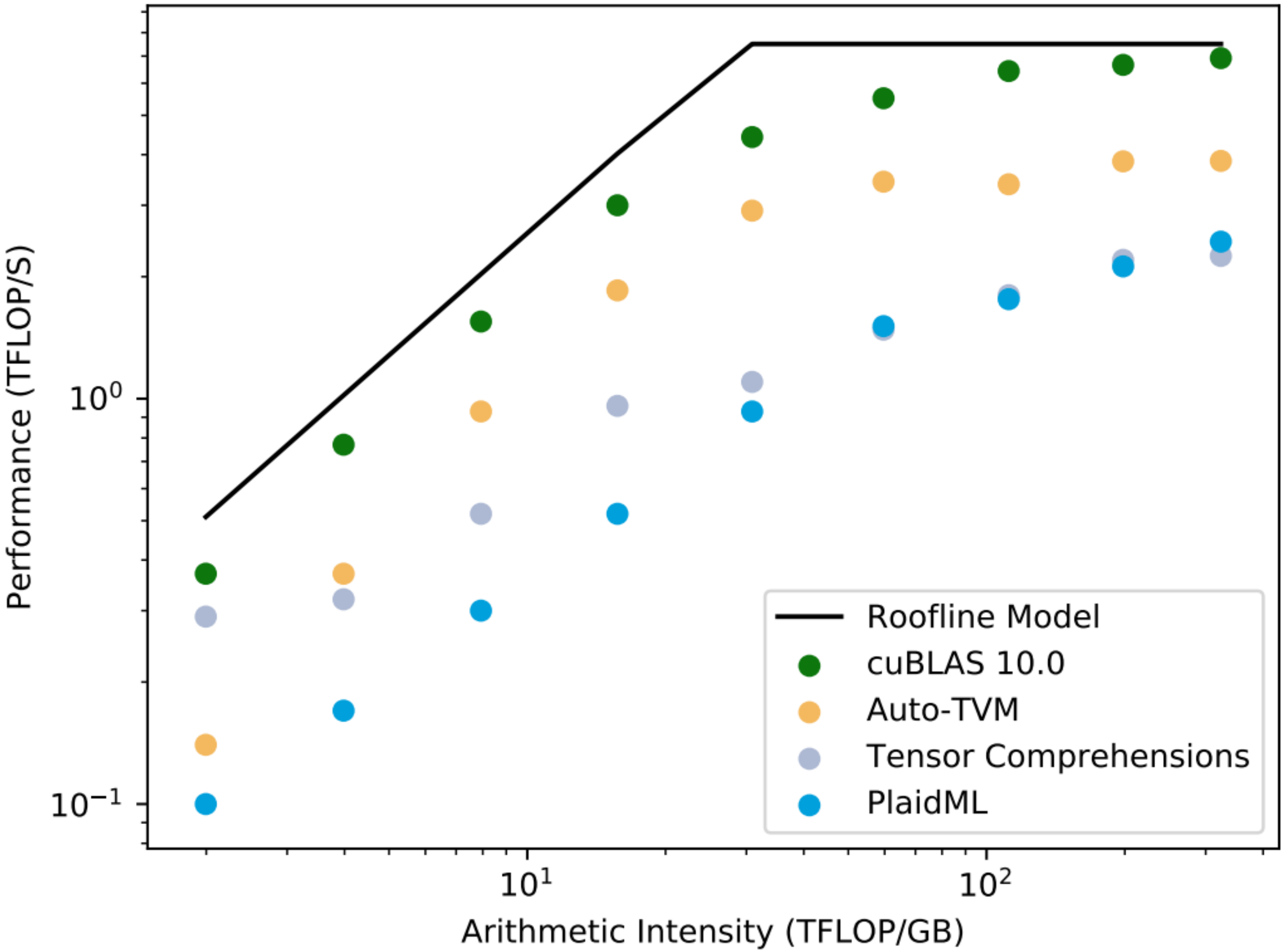
EXISTING SOLUTIONS

TensorFlow, PlaidML, Tensor Comprehensions, TVM ...

```
C = tf.matmul(A, tf.transpose(B))       // TF
C[i, j: I, J] = +(A[i, k] * B[j, k]); // PlaidML
C(i, j) +=! A(i, k) * B(j, k)           // TC
tvm.sum(A[i, k] * B[j, k], axis=k)      // TVM
```

EXISTING SOLUTIONS

GPU Performance



MY SOLUTION

Triton

- Existing functional languages lack flexibility

  *Cannot specify **how** tensors are decomposed into tiles*

- Existing imperative languages lack abstractive power

  *Cannot specify **what** the meaning of scalar variables is*

I developed **Triton**: a language & compiler which adds the concept of **tile** to a **CUDA-like** imperative programs. Best of both worlds.

MY SOLUTION

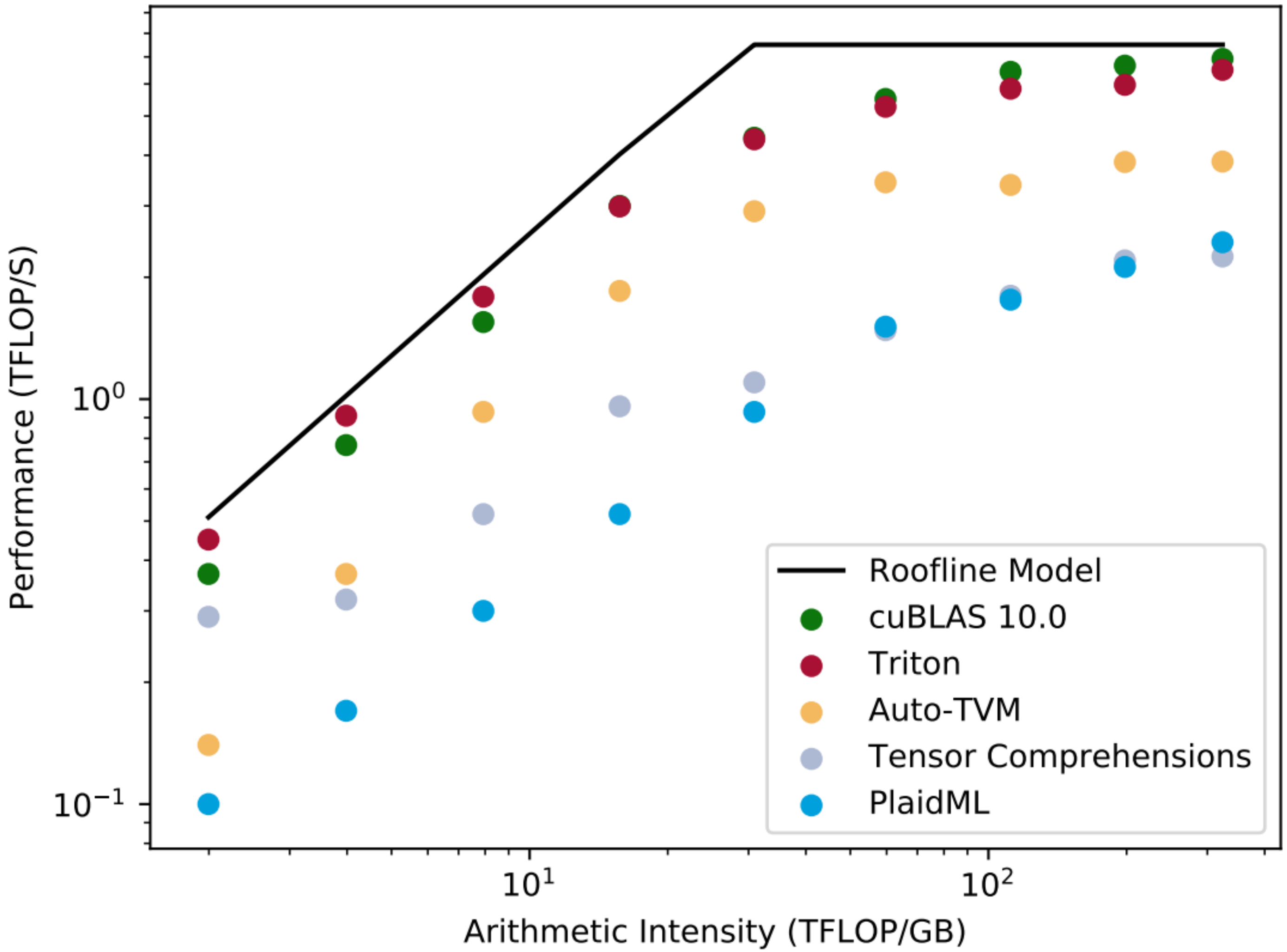
Example

```
const tunable int TM, TN, TK;

kernel void matmul_nt<TM,TN>(float* a, float* b,float* c,
                            int M, int N, int K) {
 int rm[TM] = get_global_range(0); // 1D tile
 int rn[TN] = get_global_range(1);
 int rk[TK] = 0 ... TK;
 float C[TM, TN] = 0; // 2D tile
 float* pa[TM, TK] = a + rm[:,newaxis] + rk * M;
 float* pb[TN, TK] = b + rn[:,newaxis] + rk * K;
 for(int k = K; k >= 0; k -= TK){
   bool check_k[TK] = rk < k;
   bool check_a[TM, TK] = (rm < M)[:,newaxis] && check_k;
   bool check_b[TN, TK] = (rn < N)[:,newaxis] && check_k;
   float A[TM, TK] = check_a ? *pa : 0;
   float B[TN, TK] = check_b ? *pb : 0;
   C += dot(A, B.T) + C;
   pa = pa + 8*M;
   pb = pb + 8*K;
 }
 float* pc[TM, TN] = c + rm[:,newaxis] + rn * M;
 bool check_c[TM,TN] = (rm < M)[:, newaxis] && (rn < N);
 @check_c *pc = C;
}
```

MY SOLUTION

GPU Performance



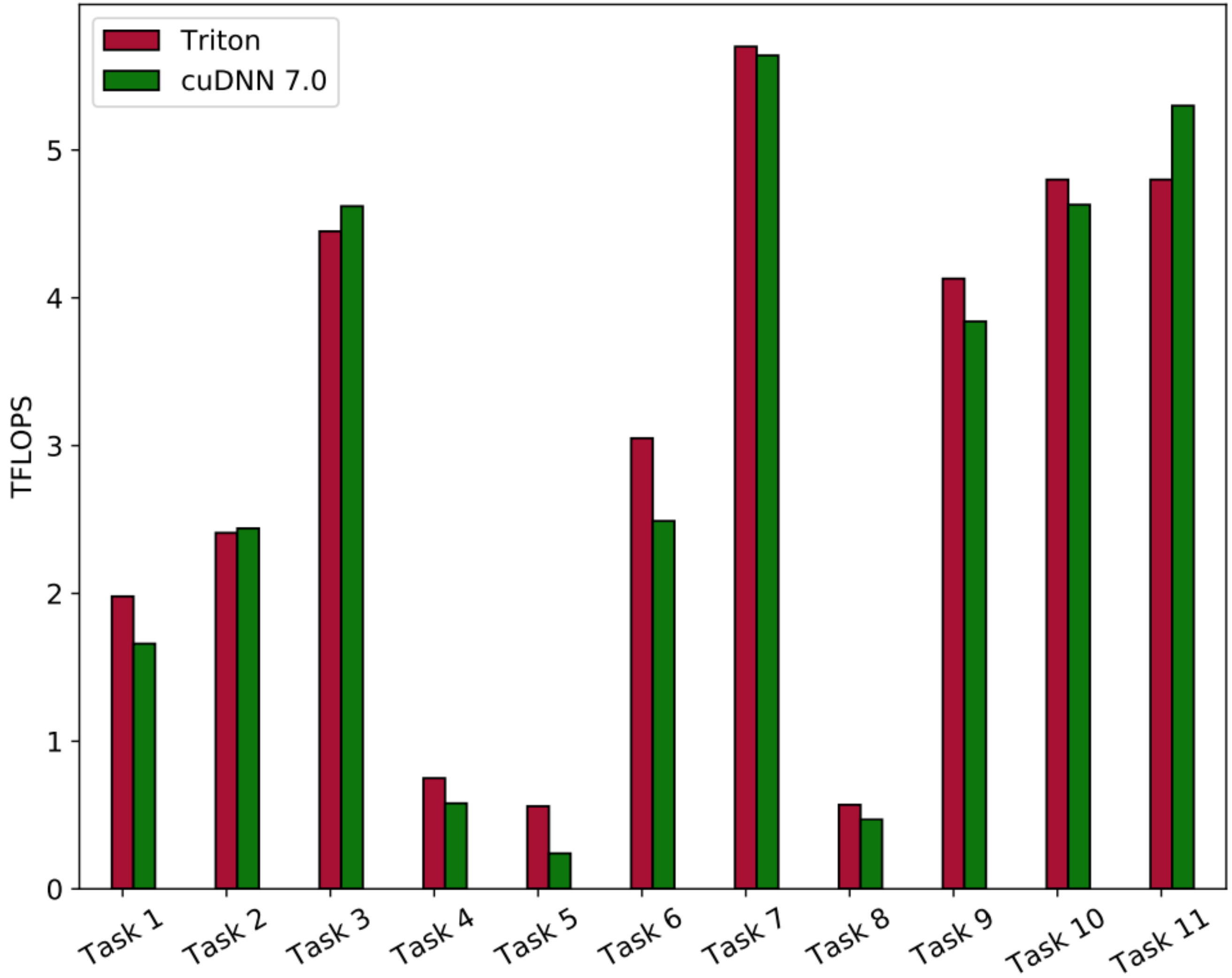
WE CAN DO MORE!

Dense convolution via implicit matrix multiplication

```
kernel void conv<TM, TN>(float* c, float* a, float* b,  int N, int H, int W, int C,
                         int P, int Q, int K, int R, int S,  float* delta) {
 int ra0[TM] = get_global_range(0);
 int rb1[TN] = get_global_range(1);
 int rl[TL] = 0 ... 8;
 float C[TM, TN] = 0;
 int rn[TM] = ra0 % N;
 int rwh[TM] = ra0 / N;
 int rw[TM] = rwh % Q;
 int rh[TM] = rwh / Q;
 ra0 = rn*H*W*C + rh*W + rw;
 int rc[TL] = rl % (R*S)
 int rrs[TL] = rl / (R*S);
 int rs[TL] = rrs % S;
 int rr[TL] = rrs / S;
 int ra1[TL] = rc * R*S + rr * S + rs
 float* pa[TM, TL] = a + ra0[:,newaxis] + ra1
 float* pb[TN, TL] = b + rb1[:,newaxis] + rb0 * C*R*S;
 int *pdelta[TL] = delta + rl
 int L = C*R*S
 for(int l = L; l >= 0; l -= 8){
   bool skipl[TL] = rl < L;
   bool skipa[TM, TL] = (ra0 < NPQ)[:, newaxis] && skipl;
   bool skipb[TN, TL] = (rb1 < K)[:, newaxis] && skipl;
   float A[TM, TL] = skipa ? *pa : 0;
   float B[TN, TL] = skipb ? *pb : 0;
   C += dot(A, B.T) + C;
   pa = pa + *pdelta;
   pb = pb + *pdelta;
 }
 float* pc[TM, TN] = c + rm[:,newaxis] + rn * M;
 bool check_c[TM, TN] = (rm < M)[:, newaxis] && (rn < N);
 @check_c *pc = C;
}
```

WE CAN DO MORE!

Performance

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ZHILIN YANG, CMU

NVIDIA

LEARNING BY GENERATIVE MODELING

Zhilin Yang, CMU

March 21, 2019

GENERATIVE MODELING

Given data x, model the probability p(x).

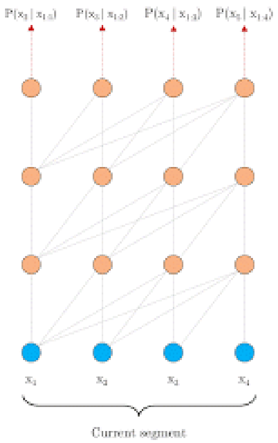
Generate data by sampling from p(x).

Goals:

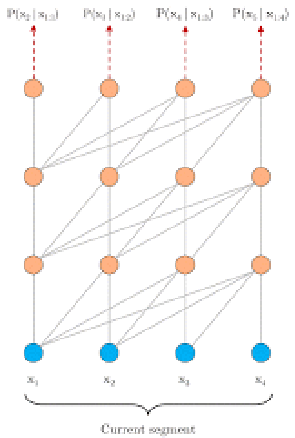
1. **Accurate, realistic generation**
   - ➢ match p(x) and true data p*(x).
2. **Generation as a scaffold**
   - ➢ use p(x) to improve p(y|x).

OUR NEW MODEL: TRANSFORMER-XL

The State-of-the-art Architecture for Language Modeling



Vanilla Transformer



Transformer-XL

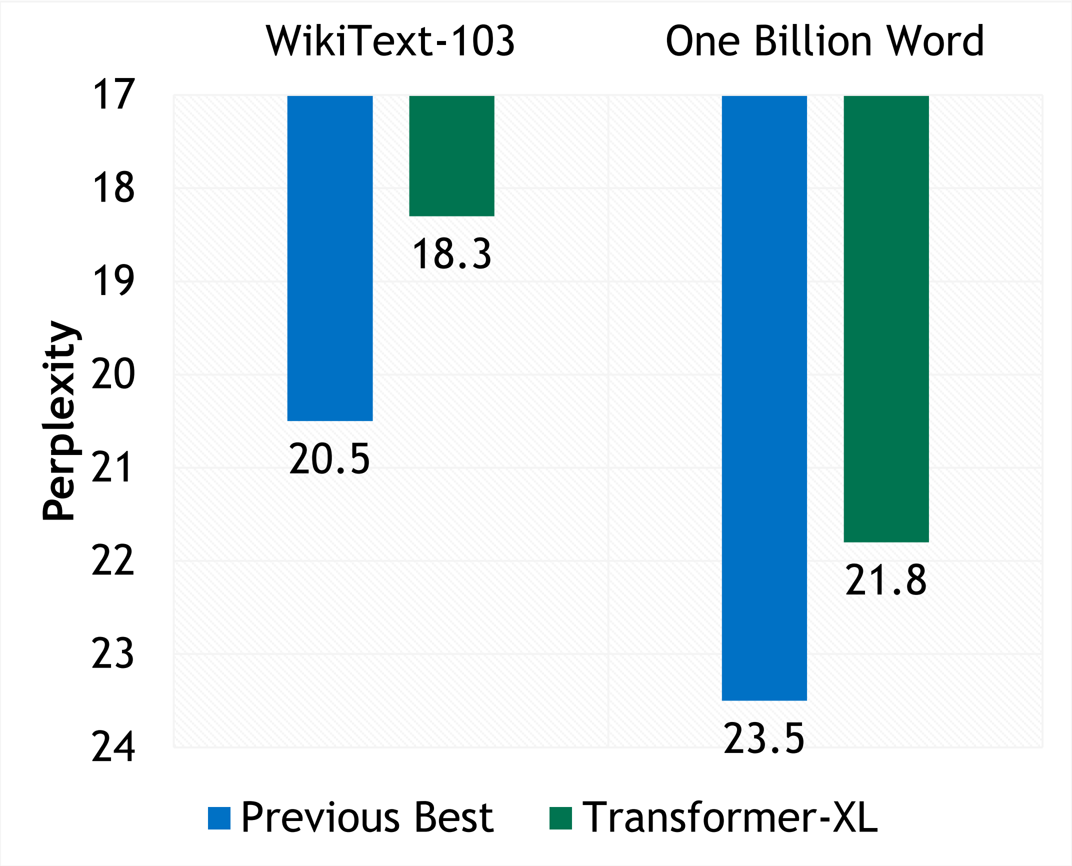
Recurrence + relative encodings

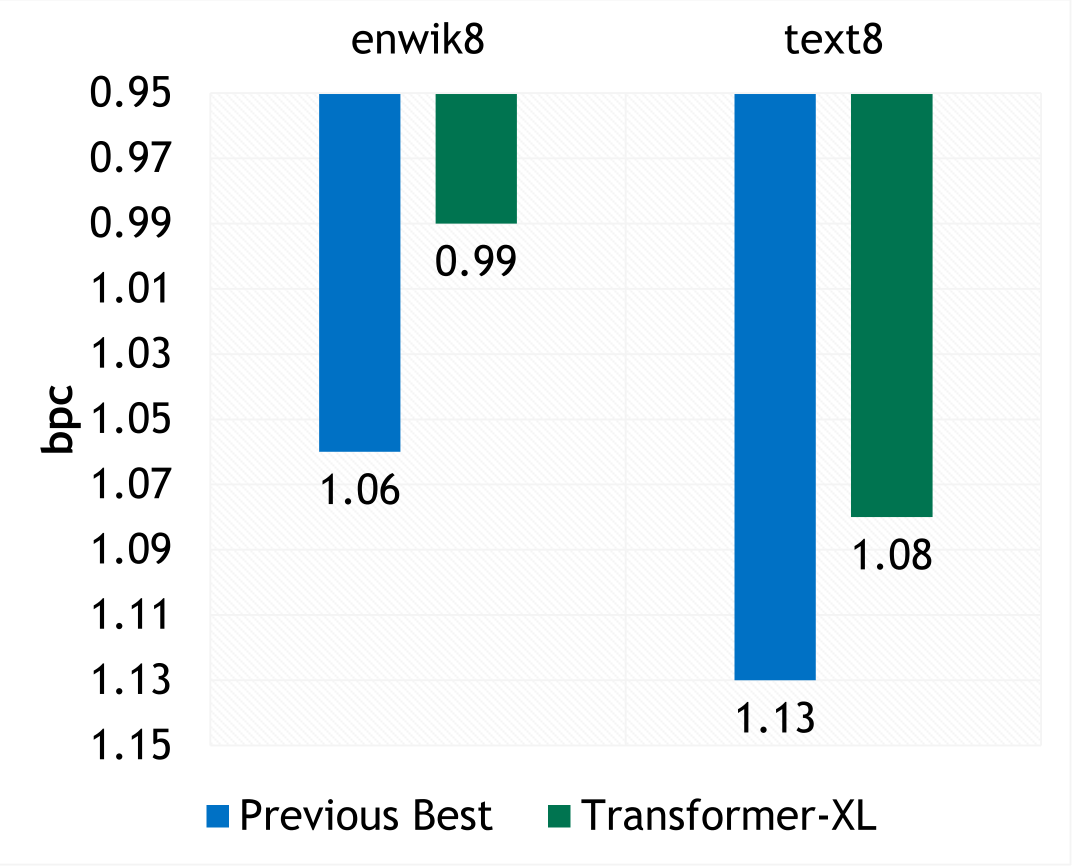
Going beyond fixed-length contexts

BENEFITS OF TRANSFORMER-XL

- Learns **longer-range dependency** (80% longer than RNNs and 450% longer than Transformers)
- Up to **1,800x faster** than Transformers during LM evaluation
- More accurate at prediction on **both long and short** sequences
- Able to generate reasonably **coherent, novel text articles** with **thousands of tokens**

STATE-OF-THE-ART LANGUAGE MODELING





Perplexity/bpc (the lower the better) measures how well a model predicts a sample.
Part of training runs on GPUs.

TEXT GENERATED BY TRANSFORMER-XL

Trained on a small 100M-token dataset.

In **July 1805**, the French 1st Army entered southern Italy. The army, under the command of Marshal Marmont, were reinforced by a few battalions of infantry under Claude General Auguste de Marmont at the town of Philippsburg and another battalion at Belluno. On **17 September 1805**, the army marched from Belluno towards Krems. By **29 September**, they had reached…

… On **9 October** the French Army … on **10 October**, he launched his attack … On **25 October**, Merveldt left Styria for Tyrol … and defeated the Austrians at the Battle of Hohenlinden on **28 October** … The Battle of Warsaw was fought on **23 November 1805** …

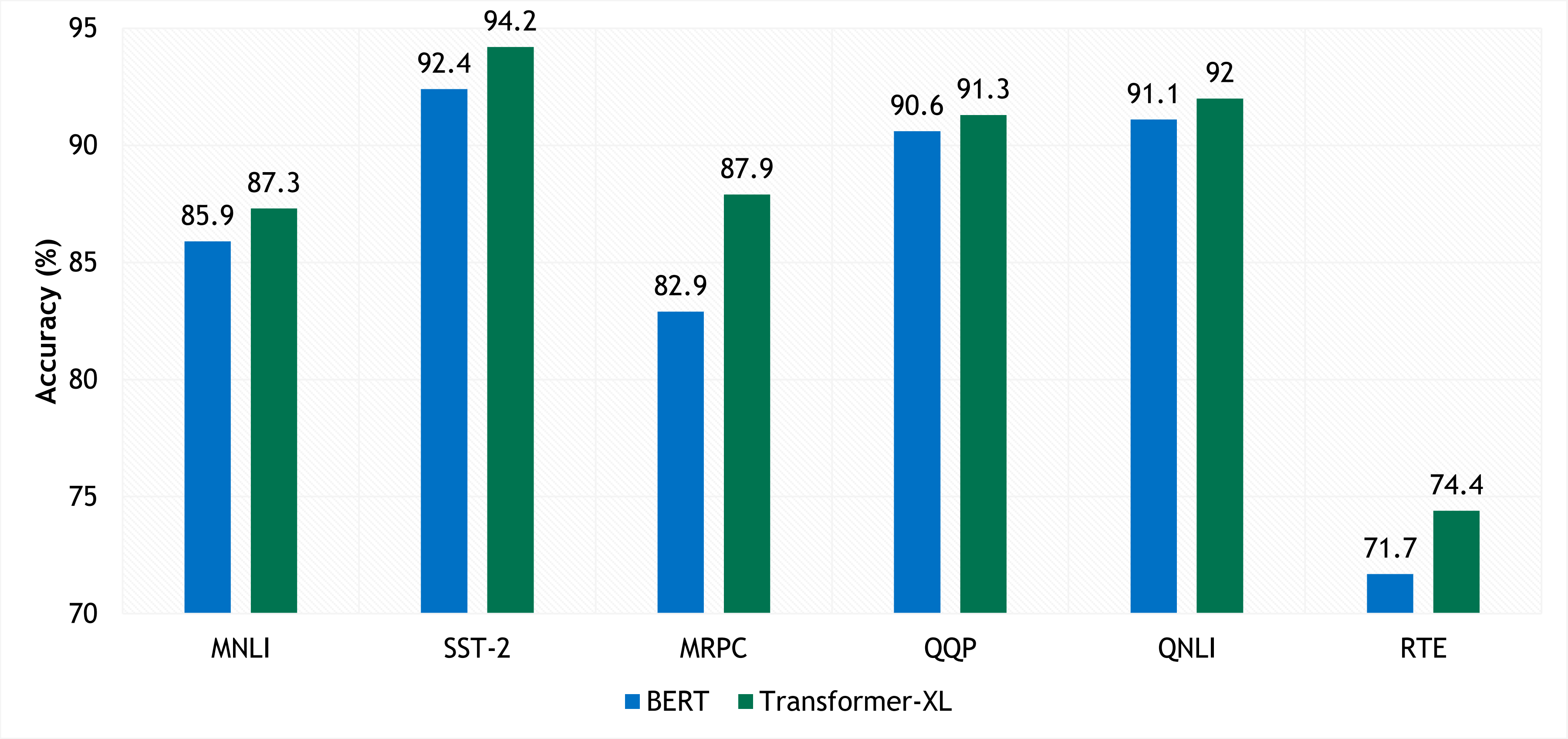
…

Long-range dependency:

- **Able to keep track of time.**
- **Reasonable coherence over thousands of tokens.**

BETTER THAN BERT

Preliminary results. We will release more results and details soon.



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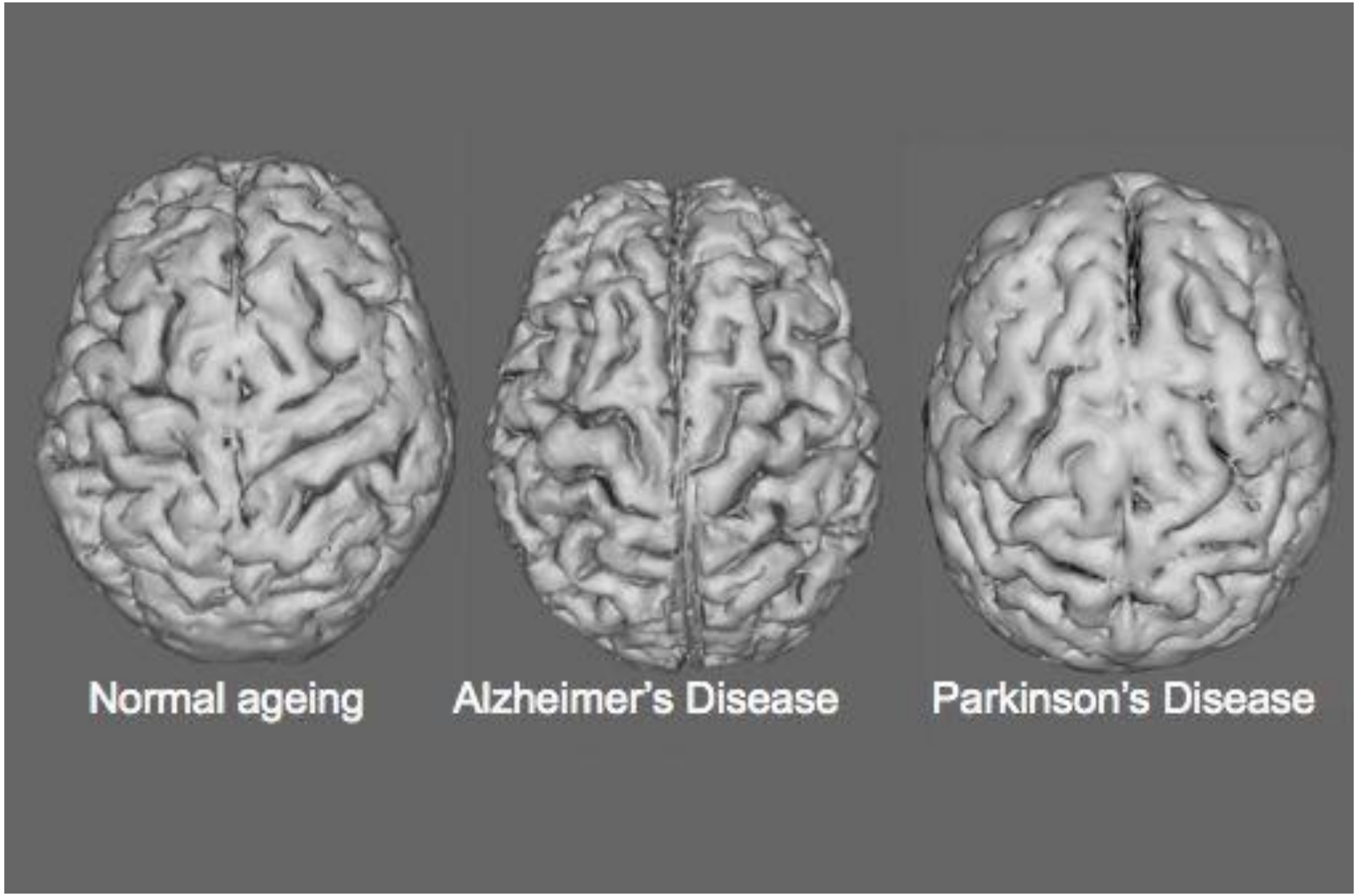
WILLIAM YUAN, HARVARD

EARLY DETECTION OF NEURODEGENERATION WITH DEEP LEARNING

William Yuan, Harvard University

March 21, 2019

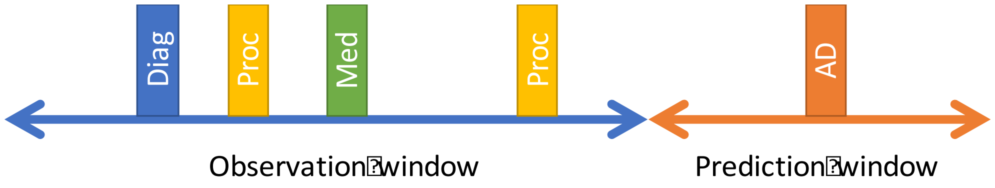
NEURODEGENERATION



Oxford FMRIB Neurodegeneration Group

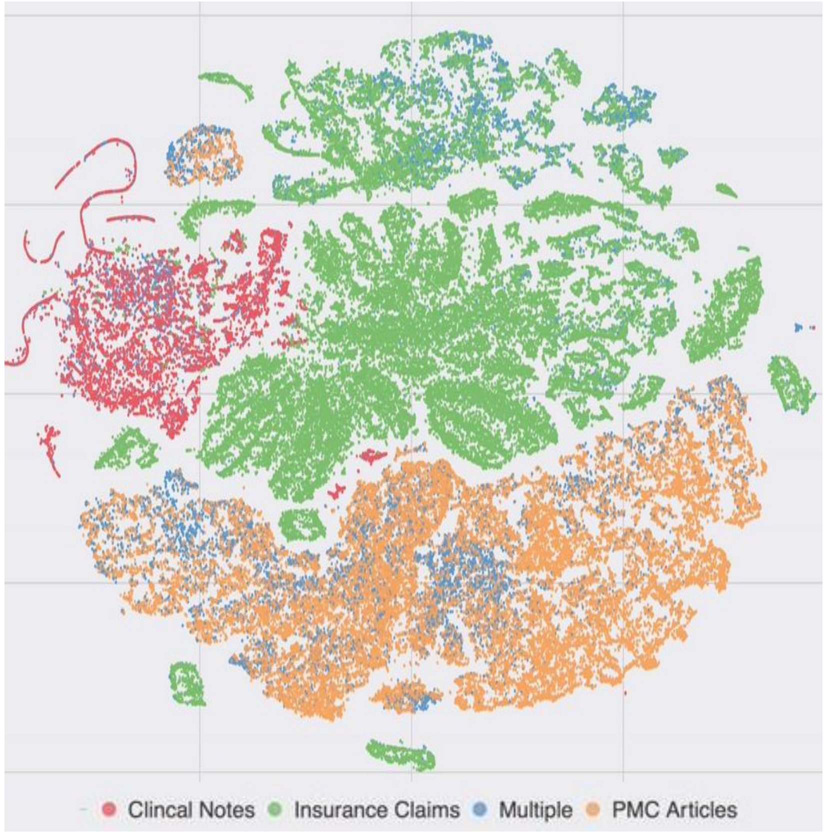
DATA

- Unidentifiable Health Insurance Claims Data
- Tens of millions of individuals → Tens of billions of individual observations
- Diagnoses/Procedures/Prescriptions
- Case/Control Study: 1 Year Prediction



METHODS

- Word2Vec Style Medical Concept Embedding
- Temporal Convolutional Nets for Sequence Classification with GPU computing
- Novel Sequence Representation
- Counterfactual Event Modeling



Beam, et al, 2018

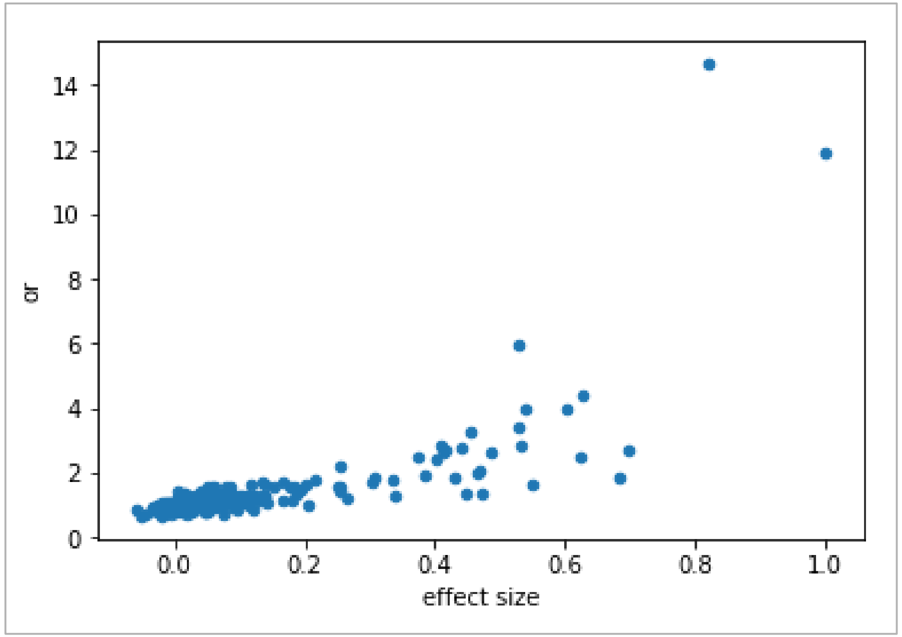
PREDICTION RESULTS (AUC)

	Alzheimer’s Disease	Parkinson’s Disease
Baseline	0.724	0.754
Event Sequence-only Prediction	0.706	0.721
Randomly Permuted Events	0.693	0.713
Temporal-only Prediction	0.583	0.599

COUNTERFACTUAL MODELING

Phenotype	Relative Effect Size
Memory Loss	1.000
Other Persistent Mental Disorders	0.8495
Mild Cognitive Impairment	0.8222
Alzheimer’s Disease*	0.8000
Parkinson’s Disease*	0.7621
Abnormal Involuntary Movements	0.6975

*unobserved by model



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Compute the Cure

NVIDIA FOUNDATION

Compute the Cure

Philanthropic initiative to advance the fight against cancer

Funds researchers using GPUs to accelerate research, diagnostics, and treatment

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PhD Fellowships to promising researchers in related fields:

2015 - 2016	John Neylon	ART Using GPU-accelerated Biomechanical Models
2016 - 2017	Gang Wu	AI for Fluorescence Lifetime Imaging
2017 - 2018	Anna Shcherbina	DL for Epigenetic Regulatory Mechanisms
2018 - 2019	William Yuan	CNN Models for Neuroblastoma Classification

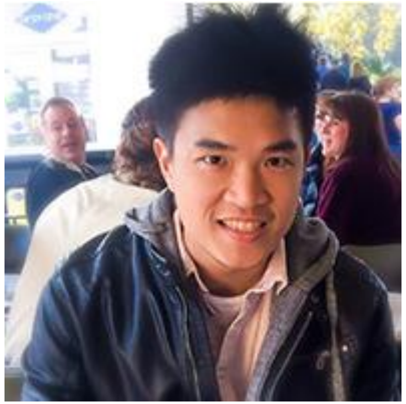
www.computethecure.org

Announcing:

The New 2019-2020 Grad Fellows And Finalists

NEW 2019-2020 GRAD FELLOWS

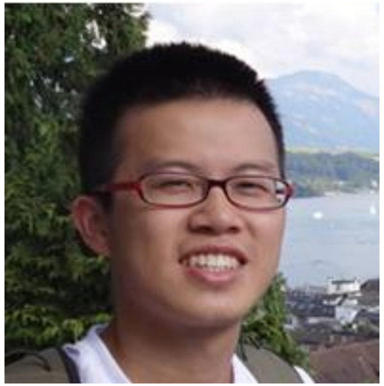
Bastian Hagedorn, Univ. Münster



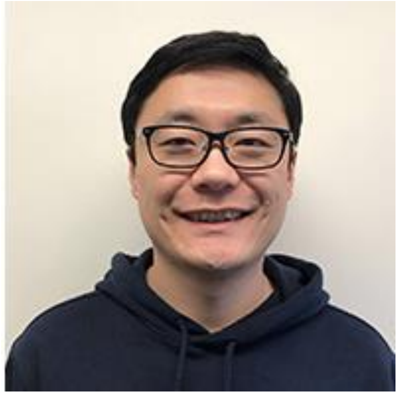
Chen-Hsuan Lin, CMU

Ching-An Cheng, Georgia Tech

Daniel Gordon, Univ. Washington



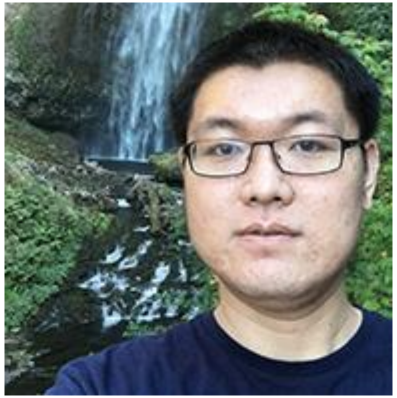
De-An Huang, Stanford



Huaizu Jiang, U. Mass. Amherst

NEW 2019-2020 GRAD FELLOWS

Jeremy Bernstein, CalTech



Lifan Wu, UC San Diego

Mariya Popova, UNC Chapel Hill

Siddharth Reddy, UC Berkeley

NEW 2019-2020 GRAD FELLOW FINALISTS

- Chao-Yuan Wu, UT Austin
- Kelvin Xu, UC Berkeley
- Nathan Otterness, UNC Chapel Hill
- Wengong Jin, MIT
- Yunzhu Li, MIT

THANK YOU