# Computational Photography at Google

## EE367/CS448I: Computational Imaging and Display

stanford.edu/class/ee367


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YouTube

2018-2023: Google Research

(Stanford EE PhD class of 2018, TAed EE367)



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# What we'll talk about:

Computational
Photography at Google (intro) & HDR+


Night Sight

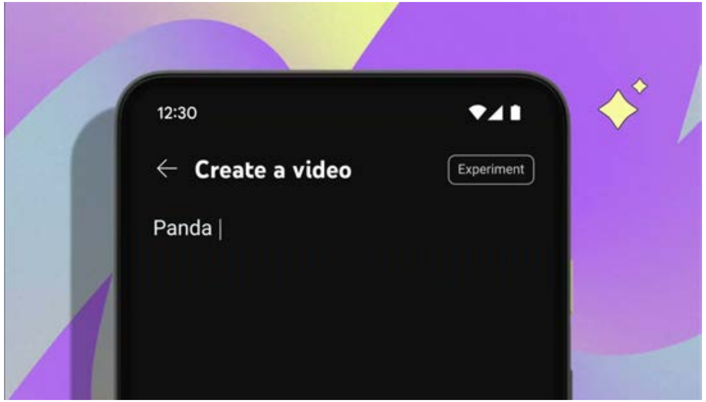
Portrait Mode

Magic Eraser and new releases

# YouTube Shorts to gain a generative AI feature called Dream Screen

Sarah Perez @sarahpereztc / 7:25 AM PDT • September 21, 2023

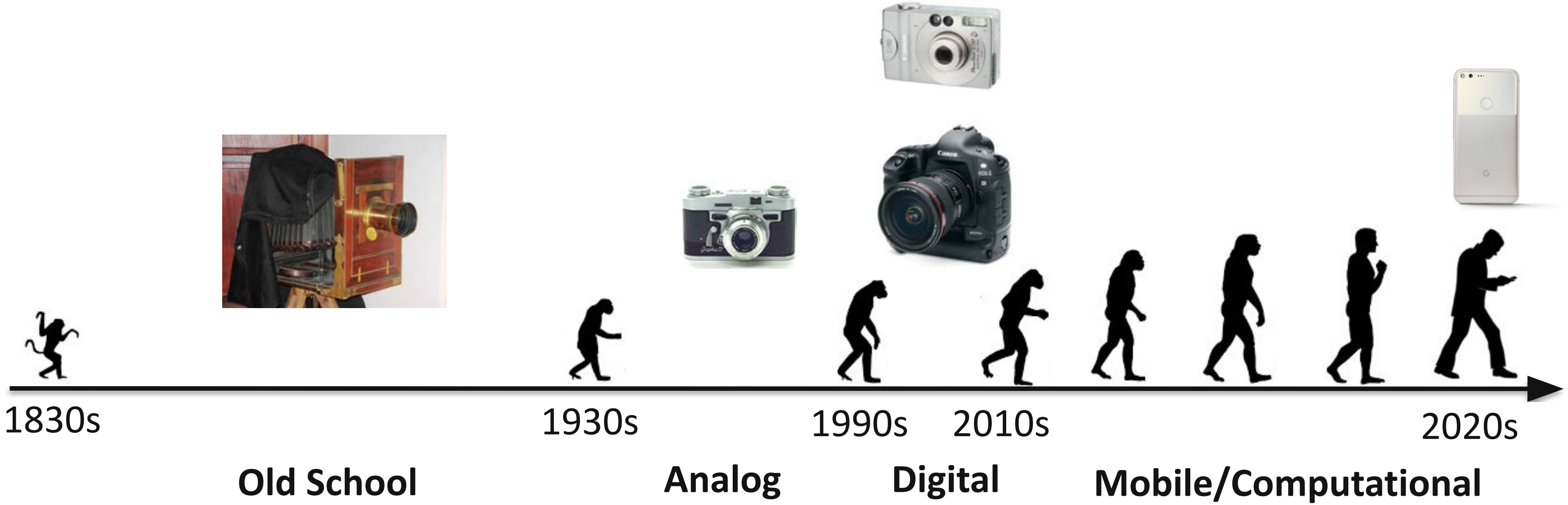
Comment

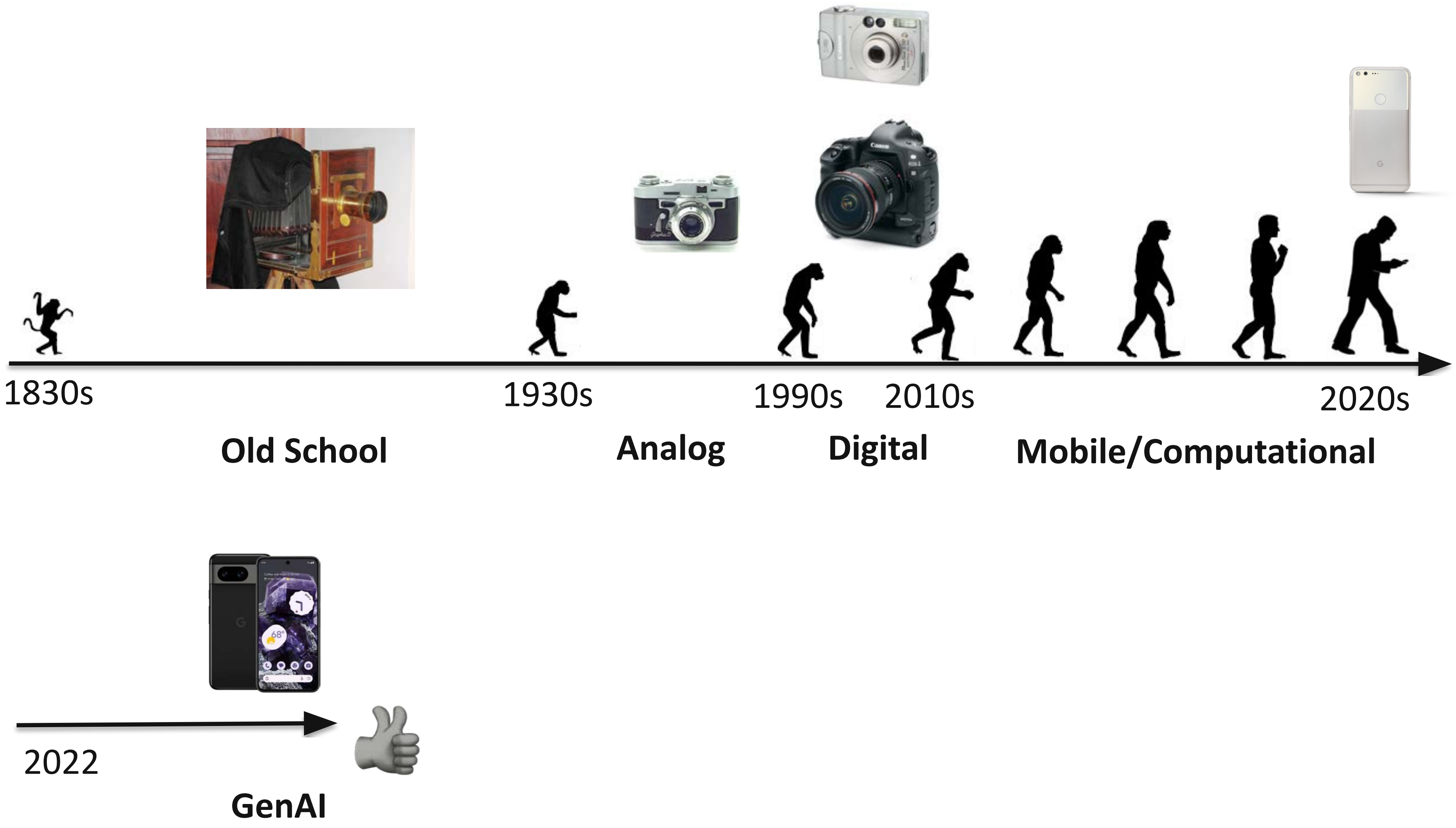



[TechCrunch](https://techcrunch.com)

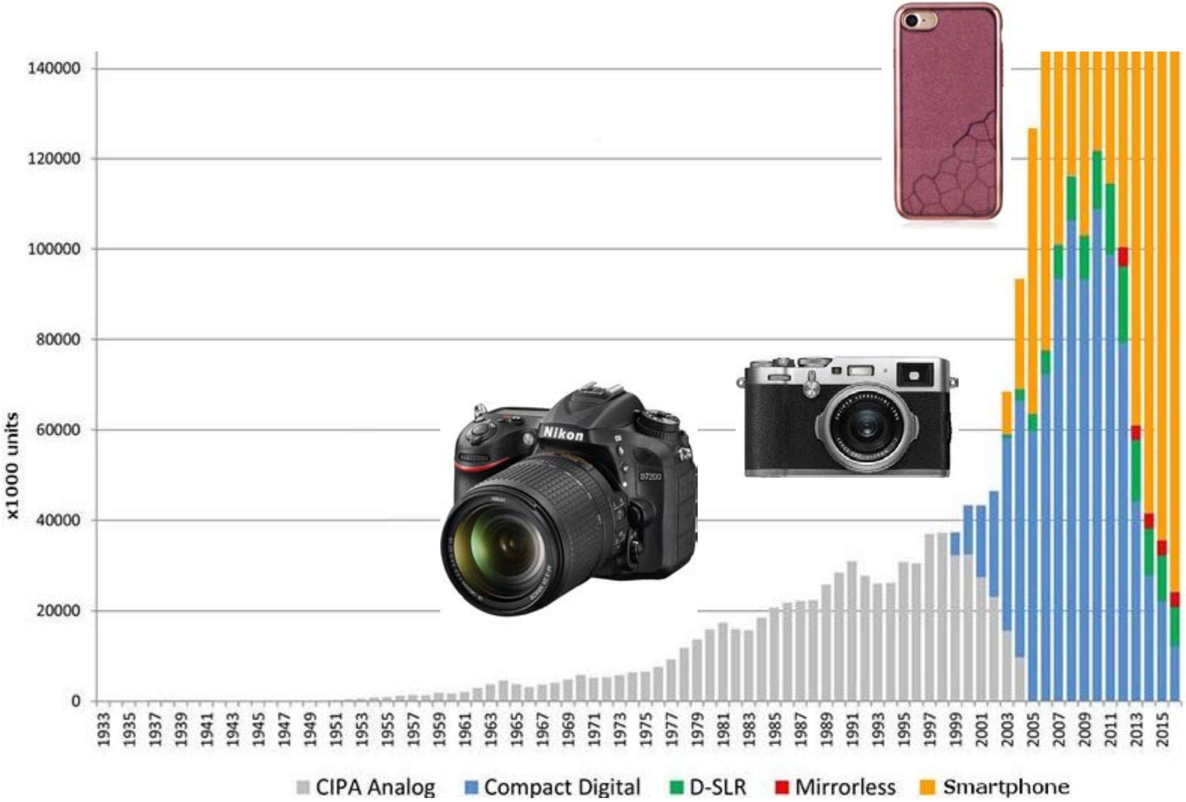
# Recent project from Google Research: Lumiere

All these videos are generated!

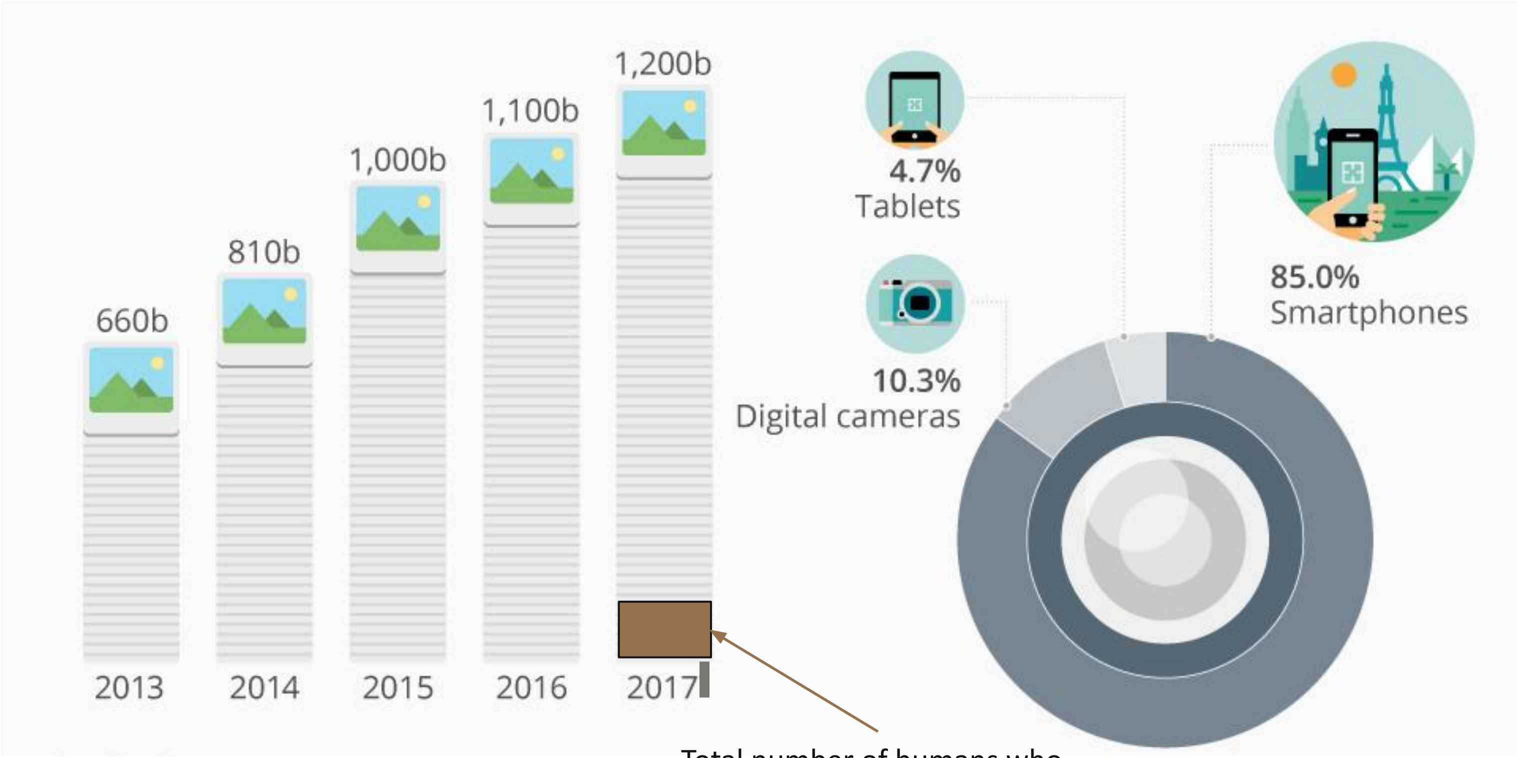

1830s
1930s
1990s
2010s
2020s
Old School
Analog
Digital
Mobile/Computational


1830s
1930s
1990s
2010s
2020s
Old School
Analog
Digital
Mobile/Computational
2022
GenAI

# The changing landscape of cameras (dpreview)




# The mobile camera is the most widely used camera in history.




Total number of humans who have **ever** lived on earth

Source: Statista

# Can we Close the Gap ?

# Less light comes in

$4.7\ mm^2$ ~ 300x = $1360\ mm^2$

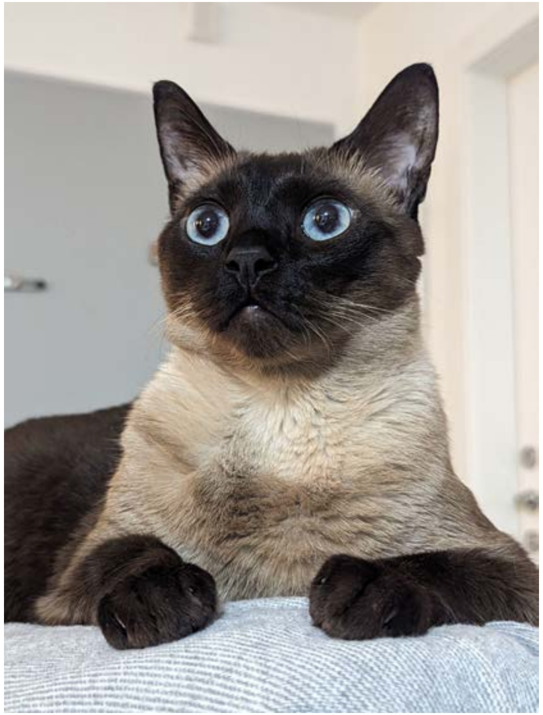
# The need for computation

vs.

PC: Matan Liba

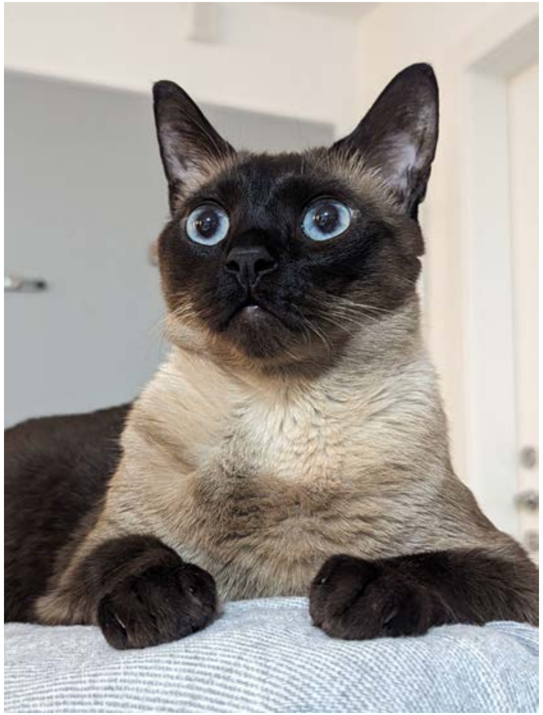
# Which was captured with Canon / Pixel?

Amigo



PC: Matan Liba

# Can we Close the Gap ?



Pixel 7, “out of the camera”

Canon EOS R10 raw + Lightroom

PC: Matan Liba, Canon EOS R10

# More photos with the Canon

# Can we Close the Gap ?

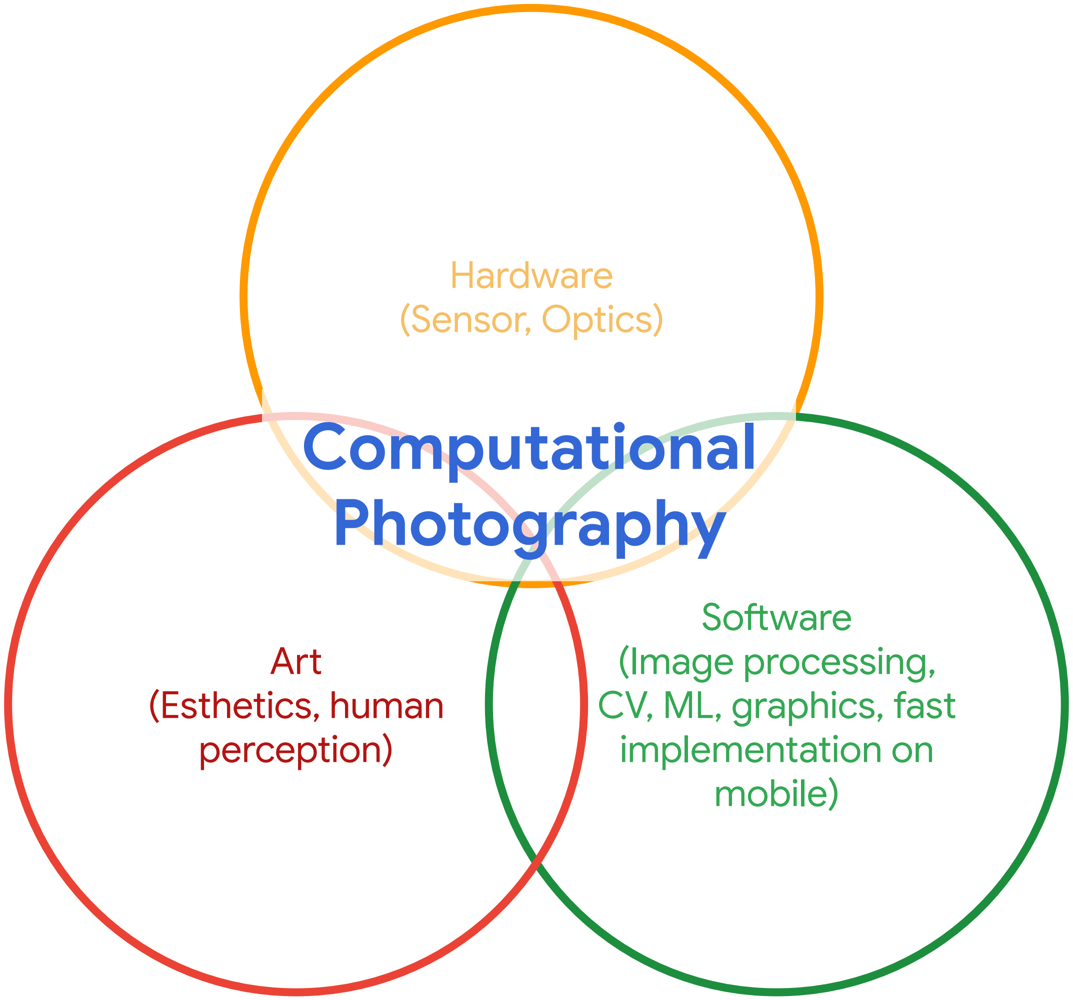
Q: How can small & cheap smartphone cameras achieve quality comparable to larger digital cameras?

A: Computational Photography

More recently:

**Expand conventional photography**

Give the users **Superpowers!**


Hardware
(Sensor, Optics)
Computational
Photography
Art
(Esthetics, human
perception)
Software
(Image processing,
CV, ML, graphics, fast
implementation on
mobile)

# GCam

- Founded in 2011 by Stanford Prof. Emeritus Dr. Marc Levoy
- First project: Burst Photography, HDR+


- Now: team has grown in size and scope, many more teams work on computational photography and editing

# Burst photography for high dynamic range and low-light imaging on mobile cameras

Samuel W. Hasinoff Dillon Sharlet Ryan Geiss Andrew Adams
Jonathan T. Barron Florian Kainz Jiawen Chen Marc Levoy
Google Research

Short exposure Brightened short exposure → noise Merged burst of short exposures

**Figure 1:** *A comparison of a conventional camera pipeline (left, middle) and our burst photography pipeline (right) running on the same cell-phone camera. In this low-light setting (about 0.7 lux), the conventional camera pipeline under-exposes (left). Brightening the image (middle) reveals heavy spatial denoising, which results in loss of detail and an unpleasantly blotchy appearance. Fusing a burst of images increases the signal-to-noise ratio, making aggressive spatial denoising unnecessary. We encourage the reader to zoom in. While our pipeline excels in low-light and high-dynamic-range scenes (for an example of the latter see figure 10), it is computationally efficient and reliably artifact-free, so it can be deployed on a mobile camera and used as a substitute for the conventional pipeline in almost all circumstances. For readability the figure has been made uniformly brighter than the original photographs.*

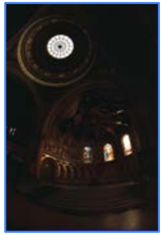
# Our approach

- burst with constant exposure
  - more robust merge
  - underexposed up to 8x
- reference image
  - physically consistent fallback
- raw images
  - merge in raw too

# Underexposure for HDR

- HDR capture as noise reduction [Hasinoff et al. 2010] [Zhang et al. 2010]

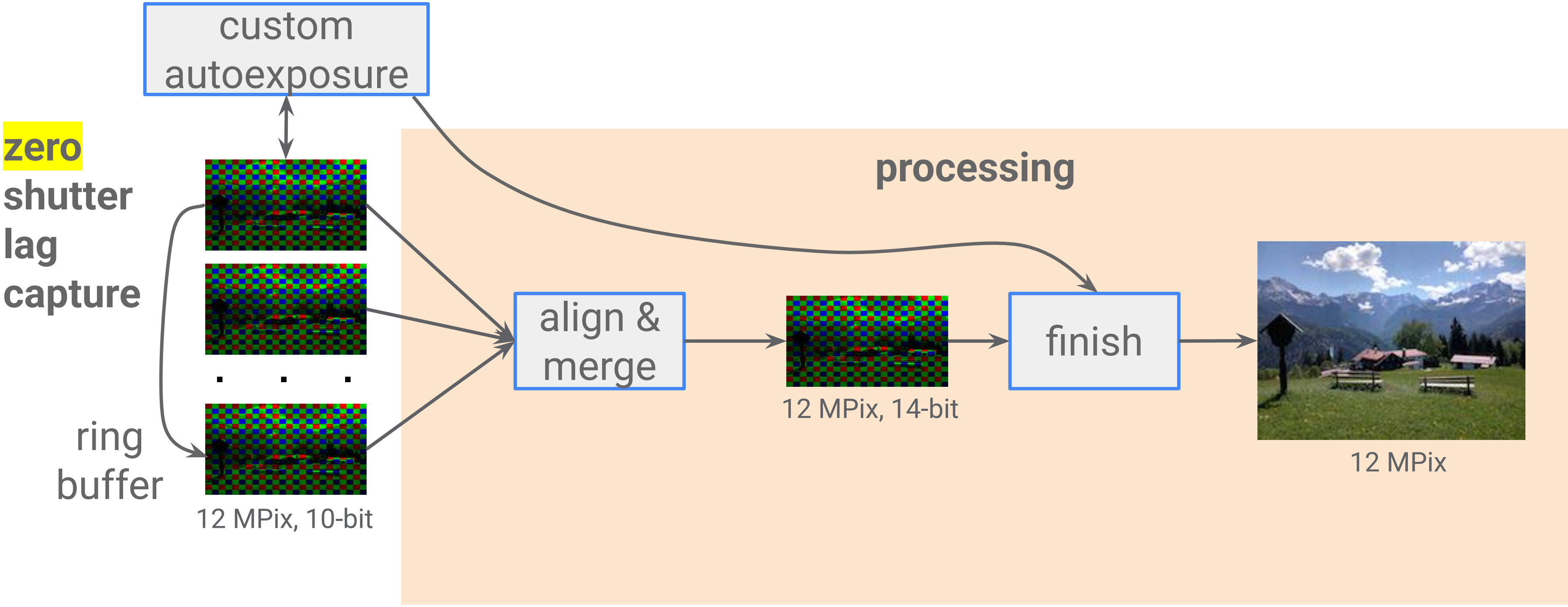
single underexposed shot
- low SNR



exposure bracketing
- higher SNR
- challenging merge

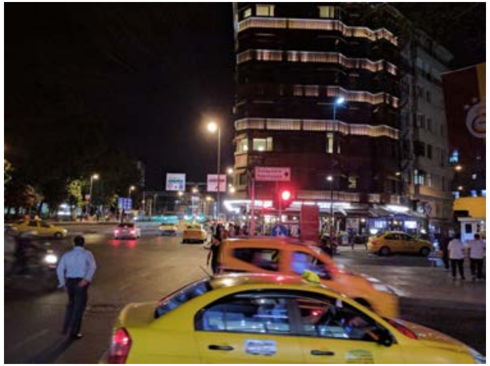
underexposed burst
- moderate SNR
- more robust merge

# System overview

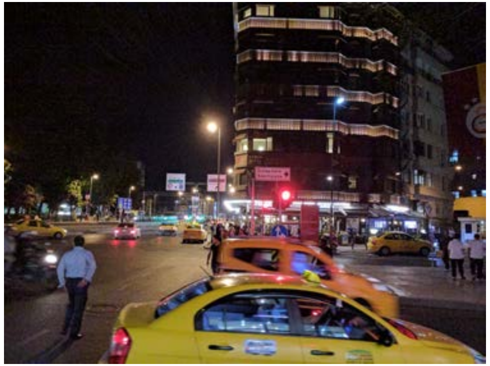



Google

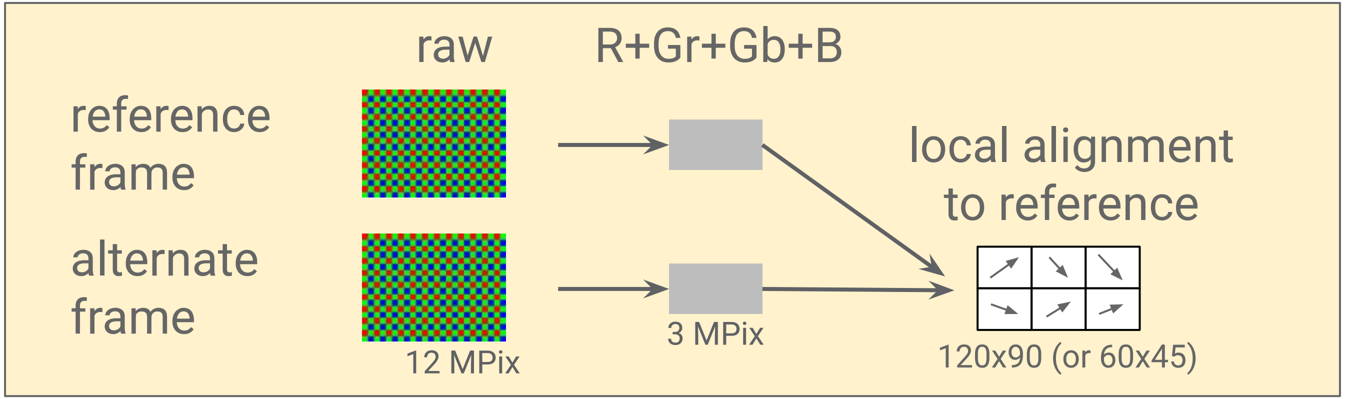
# Burst alignment



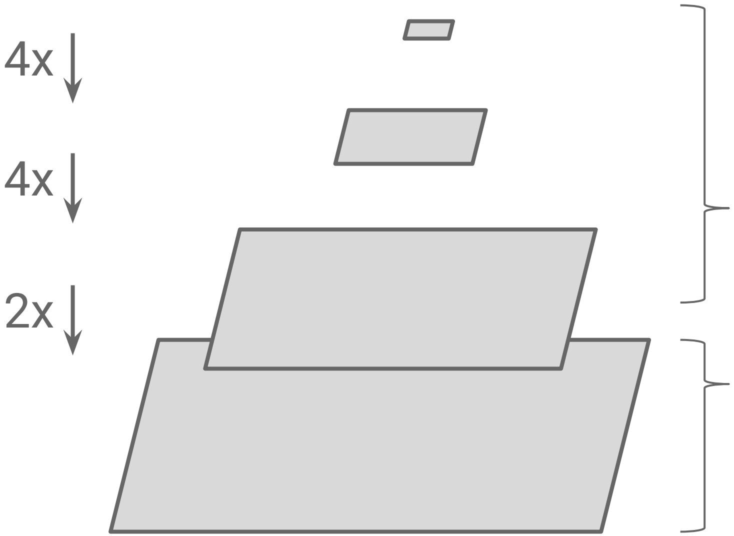
input burst



reference frame



# Coarse to fine alignment




| metric | search range | subpixel? |
|---|---|---|
| L2 | 9x9 | yes |
| L1 | 3x3 | no |

- 4 pyramid levels
- upsample with multiple hypotheses [Tao et al., 2012]

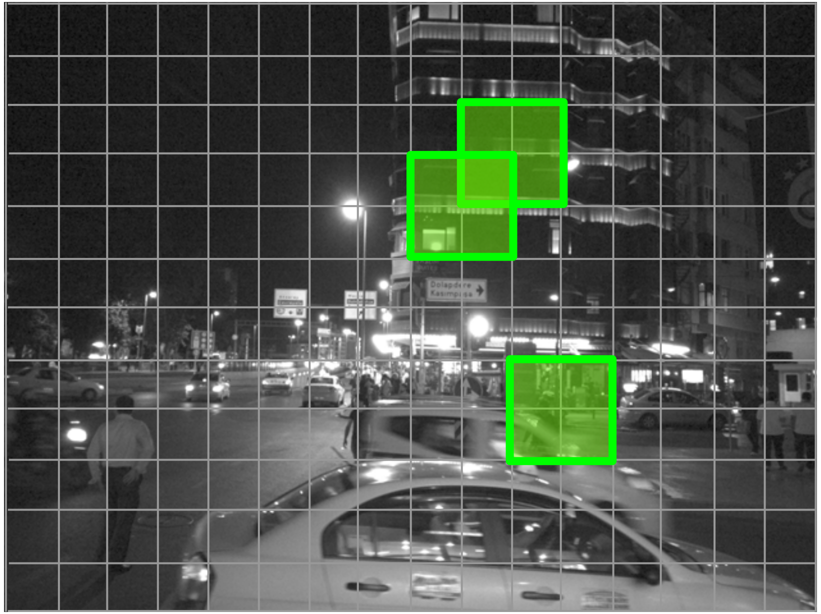
# Example alignment

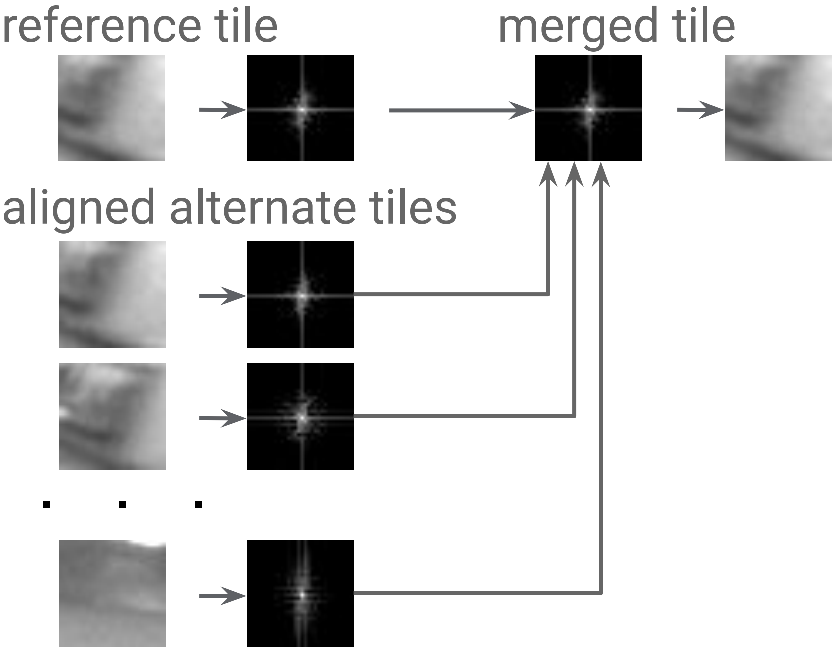
reference frame


aligned to reference


# Tiled Fourier-based merge

- divide into 16x16 or 32x32 tiles
  - 50% overlap - every pixel covered by 4 tiles
- merge in Fourier domain





# Robust per-frequency merge

reference frame

$$T_0$$

aligned average

$$\frac{1}{N}\sum T_i$$

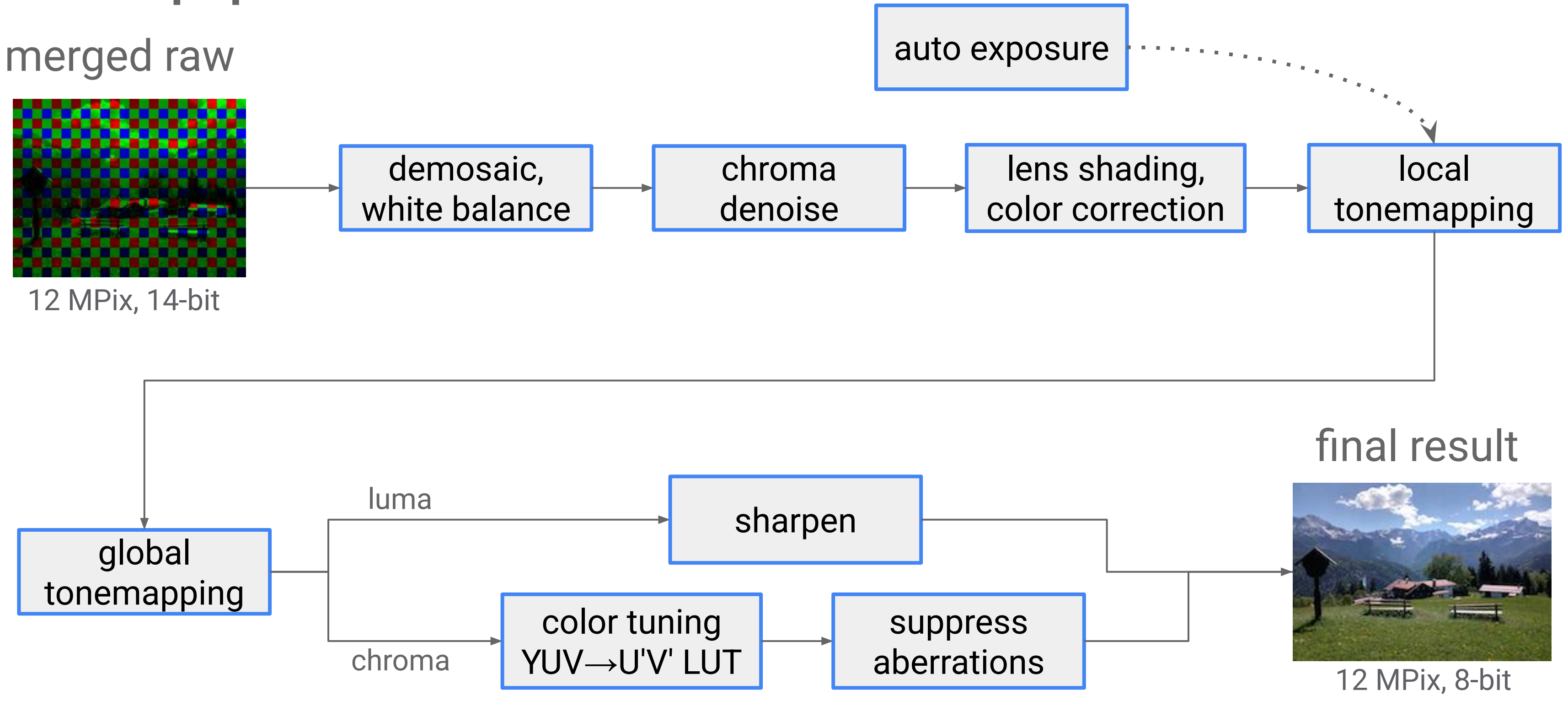
robust pairwise merge

$$\frac{1}{N}\sum(1 - A_i)\,T_i + A_i\,T_0$$

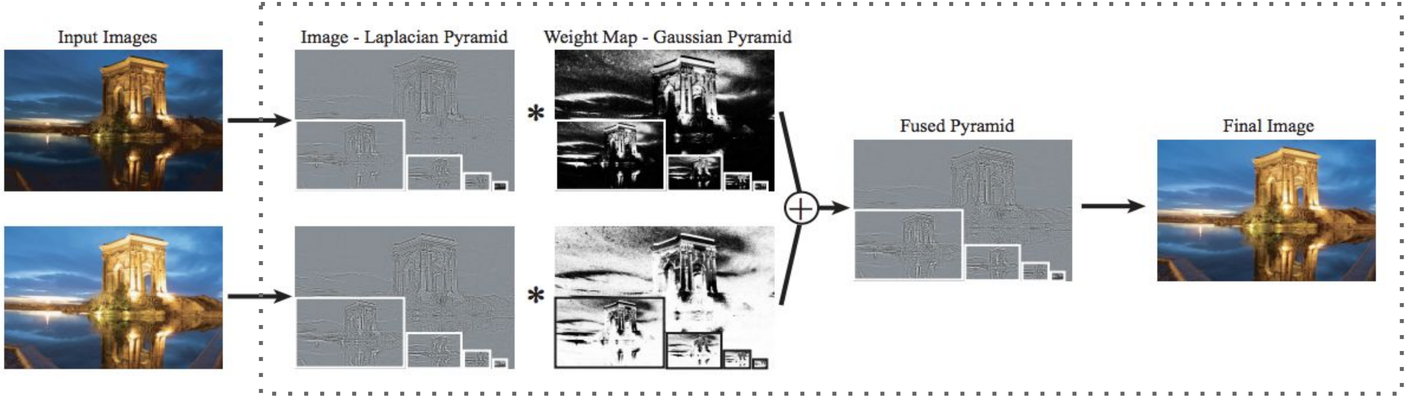
$$A_i = \frac{||T_0 - T_i||^2}{||T_0 - T_i||^2 + k\sigma^2} \in [0, 1]$$

# Finish

# Finish pipeline



# Local tonemapping

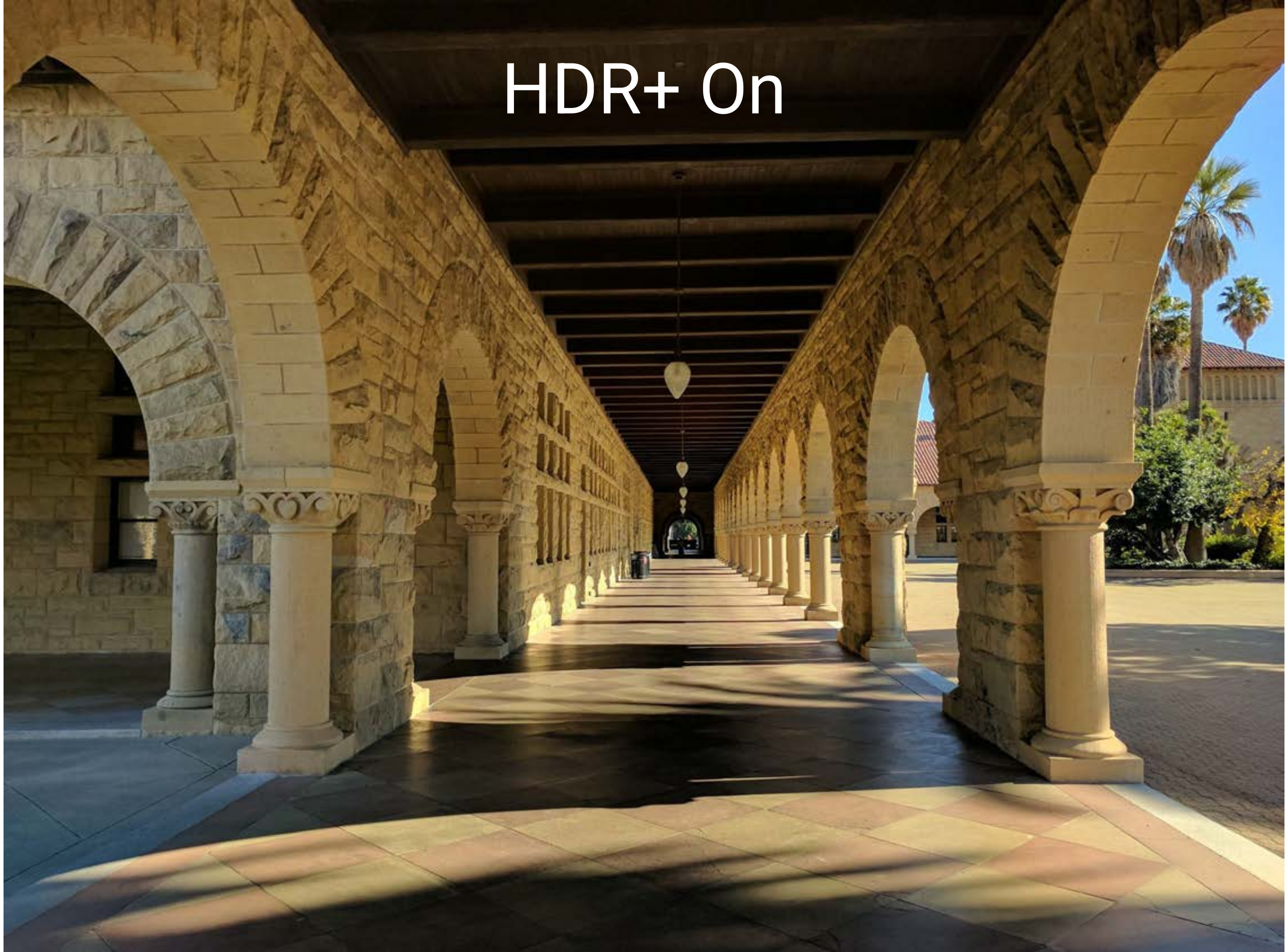



pyramid blending for HDR tonemapping
[Mertens et al., 2007]
[Paris et al. 2011]
[Aubry et al. 2014]

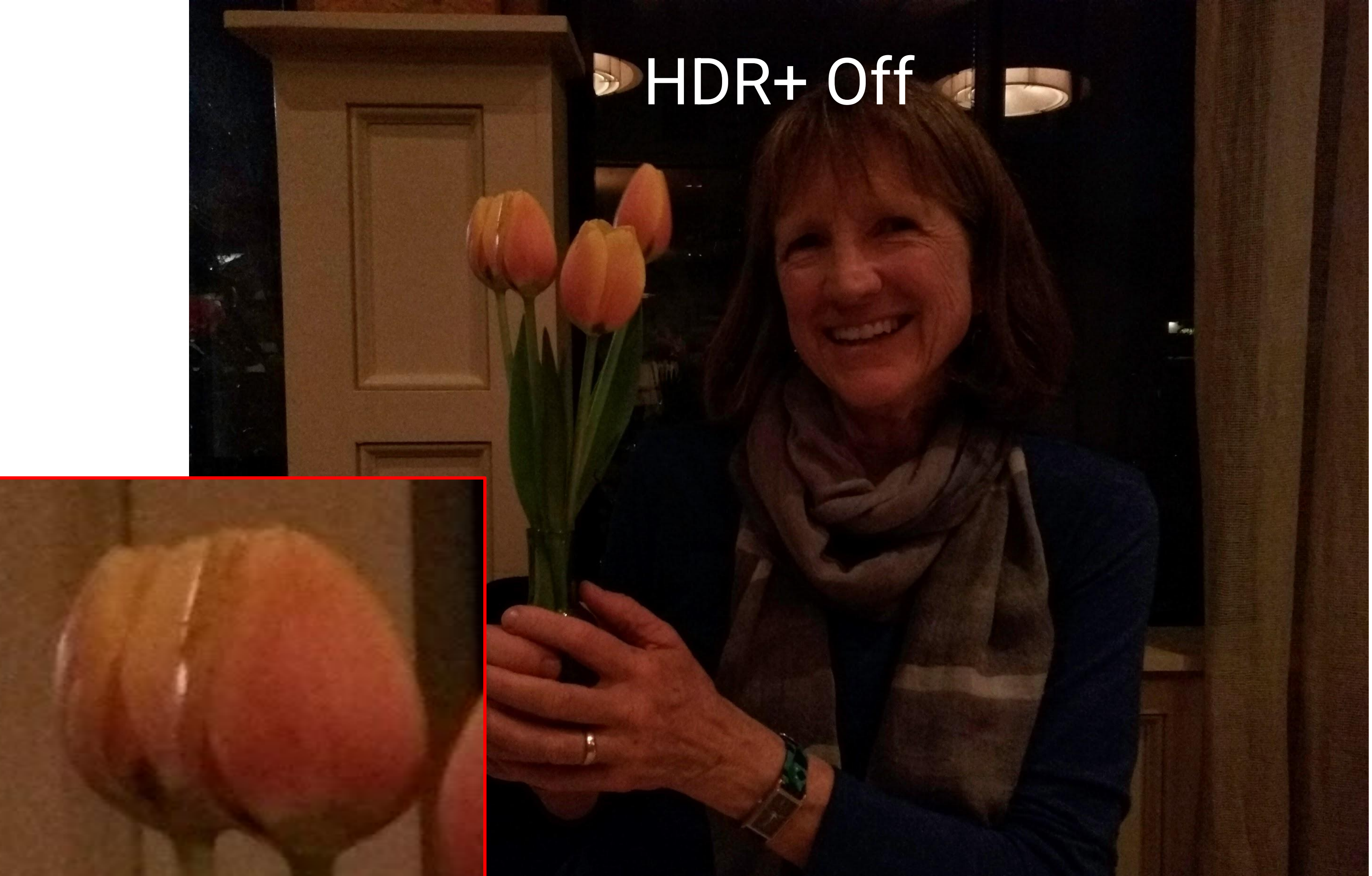
- **synthetic** exposures from AE
  - single merged input image
  - digital gains
- automatically set tuning parameters

# Results


HDR+ Off




Google


HDR+ Off


HDR+ On

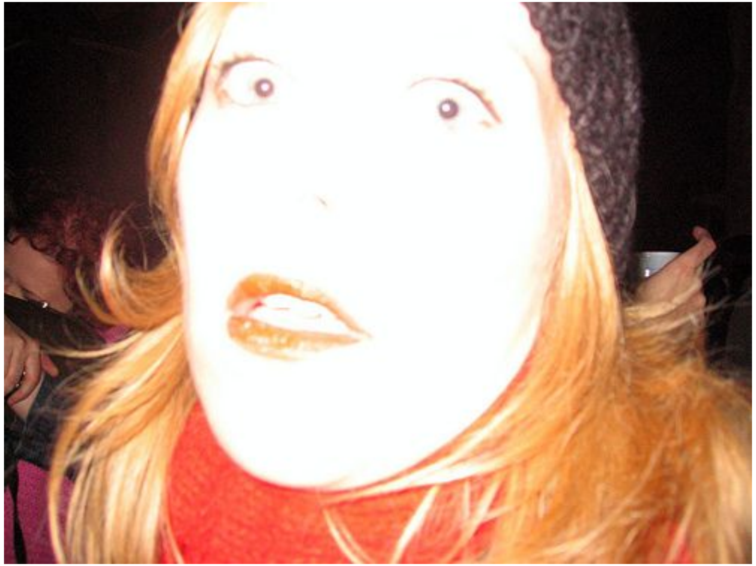

Night Sight


# Capture Low Light Photos

DSLR + Tripod

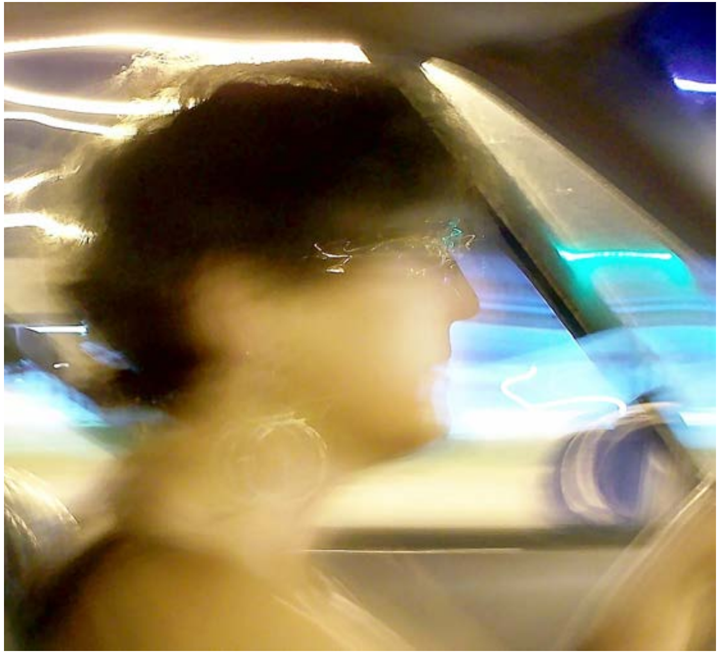

# Capture Low Light Photos

- ~~Large camera / Tripod~~
- Flash



# Capture Low Light Photos

- ~~Large camera / Tripod~~
- ~~Flash~~
- Long Exposure, handheld
  - motion blur from moving subjects
  - motion blur from hand shake



# Capture Low Light Photos

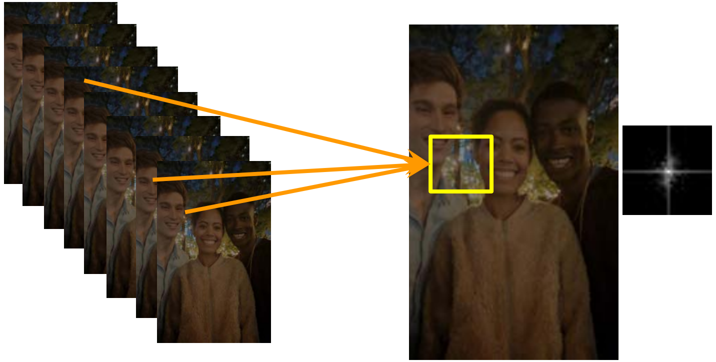
- No Tripod
- No Flash
- No motion blur
  - moving subjects
  - hand shake
- Fast processing on mobile device

HDR+

**Auto Exposure**

**Underexposed Burst**

**Align & merge**



**Finish:**
**Denoise, Tonemap /sharpen**

**Burst photography for high dynamic range and low-light imaging on mobile cameras,**
Samuel W. Hasinoff, Dillon Sharlet, Ryan Geiss, Andrew Adams, Jonathan T. Barron, Florian Kainz, Jiawen Chen, Marc Levoy , SIGGRAPH Asia 2016

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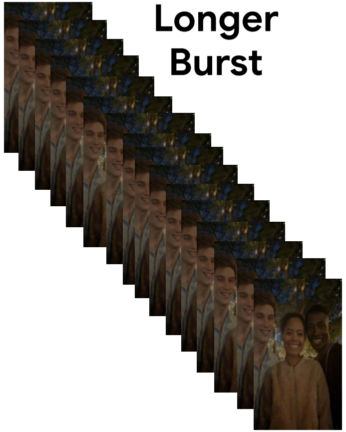
Night Sight

**Motion Metering**

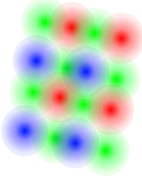


**Longer Burst**

**Modified Merge**

**Motion maps**

**Super-res Merge**



**Learning Based Auto White Balance**

**Night Sight "Look"**

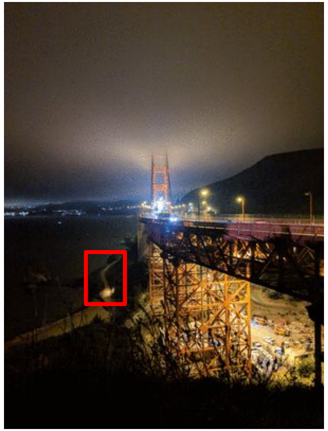
# Night Sight

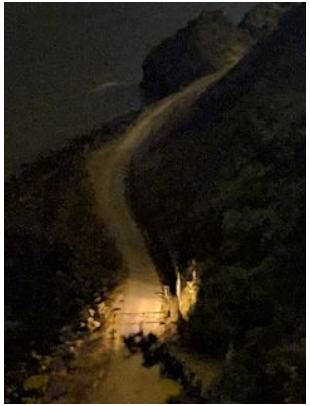
- Dedicated mode
  - positive shutter lag
  - heavier processing
- More light
  - bigger bursts
  - much longer exposures
- Motion metering
- Stronger merge
  - more aggressive
  - super-resolution merge
- ML-based AWB
- Night "look"
  - brighter AE
  - more HDR

Google

# By measuring scene motion in real-time, we can:

Increase exposure time to capture more detail in mostly static scenes...

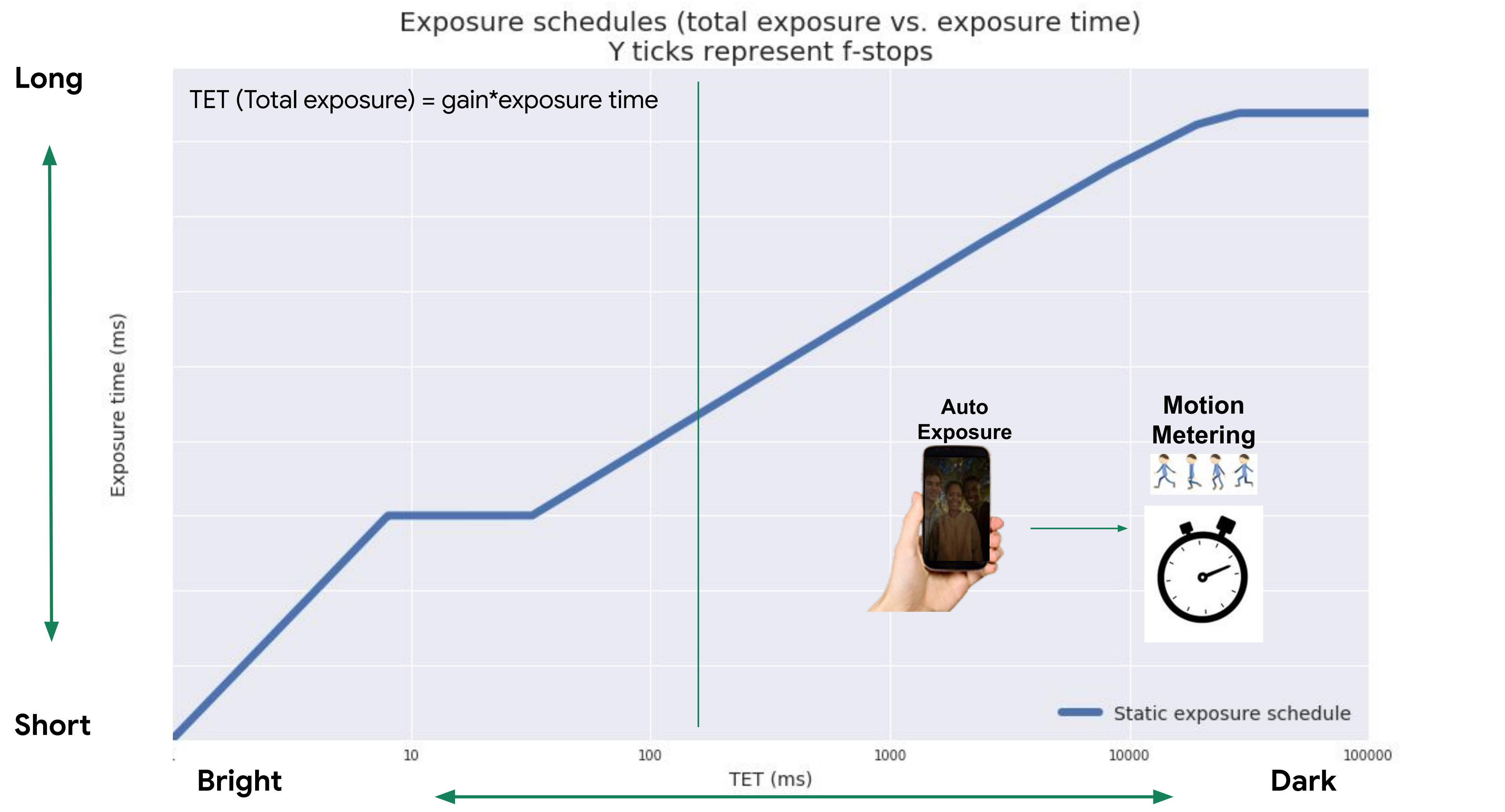




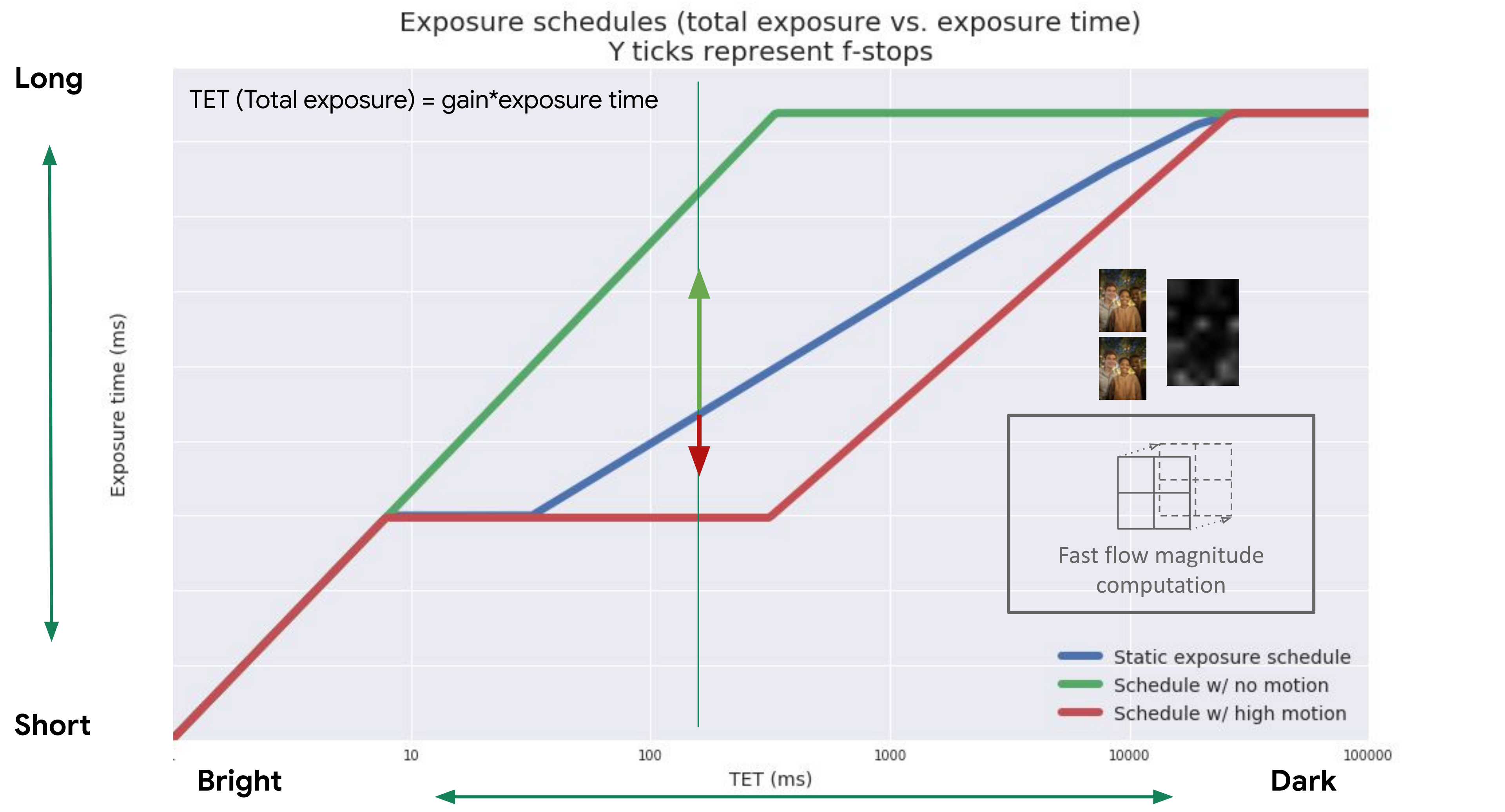
With motion metering

...while reducing exposure time to prevent motion blur in moving scenes

With motion metering



Exposure schedules (total exposure vs. exposure time)
Y ticks represent f-stops
Long
Short
TET (Total exposure) = gain*exposure time
Exposure time (ms)
Auto
Exposure
Motion
Metering
Static exposure schedule
10
100
1000
10000
100000
TET (ms)
Bright
Dark



Exposure schedules (total exposure vs. exposure time)
Y ticks represent f-stops
Long
Short
TET (Total exposure) = gain*exposure time
Exposure time (ms)
Fast flow magnitude computation
Static exposure schedule
Schedule w/ no motion
Schedule w/ high motion
10
100
1000
10000
100000
TET (ms)
Bright
Dark

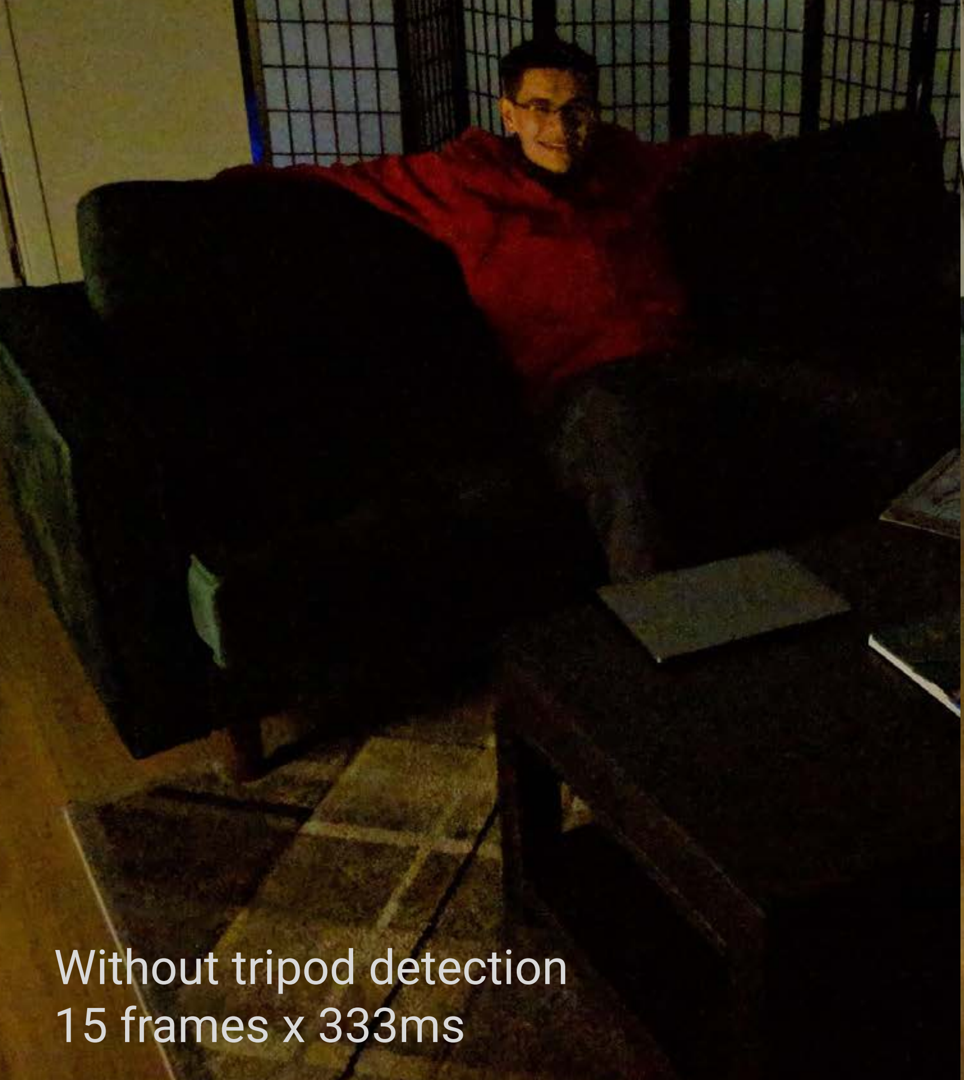
# Stability ("tripod") detection (gyro data analysis)

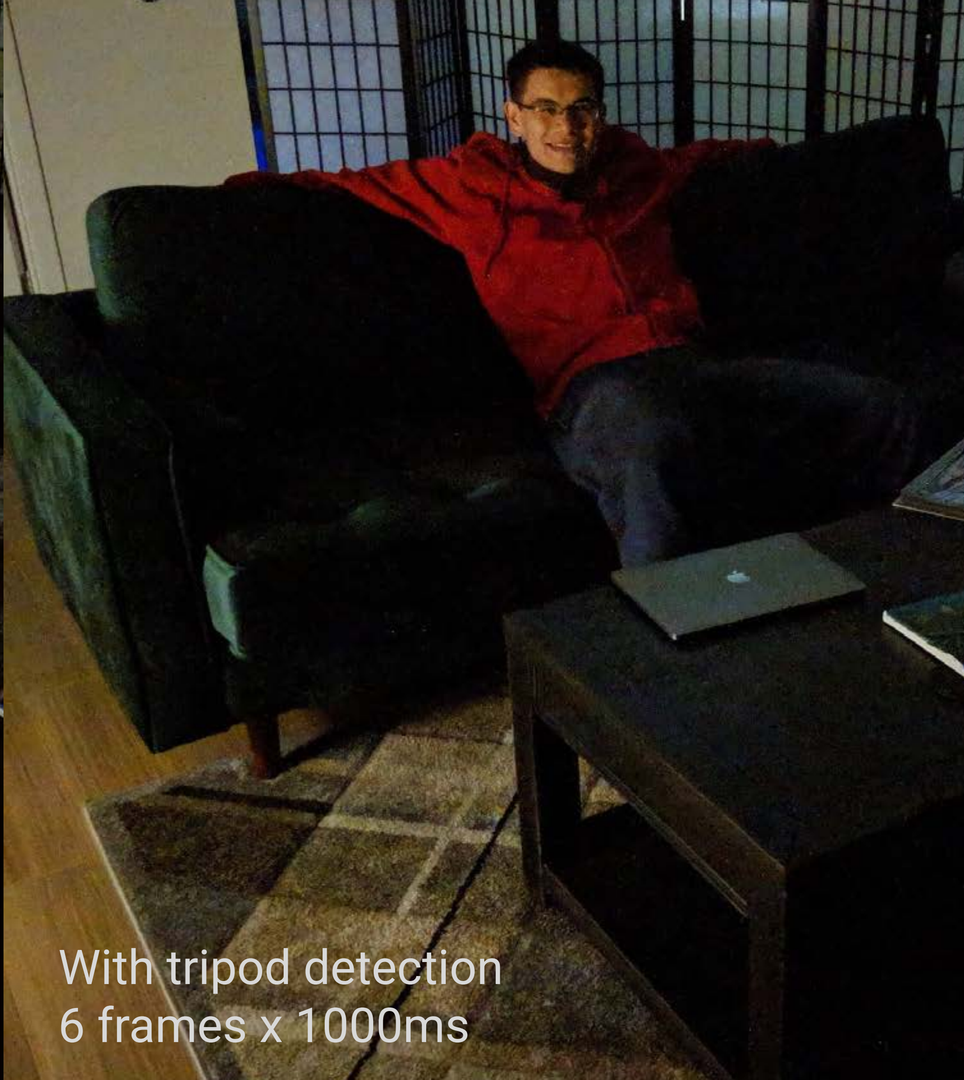
Angular rate measurements

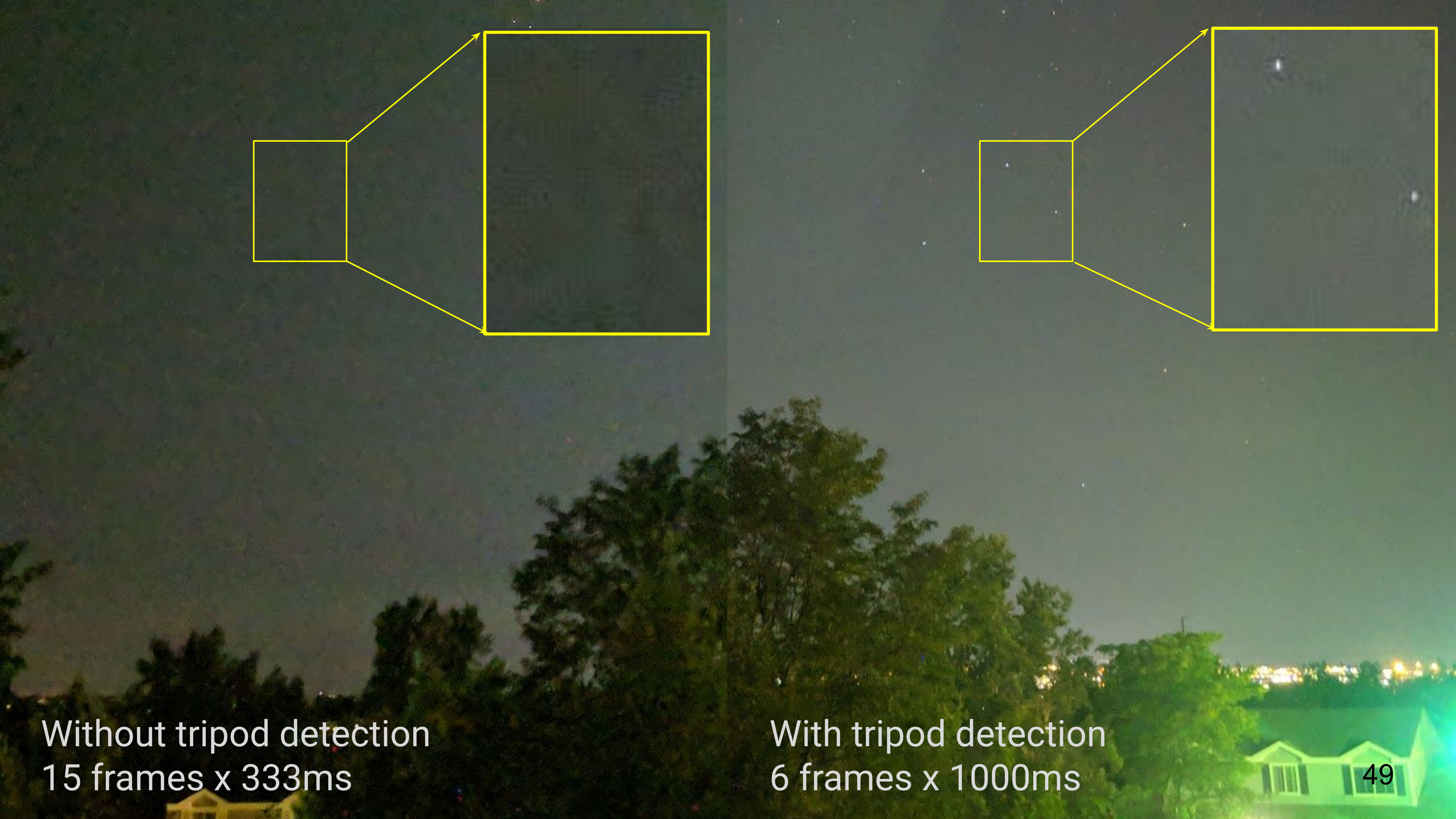
- Asses device's physical stability using angular rate  measurements from a gyro sensor.
- Use even longer exposures when camera is very still or on a tripod.
- Capture less frames.

Improvements:

- More photons!
- Less read noise


Without tripod detection
15 frames x 333ms


With tripod detection
6 frames x 1000ms


Without tripod detection
15 frames x 333ms
With tripod detection
6 frames x 1000ms

# Challenges for Night Sight merge

object motion


camera motion

low SNR

# Merge Challenges : Robust to Motion ⟵⟶ Low Noise

Solution:

- Calculate motion maps
- **Use spatially varying merge**
  - Motion ⟶ merge less
  - Static ⟶ merge more
- **Challenge:**
  **Differentiate high noise from motion**

Once we reduce the noise,

We can brighten the image!

Merge increases →

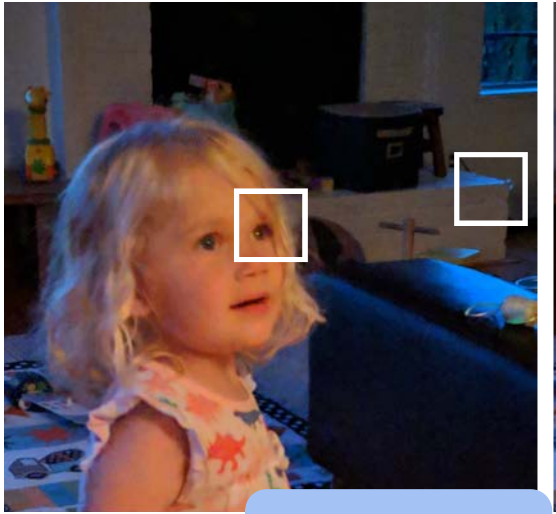
High noise, motion robust

Low noise, motion blur

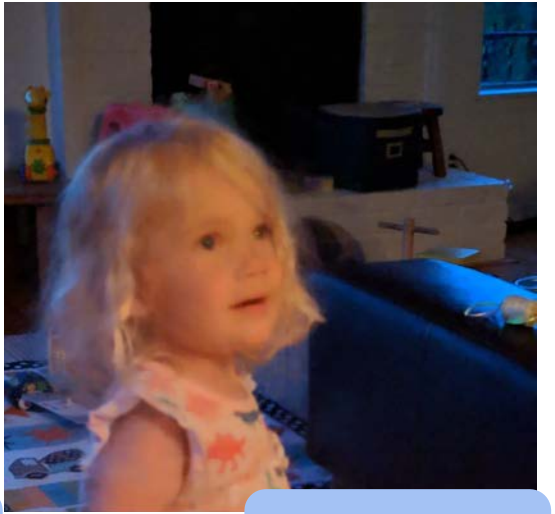
# Example

# Modifying the merge strength

HDR+

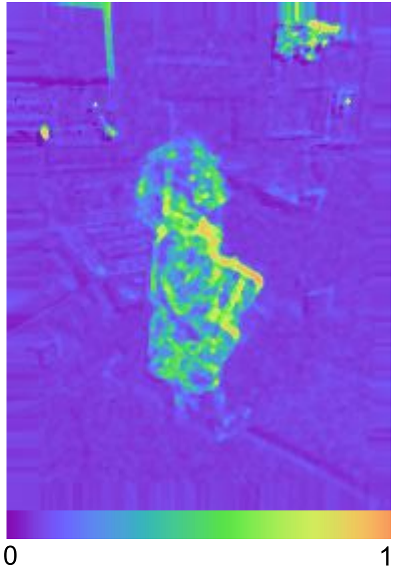


Increased merge



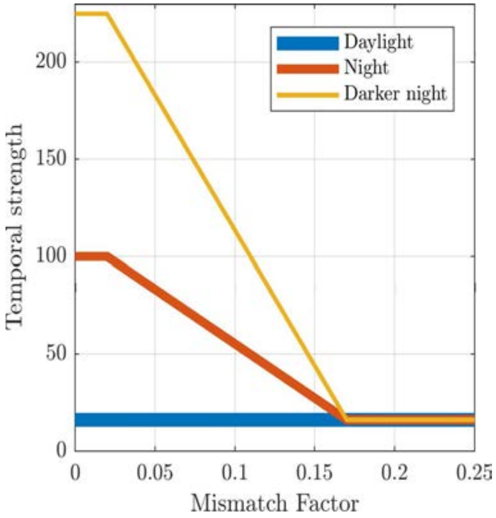
# Modified merge: spatially varying temporal strength

Mismatch map of one frame
(these are calculated for every frame)



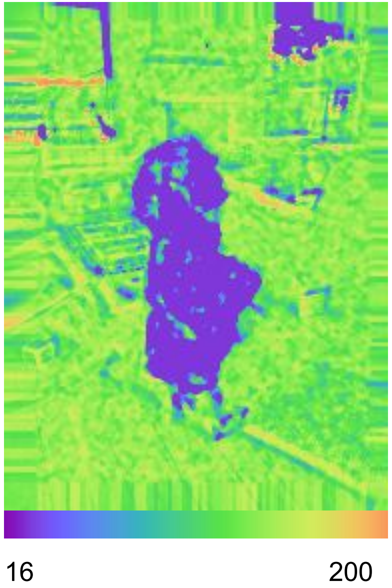

$$M_{tz} = \frac{D_{tz}^2}{D_{tz}^2 + \sigma^2/2}$$

Linear transformation,
depends on the SNR of the burst




Tuned to reject motion blur while allowing more noise

Temporal strength map

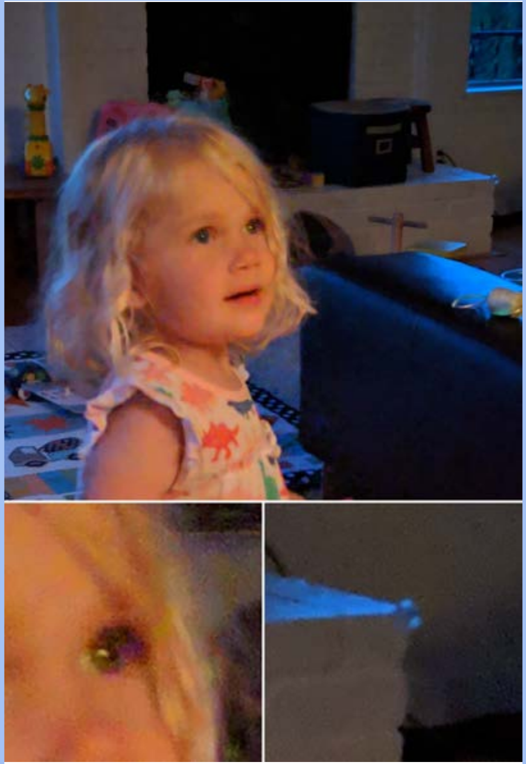



$$A_{tz}(\omega) = \frac{|D_{tz}(\omega)|^2}{|D_{tz}(\omega)|^2 + lintran(M_{tz})\sigma^2}$$

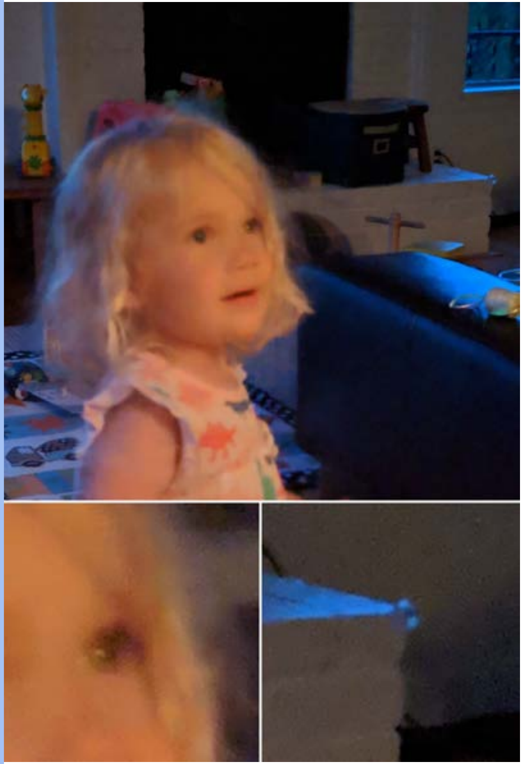
$D_{tz}$ the L1 difference between tile t in frame z and the tile it was aligned to in the reference frame

# Modified merge: spatially varying merge strength

HDR+
Temporal strength = 16



Ours: Tile-wise merge
using mismatch maps



Increased merge
Temporal strength = 200

# Super Res Zoom on Pixel 3

Google AI Blog

The latest news from Google AI

## See Better and Further with Super Res Zoom on the Pixel 3

Monday, October 15, 2018

Posted by Bartlomiej Wronski, Software Engineer and Peyman Milanfar, Lead Scientist, Computational Imaging

Digital zoom using algorithms (rather than lenses) has long been the “ugly duckling” of mobile device cameras. As compared to the optical zoom capabilities of DSLR cameras, the quality of digitally zoomed images has not been competitive, and conventional wisdom is that the complex optics and mechanisms of larger cameras can't be replaced with much more compact mobile device cameras and clever algorithms.

With the new Super Res Zoom feature on the Pixel 3, we are challenging that notion.

The Super Res Zoom technology in Pixel 3 is different and better than any previous digital zoom technique based on upscaling a crop of a *single* image, because we merge *many frames* directly onto a higher resolution picture. This results in greatly improved detail that is roughly competitive

Siggraph 2019

## Handheld Multi-Frame Super-Resolution

BARTLOMIEJ WRONSKI, IGNACIO GARCIA-DORADO, MANFRED ERNST, DAMIEN KELLY, MICHAEL KRAININ, CHIA-KAI LIANG, MARC LEVOY, and PEYMAN MILANFAR, Google Research

# White balance gains are applied to make “white” appear white

Captured image

/

Inverse
*rgb* gains



Predicted
“illumination”

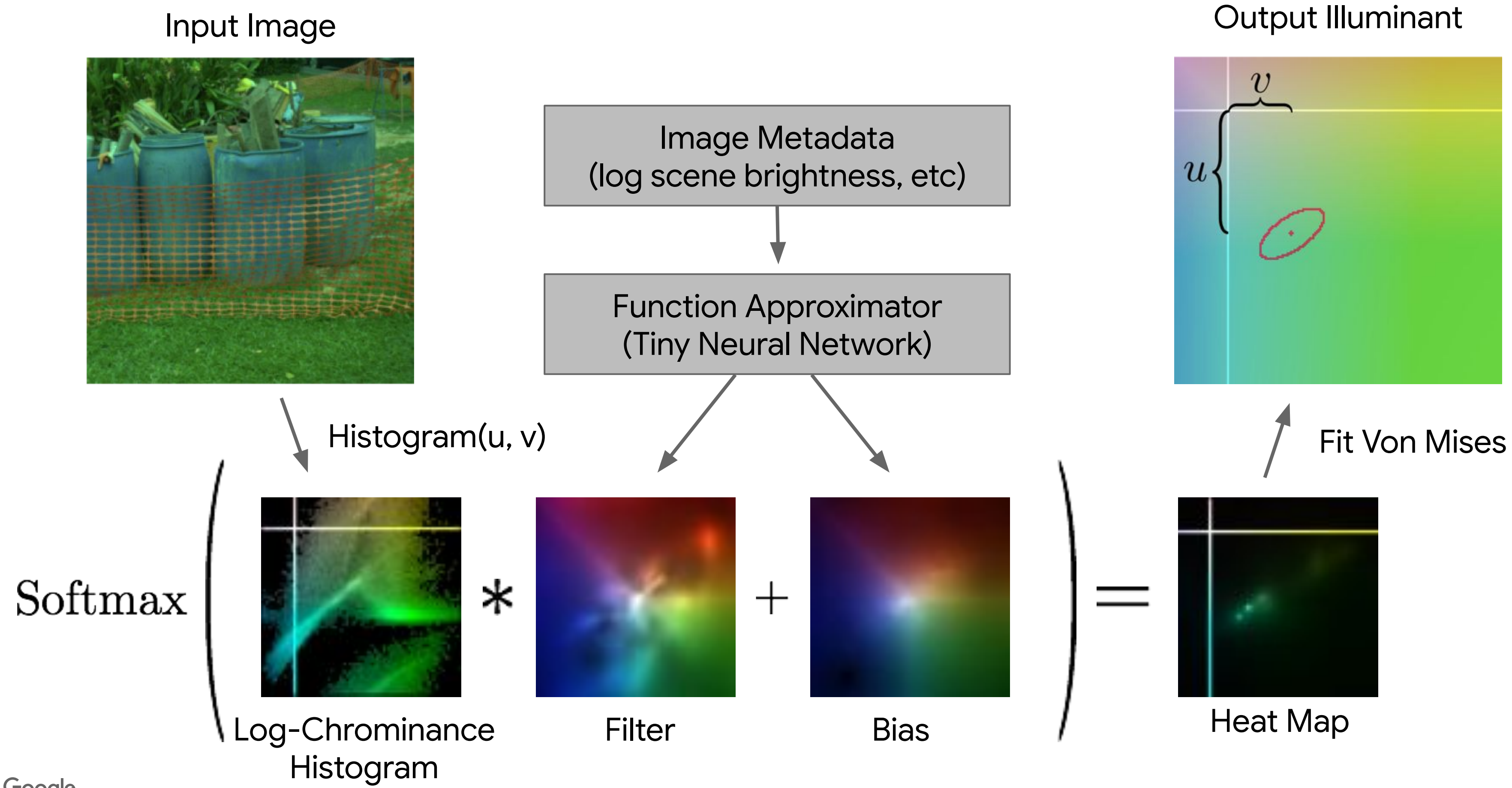
=

Predicted image

# White balance is an ill-posed problem

Learning based white balance:
"Fast Fourier Color Constancy",
Barron & Tsai, 2017

Extended to low-light scenes



Input Image
Image Metadata
(log scene brightness, etc)
Function Approximator
(Tiny Neural Network)
Output Illuminant
v
u
Histogram(u, v)
Fit Von Mises
Softmax
*
+
=
Log-Chrominance
Histogram
Filter
Bias
Heat Map

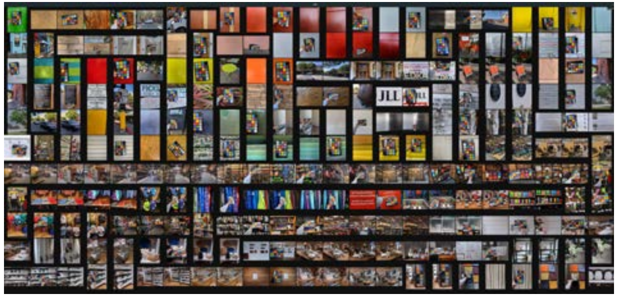

Google

# Challenges of Color Constancy in low light

## Noisier images

➡ Train on real images that have noise

➡ New training data set for low light (3,500 images)



## Various illuminants:

Highly colorful illuminants result in color channels with practically zero signal ("missing channels")

➡ New error metric: Anisotropic Reproduction Error (ARE)

# Auto white balance results

Left: camera default, Right: ours

# The Night Sight “Look”: Tone Mapping

**Local Tone Mapping:** A function mapping 16 bit pixel values to 8 bit pixel values and compresses the high dynamic range.

# Night Sight "Look"

- Too bright: turns nighttime into day and can create overexposed halos. May also over-brighten noise.
- Too dark: hides shadow detail.

→ We carefully tuned a tone curve that suppresses noise in the darks, reveals details in the shadows, exposes the midtones well, and preserves highlights.

Different tone curves applied to the same evening scene

Too bright (looks like daytime)

Too dark (details are not visible)

# Putting it all together

Baseline system (HDR+, Hasinoff et al, 2016)

13 frames, exposure time: 1/15 s

Adding new tone mapping to baseline

Results are noisy

Adding motion metering

Exposure time 1/3 s

Noise and detail improve

Adding motion-robust merge

Noise and detail improve further

Adding motion-robust merge

Noise and detail improve further


Google

Adding low-light auto white balance

Color improves

# Side by side comparison

Previously described result
(HDR+, Hasinoff et al 2016)


Our result

# Results across a variety of scenes: indoor

Previously described result
(HDR+, Hasinoff et al 2016)


Our result

# Results across a variety of scenes: outdoor

Previously described result
(HDR+, Hasinoff et al 2016)

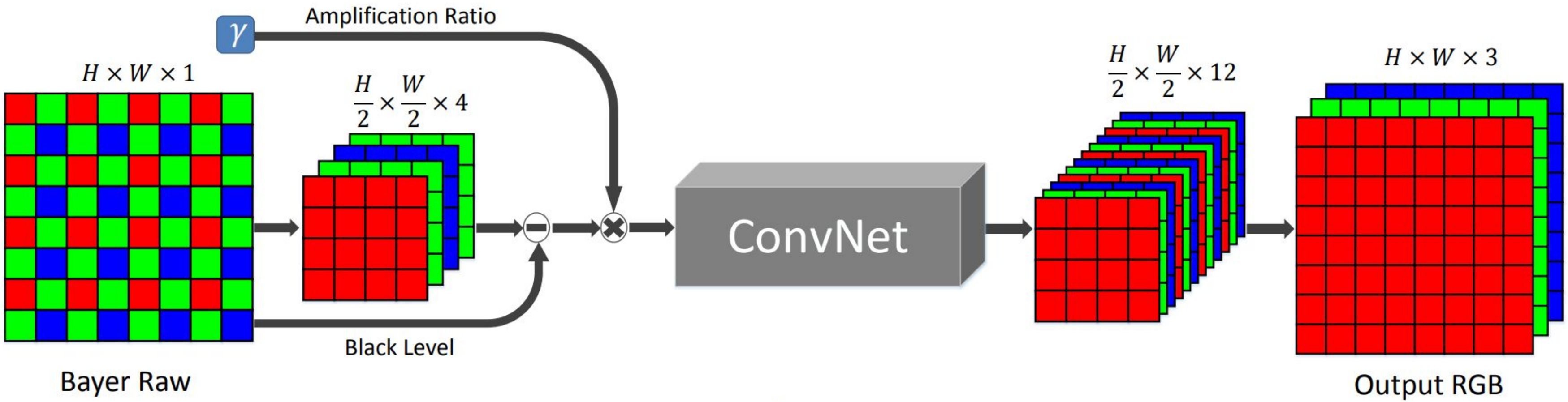
Our result

Google

# “Learning to see in the dark”, Chen et al, 2018

End to end network

Training set is pairs on short and long exposures




(b)

# Comparison to “Learning to See in the Dark” (Chen et al, 2018)

Chen et al 2018

Our result

Google

# Comparison to “Learning to See in the Dark” (Chen et al, 2018)

Chen et al 2018

Our result

Google

# Siggraph Asia 2019

## Handheld Mobile Photography in Very Low Light

ORLY LIBA, KIRAN MURTHY, YUN-TA TSAI, TIM BROOKS, TIANFAN XUE, NIKHIL KARNAD, QIURUI HE, JONATHAN T. BARRON, DILLON SHARLET, RYAN GEISS, SAMUEL W. HASINOFF, YAEL PRITCH, and MARC LEVOY, Google Research

(a) Previously described result (b) Previously described result, gained (c) Our result

DPREVIEW
AWARDS
2018
INNOVATION
OF THE YEAR
Google Pixel 3
Tuesday, Oct 9 | 68 °F

# Astrophotography

Google AI Blog
The latest news from Google AI

## Astrophotography with Night Sight on Pixel Phones

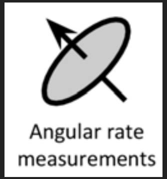
Tuesday, November 26, 2019

Posted by Florian Kainz and Kiran Murthy, Software Engineers, Google Research

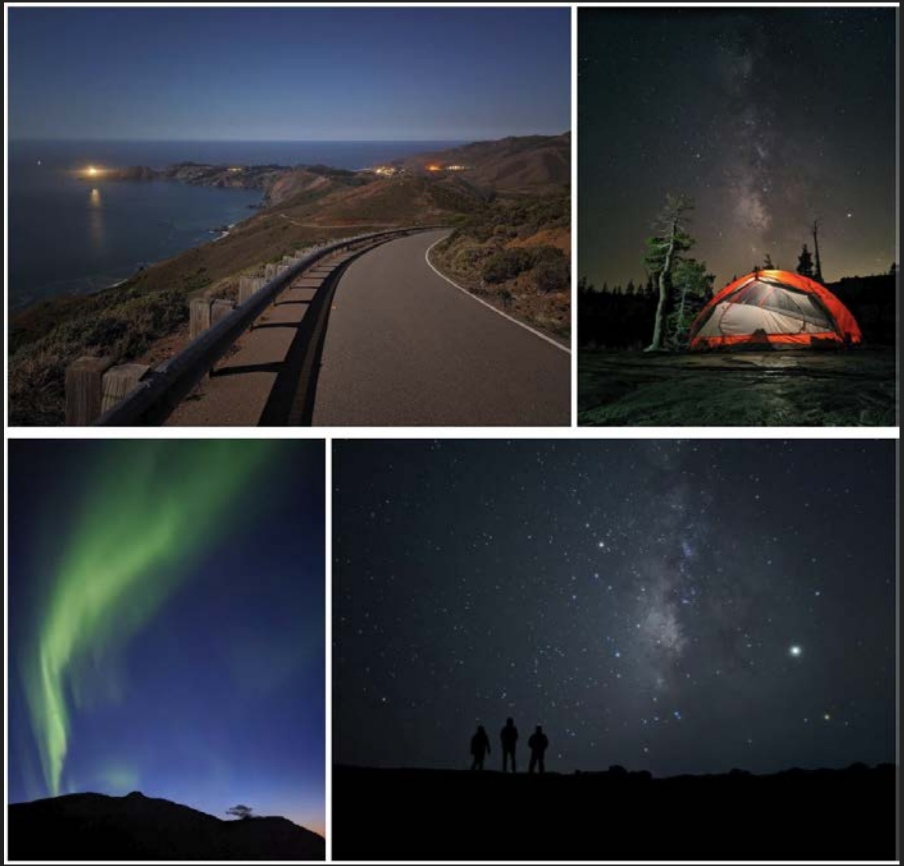
# Astrophotography

Extending exposure time

- Up to 4 minutes total exposure:
  - Capture even more light to improve signal to noise
  - Extend the capture time per frame
- Detect when the camera is static using gyro signals




- Detect when the scene is static



# Extending exposure time for astrophotography

- Dark current becomes significant with multi-second exposures.
- Solution: outlier detection and removal

Dark current appears as “warm pixels”

After outlier correction

Google

# Sky Optimization

**Sky Optimization: Semantically aware image processing of skies in low-light photography**
Orly Liba, Longqi Cai, Yun-Ta Tsai, Elad Eban, Yair Movshovitz-Attias, Yael Pritch, Huizhong Chen, and Jonathan T. Barron
NTIRE, CVPRW, 2020

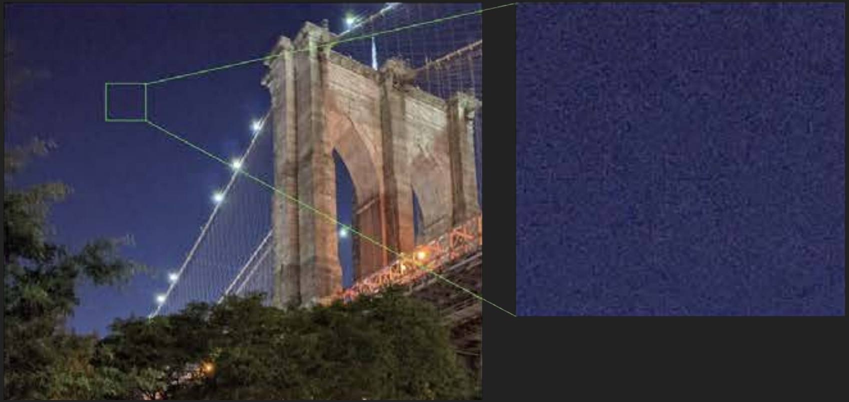
# Sky Optimization: Motivation

- The brightness of the sky influences our perception of the time of day
  - ➡ Brightening the image causes a “night into day” effect, which is confusing

Sky darkening

# Sky Optimization: Motivation

- The sky has predictable features and is mostly uniform
  - ➡ Noise is more visible in the uniform regions
  - ➡ The skies can be denoised more aggressively



Sky denoising

# Sky Optimization: Motivation

- The sky and foreground are illuminated by different sources

➡ Color constancy assumes a single light source, which can cause errors in color predictions

Magenta skies: white balance is optimal on the face

# Sky Optimization: Motivation

- The sky and foreground are illuminated by different sources

➡ Color constancy assumes a single light source, which can cause errors in color predictions

Blue skies: white balance is optimal on the sky,
but the skin has greenish tint

# Sky Optimization: Motivation

- The sky and foreground are illuminated by different sources
  - ➡ Color constancy assumes a single light source, which can cause errors in color predictions
  - ➡ Spatially varying white balance can produce natural colors on both sky and foreground

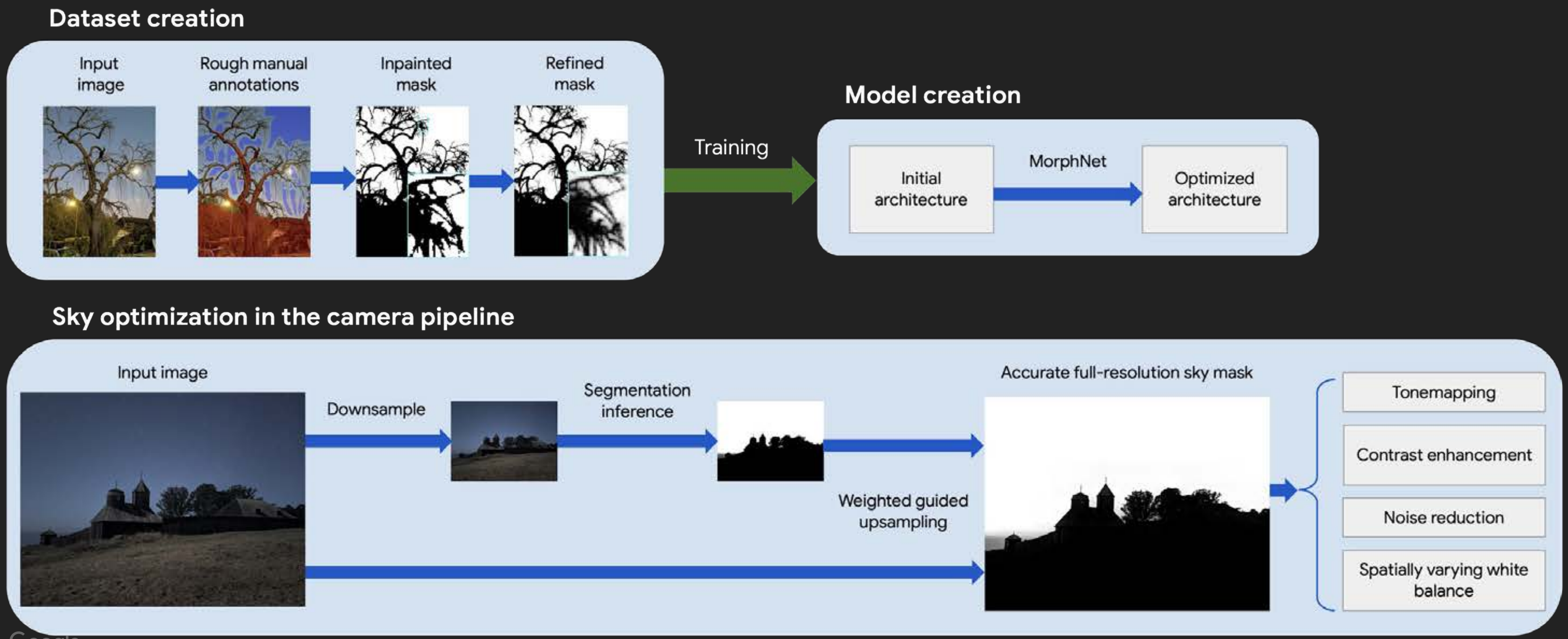
Full scene white balance

Sky white balance

Spatially varying white balance

Google

# Sky Optimization: Overview



# In Summary,
# To Capture Low Light Scenes:

- Traditional: extend the exposure time
- Computational:
  - Burst photography
  - Motion metering
  - Motion-adaptive merge
  - Tone mapping for nighttime scenes
  - Device stability detection
  - “Warm pixel” removal
- Machine learning:
  - Learning based white balance
  - Semantically aware image processing of the skies
- Implemented on a mobile device

# 2019 Smartphone Camera of the year award


"If you shoot **Night Sight** - even during daylight hours - you'll be rewarded with some of the best detail retention and balanced noise reduction we've seen from a smartphone... A new **astrophotography** mode is not just cool but inspiring, and also benefits any nighttime scene where longer exposures can be used. The combination of super-res zoom and a new telephoto module make 'zoomed in' photos better than many peers." dpreview.com

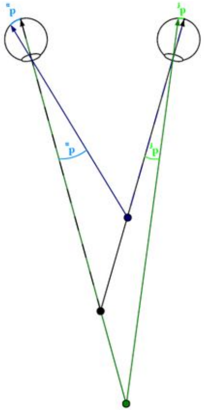
# Sky optimization was leveraged for Sky palette transfer, which is an editing mode in Google Photos.

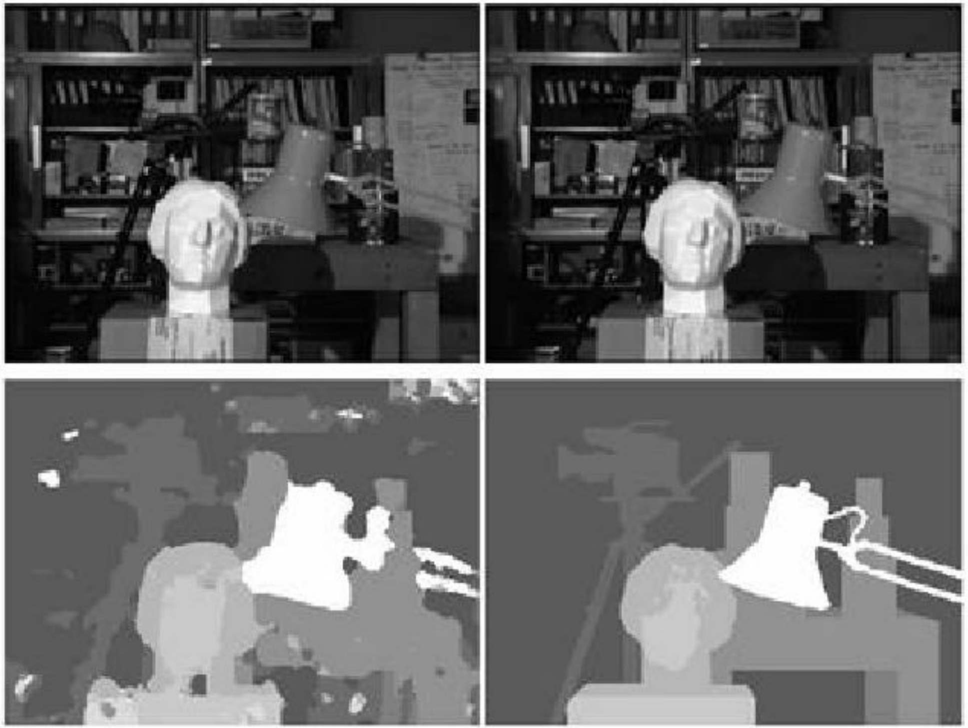
Sky Palette Transfer (Dec 2020)

# Portrait Mode on Pixel 2 / 3 Camera

# Goal


# Using Depth Maps for shallow depth of field





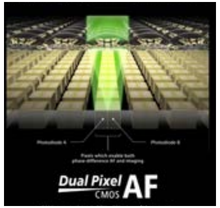
# Overview

**Front Camera**

- 8MP
- 1.4µm
- f/2.4 aperture
- Fixed focus

**Rear Camera**

- 12.2MP
- 1.4µm
- **Autofocus** with laser + **dual pixel phase detection (PD)**
- Optical + electronic image stabilization
- f/1.8 aperture

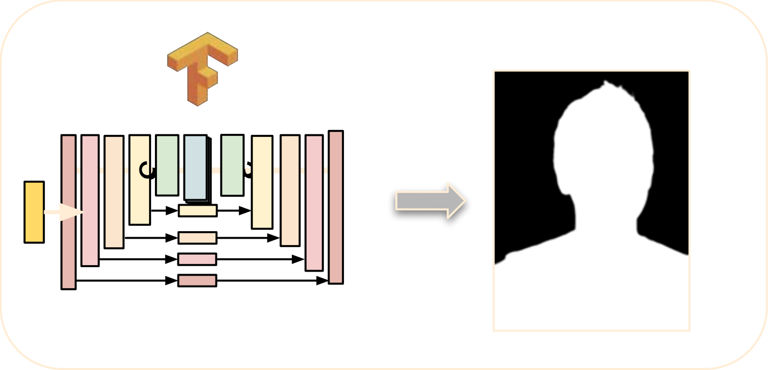



Pixel 2 - No Dual camera

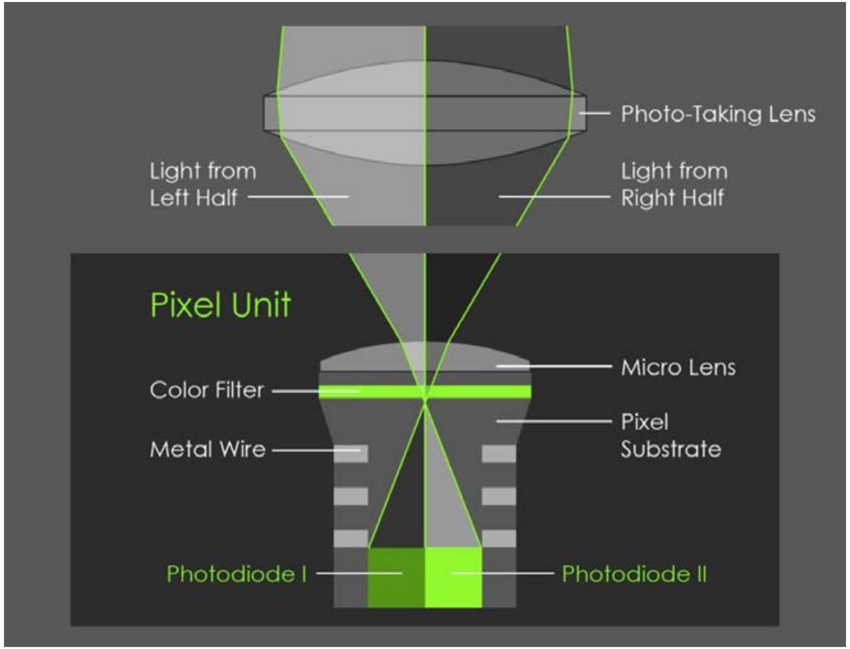
- High Quality
- Robust
- Fast

# ML + Dual Pixel (HW) + SW -> Computational Photography

**ML based Segmentation**



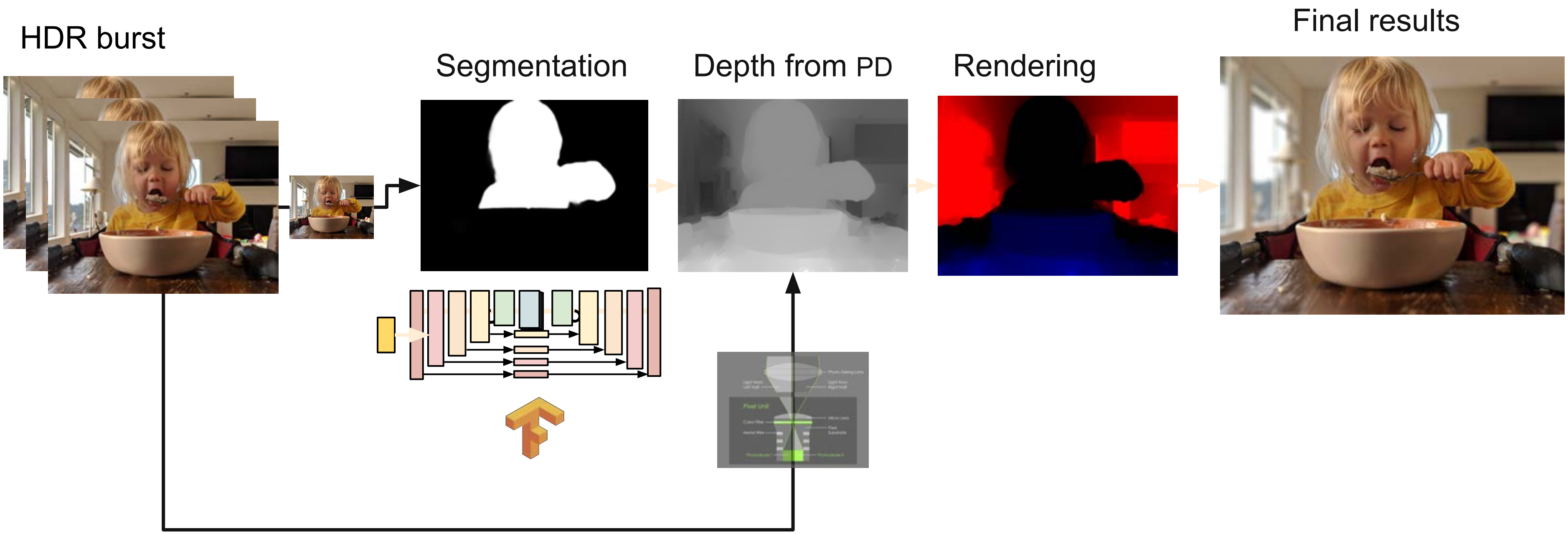
+



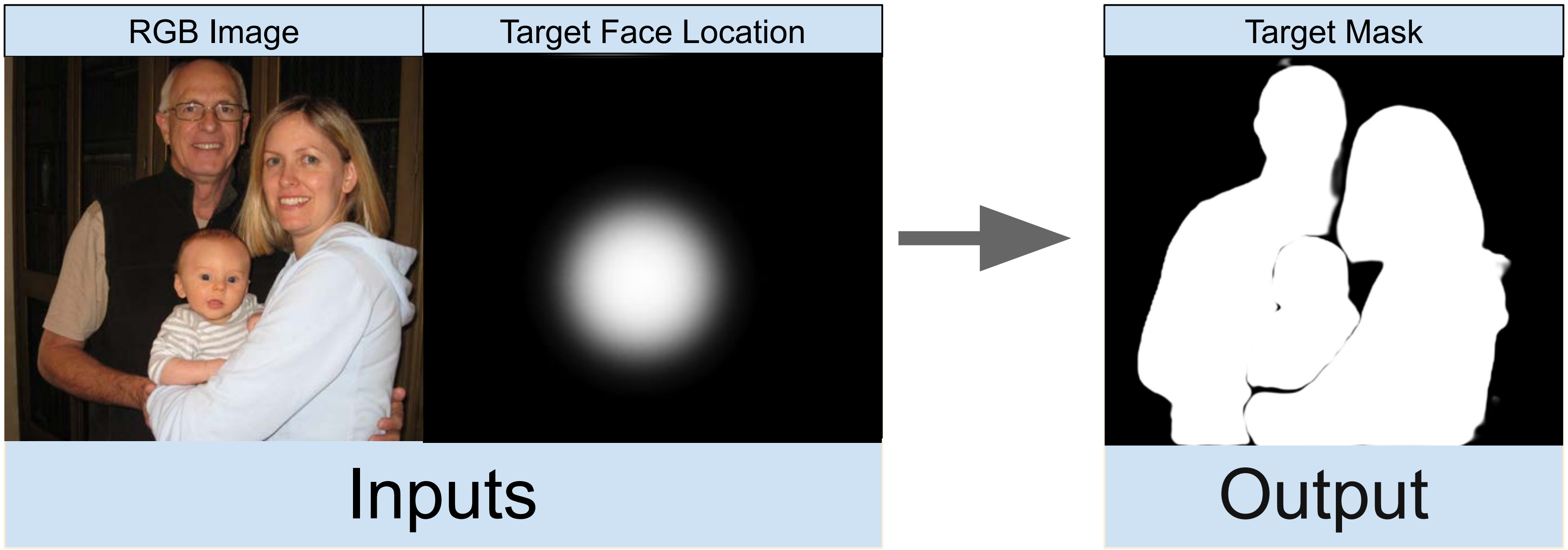

Autofocus with laser + dual pixel phase detection

# Pipeline

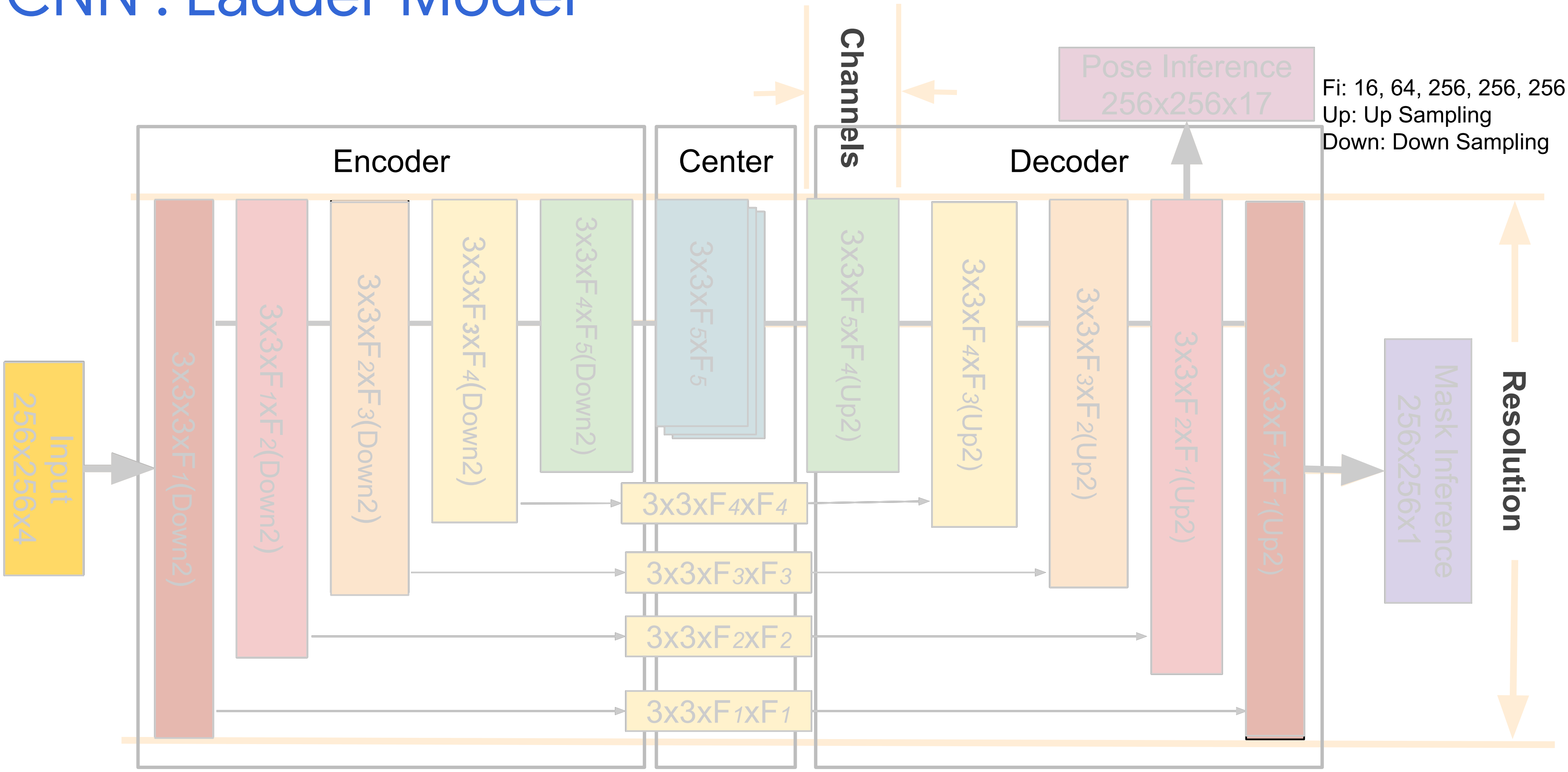
Best case scenario - **people** with **back facing camera**



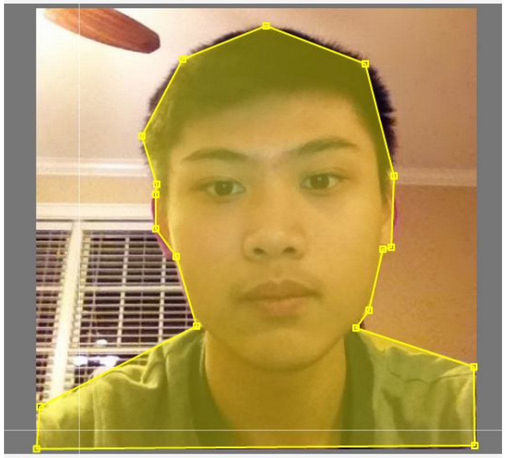
# CNN: Inputs and Output



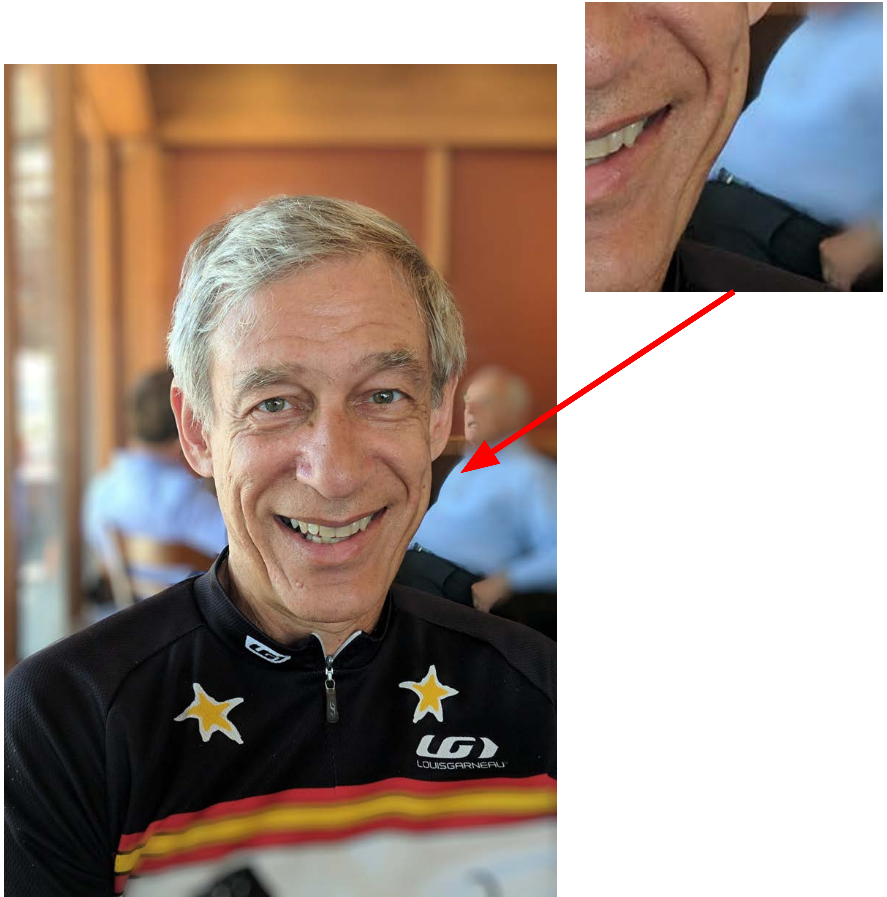
# CNN : Ladder Model



# Annotating training data



# Challenge - Get the edges right - better training data

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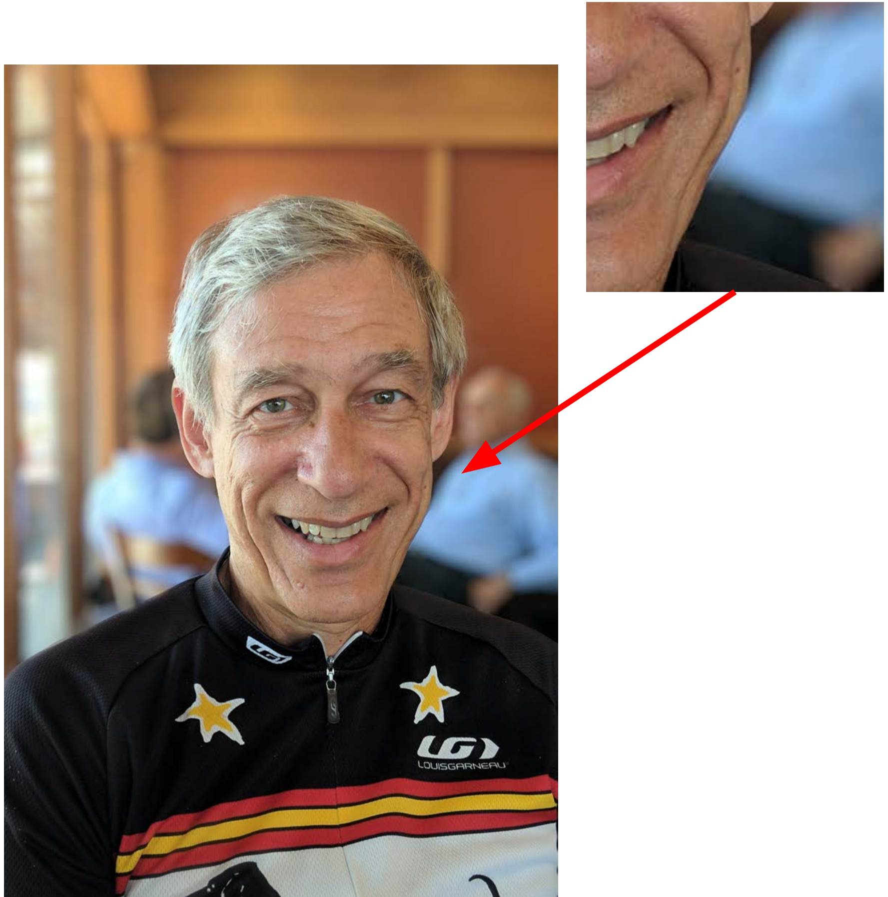
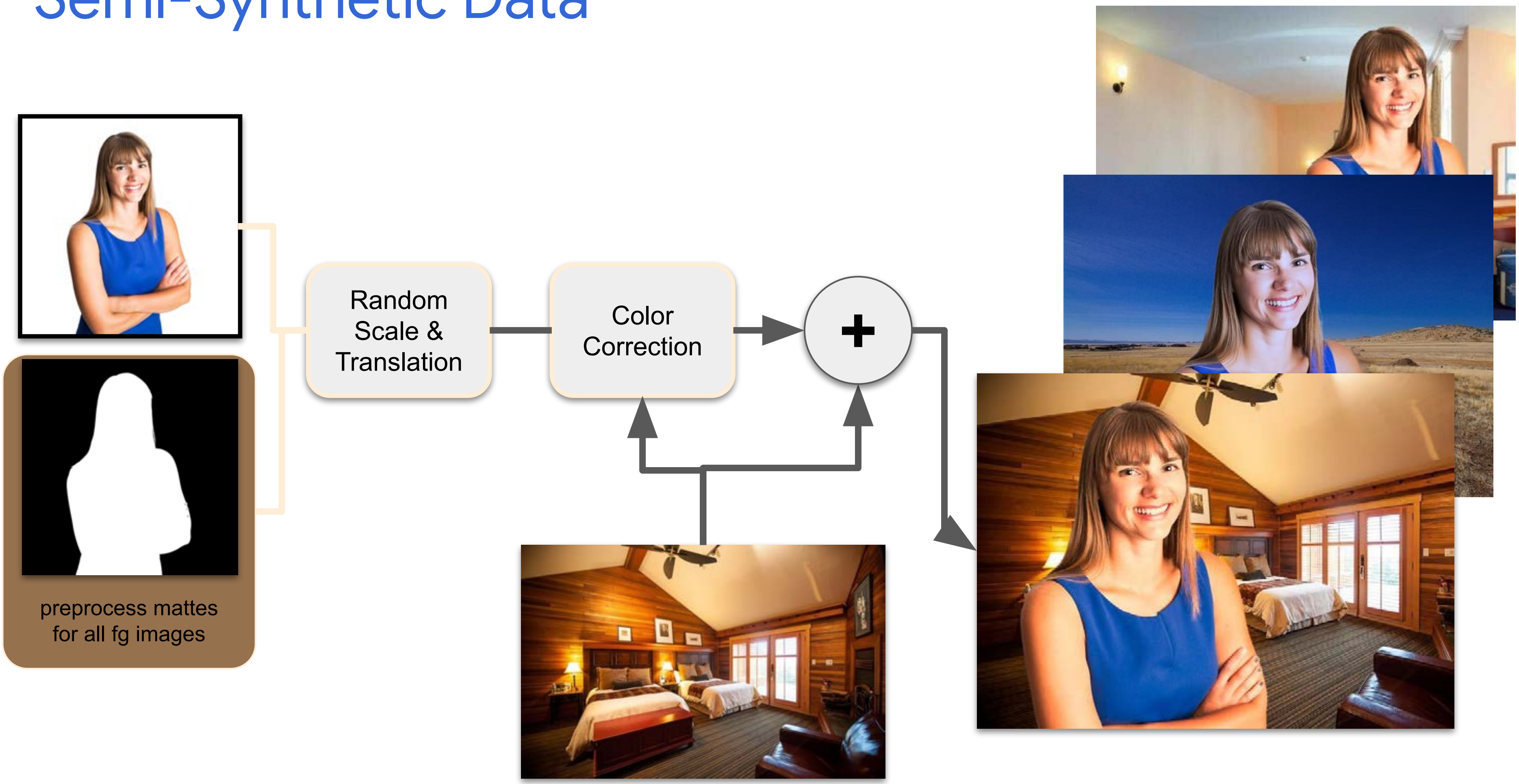
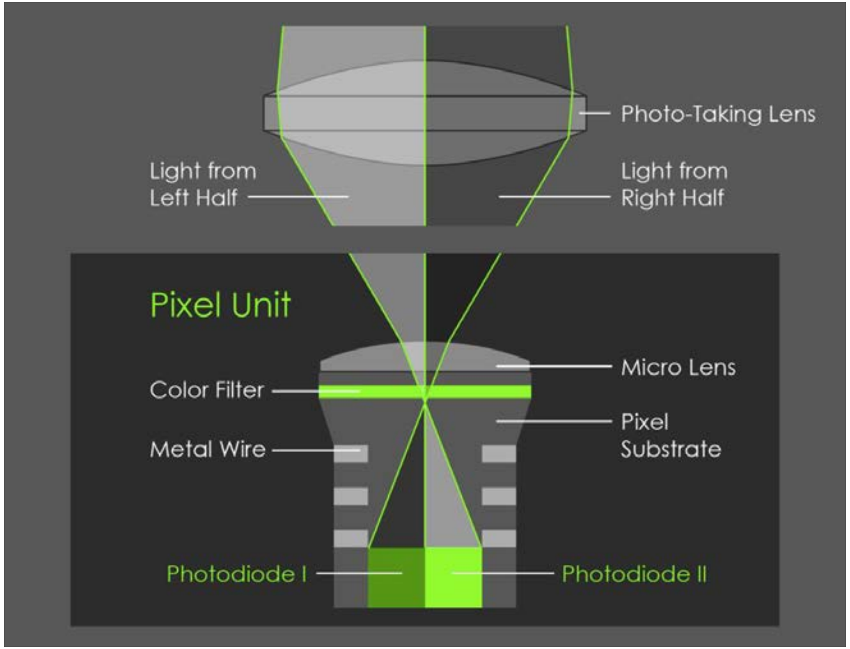



# Refine Ground Truth Polygon Mask

# Semi-Synthetic Data



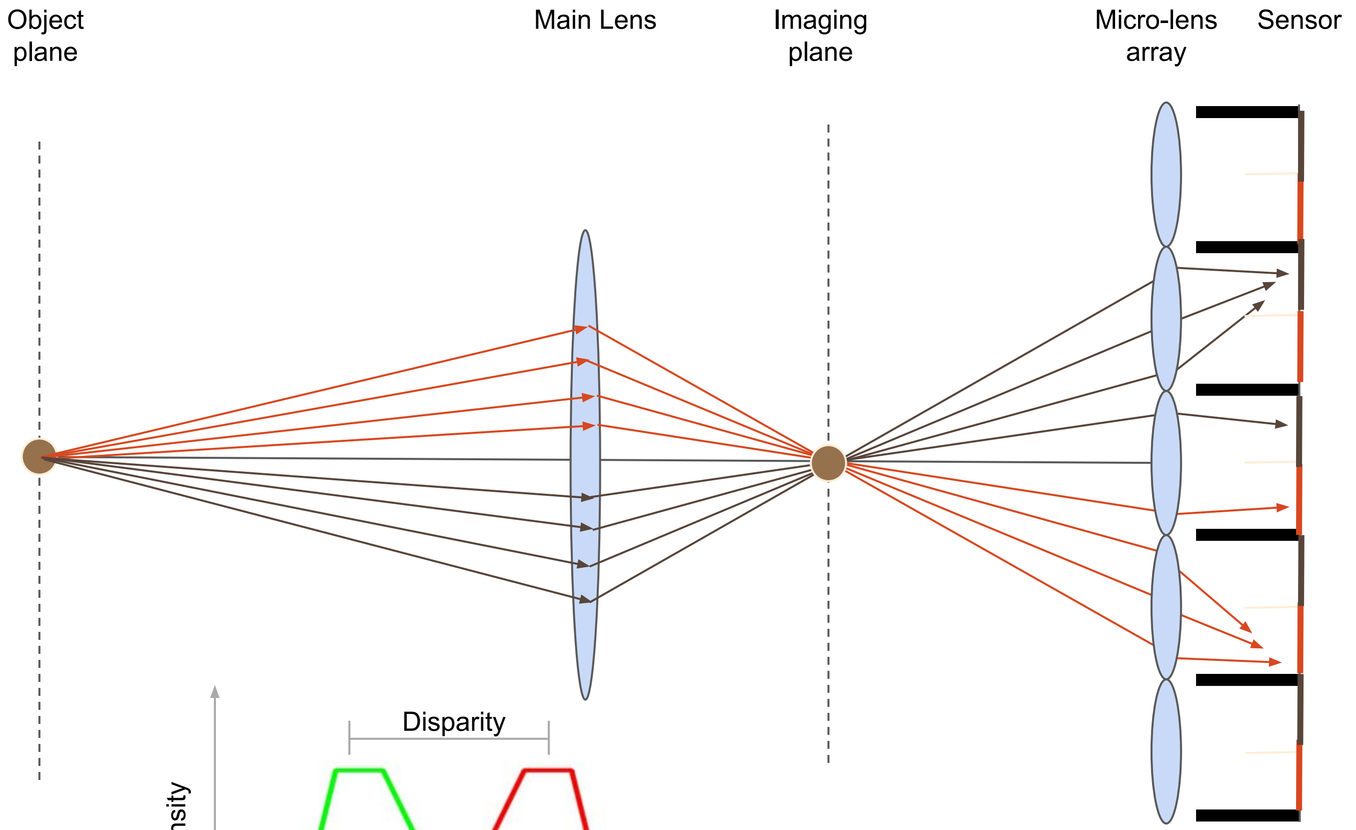
# Dual Pixels for depth estimation

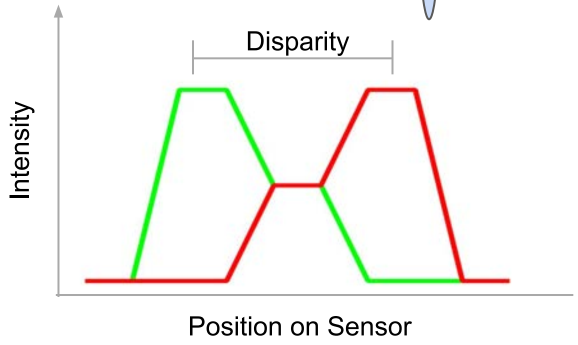



Autofocus with laser + dual pixel Phase Detection (PD)

# Dual Pixels

- Pixels are split in half.
- Top half aperture goes to bottom half pixels.
- Bottom half aperture goes to top half pixels.
- Disparity between halves corresponds to depth.
- Normally used for autofocus.



# Approximately Stereo Camera with a ~0.6mm Baseline

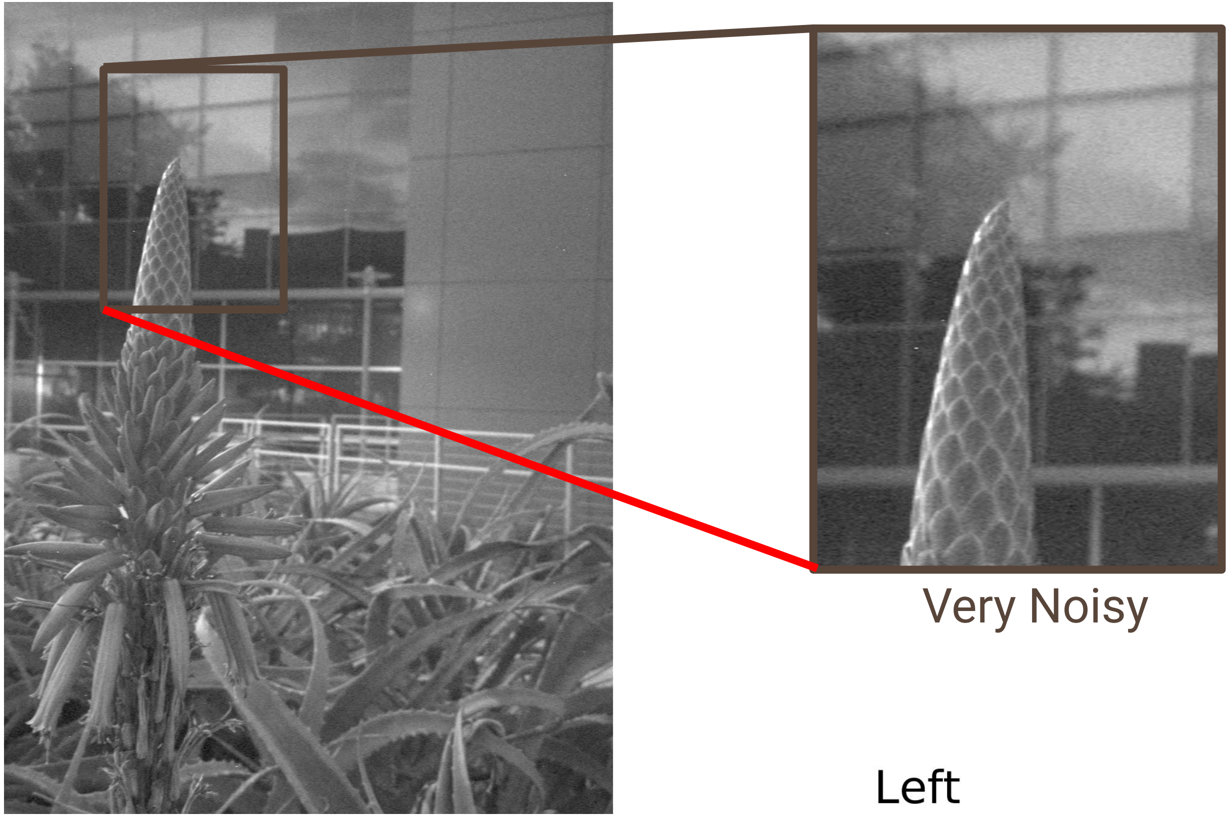
Color Image (RGB)

Left half pixels (green only)

Right half pixels (green only)

## Approximately Stereo Camera with a ~0.6mm Baseline

Color Image (RGB)



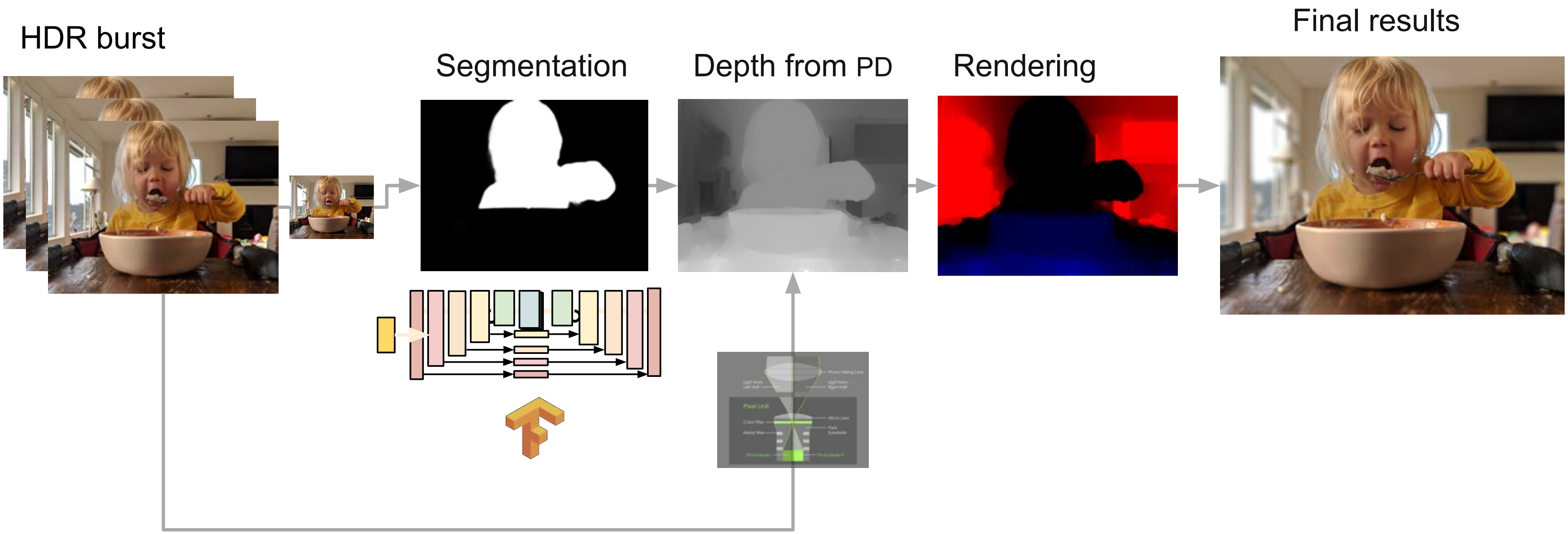
Very Noisy

Left

In-focus objects have zero disparity.

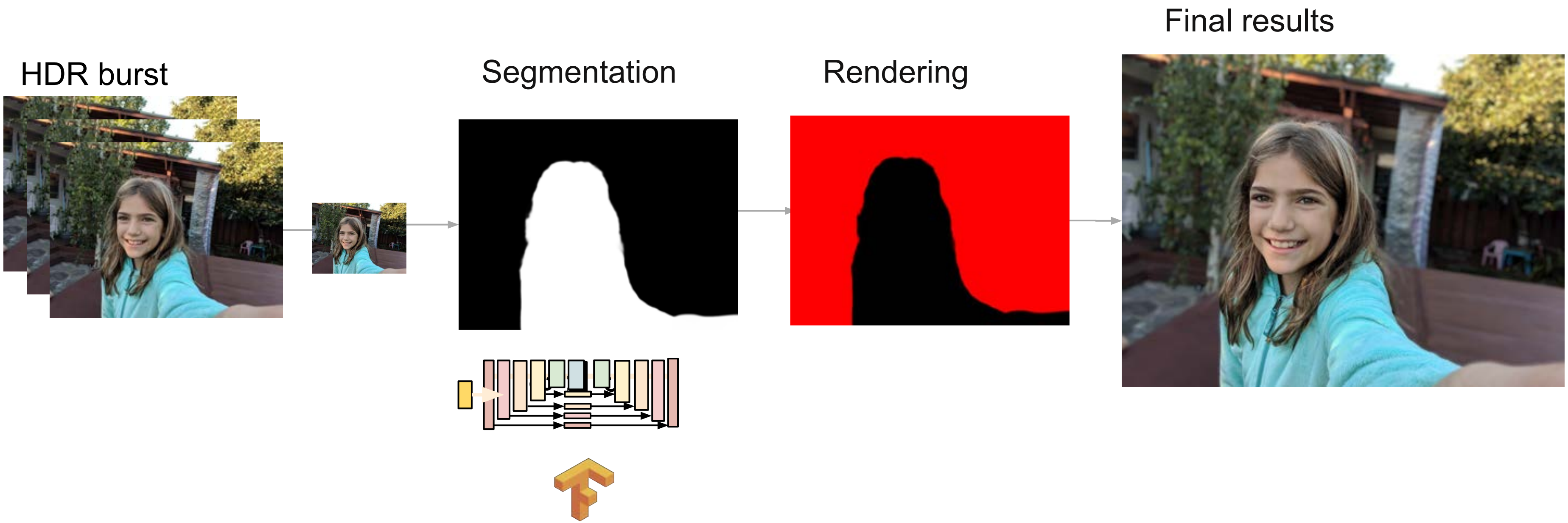
# Pipeline

Best case scenario - **people** with **back facing camera**



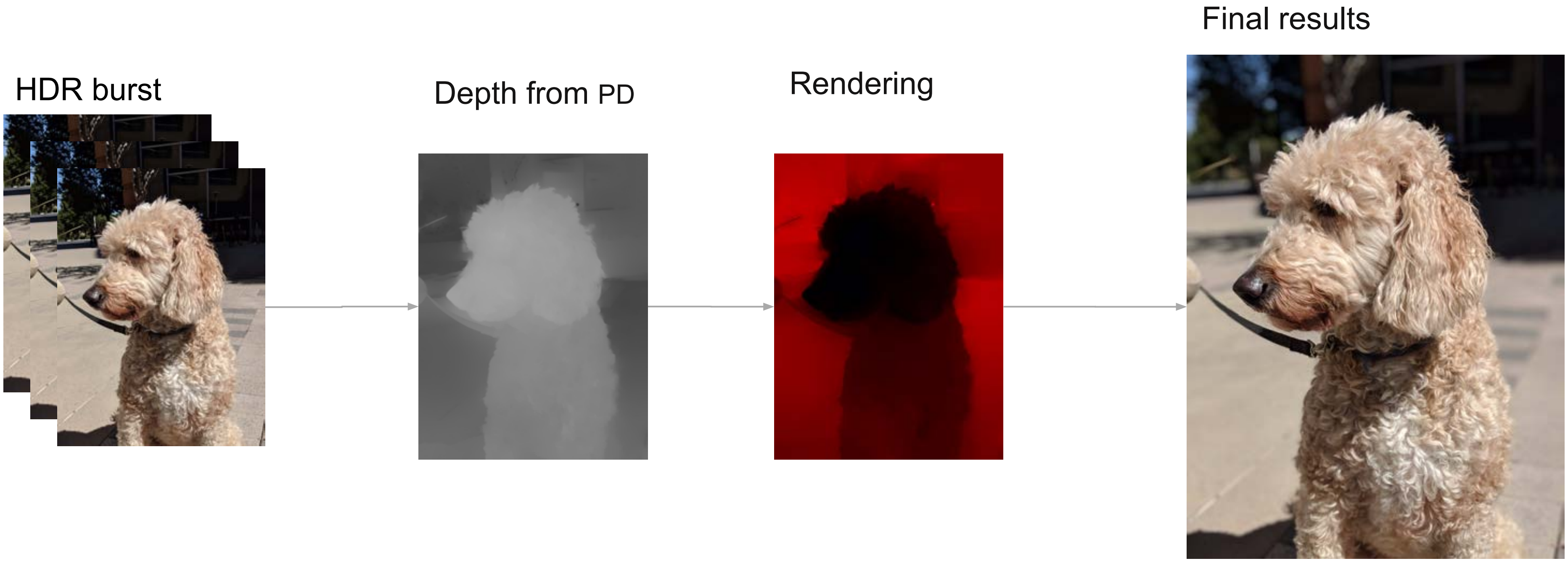
# Pipeline

ML only pipeline - **people** with **front facing camera**



# Pipeline

## Depth only pipeline - **objects/animals** with **back facing camera**



# Portraits

[portraits](), [mixed images]() from [#teampixel]() on instagram








# Selfies!!!

portraits, mixed images from #teampixel on instagram

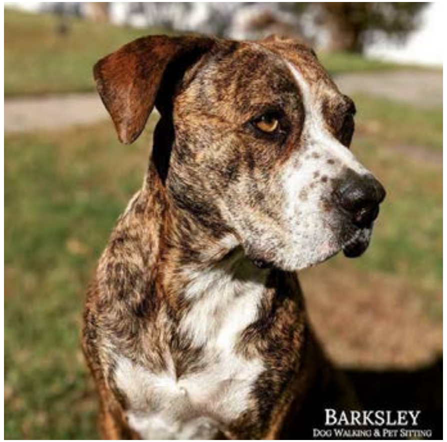







# Animals

portraits, mixed images from #teampixel on instagram









# Objects

portraits, mixed images from #teampixel on instagram






SIGGRAPH 2017:

Synthetic Depth of Field with a Single-Camera Mobile Phone

# Synthetic Depth-of-Field with a Single-Camera Mobile Phone

NEAL WADHWA, RAHUL GARG, DAVID E. JACOBS, BRYAN E. FELDMAN, NORI KANAZAWA, ROBERT CARROLL, YAIR MOVSHOVITZ-ATTIAS, JONATHAN T. BARRON, YAEL PRITCH, and MARC LEVOY, Google Research

(a) Input image with detected face (b) Person segmentation mask (c) Mask + disparity from DP (d) Our output synthetic shallow depth-of-field image

Fig. 1. We present a system that uses a person segmentation mask (b) and a noisy depth map computed using the camera's dual-pixel (DP) auto-focus hardware (c) to produce a synthetic shallow depth-of-field image (d) with a depth-dependent blur on a mobile phone. Our system is marketed as "Portrait Mode" on several Google-branded phones.

Shallow depth-of-field is commonly used by photographers to isolate a subject from a distracting background. However, standard cell phone cameras cannot produce such images optically, as their short focal lengths and small apertures capture nearly all-in-focus images. We present a system to computationally synthesize shallow depth-of-field images with a single mobile camera and a single button press. If the image is of a person, we use a person

**ACM Reference Format:**
Neal Wadhwa, Rahul Garg, David E. Jacobs, Bryan E. Feldman, Nori Kanazawa, Robert Carroll, Yair Movshovitz-Attias, Jonathan T. Barron, Yael Pritch, and Marc Levoy. 2018. Synthetic Depth-of-Field with a Single-Camera Mobile Phone. *ACM Trans. Graph.* 37, 4, Article 64 (August 2018), 13 pages. https://doi.org/10.1145/3197517.3201329


DPREVIEW
AWARDS
2017
INNOVATION
OF THE YEAR
Google Pixel 2 computational camera

# Depth from Dual-Pixels

- A stereo pair with very small baseline ~ 0.6mm
- Use stereo algorithms to estimate depth

Depth from disparity

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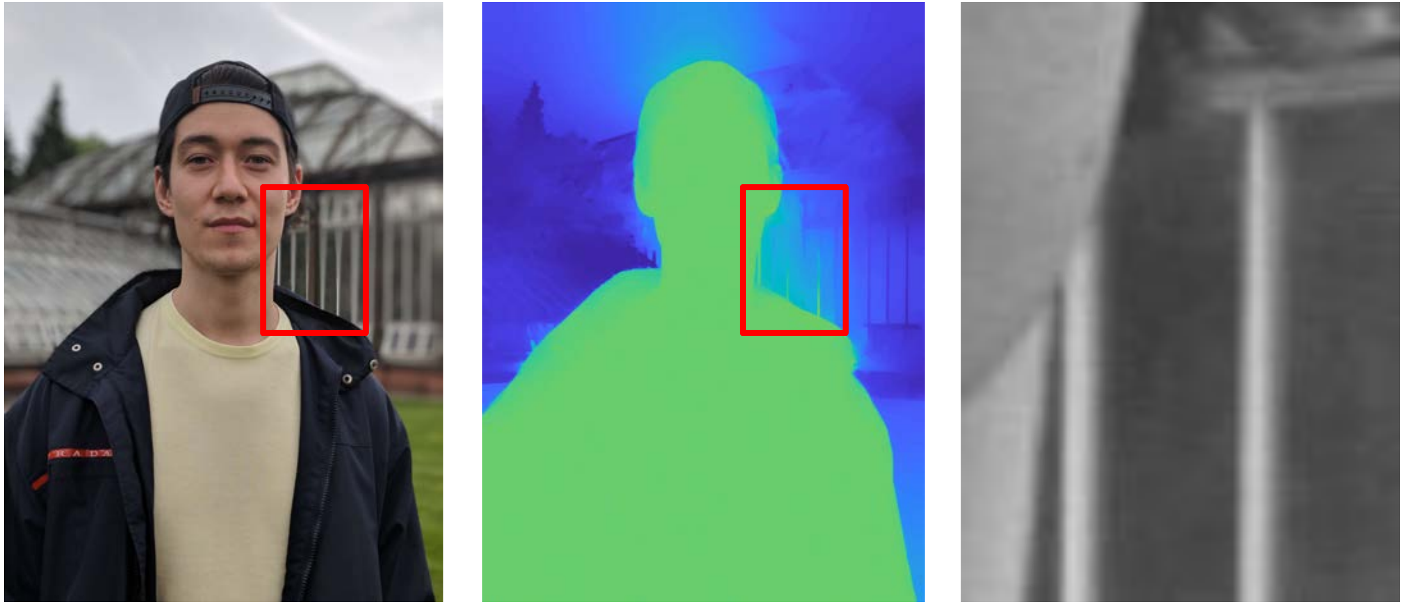
Depth from disparity

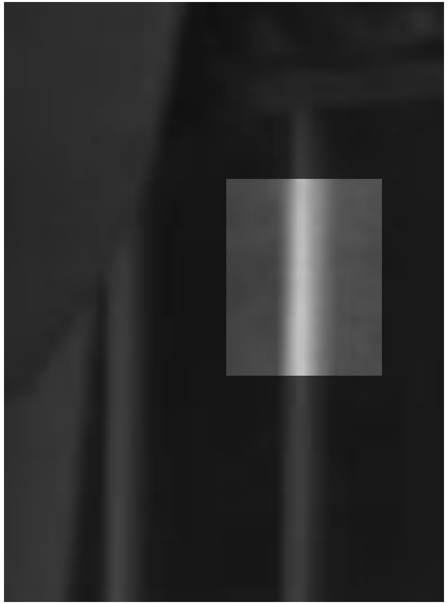


# Depth from Dual-Pixels

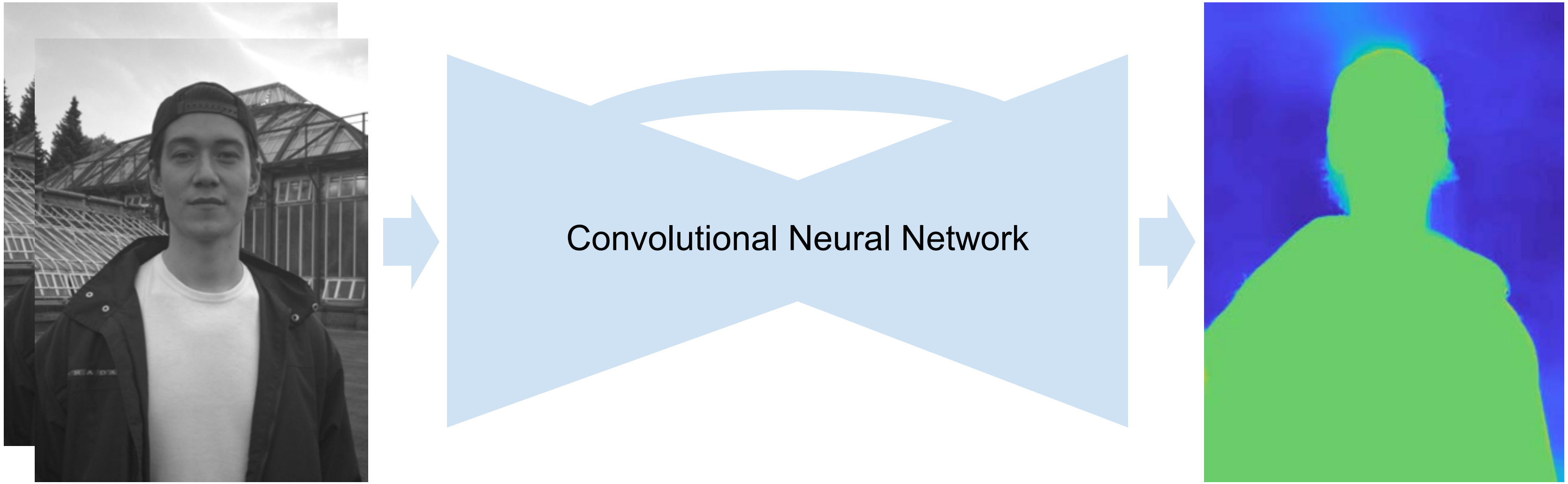
- A stereo pair with very small baseline ~ 0.6mm
- Use stereo algorithms to estimate depth


Depth from disparity

The “aperture problem”



# Learning to Predict Depth from Dual-Pixels




- Better matching than hand crafted stereo algorithms
- Use other cues, e.g., semantics
- Powers Portrait Mode in Google Pixel 3 camera

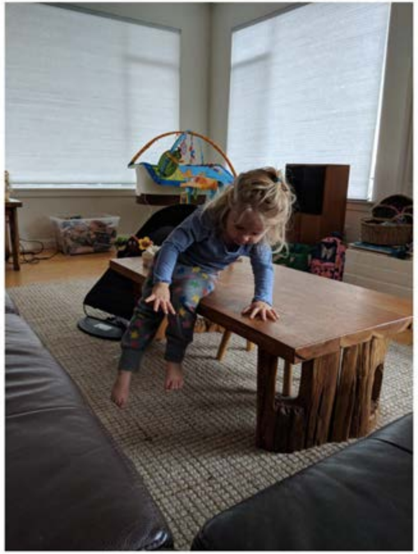
# Training Data

**Dual-pixel data** with high quality **ground truth depth** captured **in the wild**.

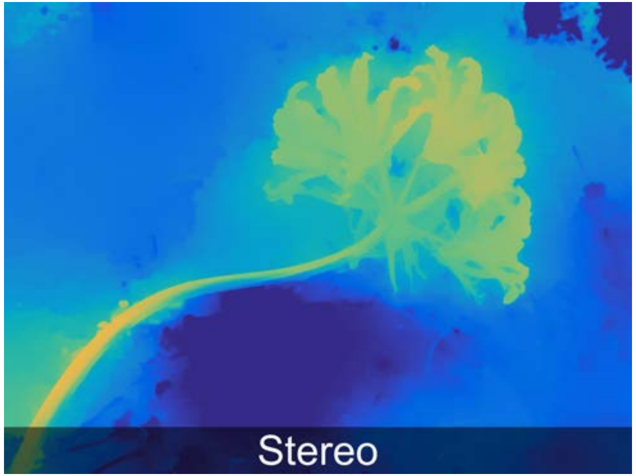
- Custom rig with five Pixel 3 phones
- Synchronized to an accuracy of 33ms
- Multi view stereo to compute high quality ground depth
- Portable - capture data in the wild

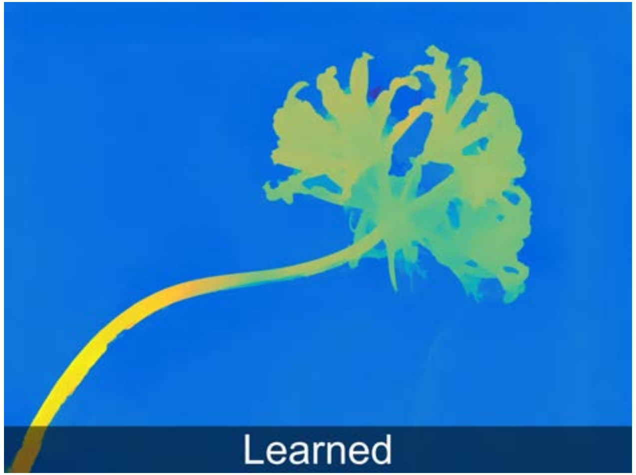
# Training Data

~10K captures, ~50K photos

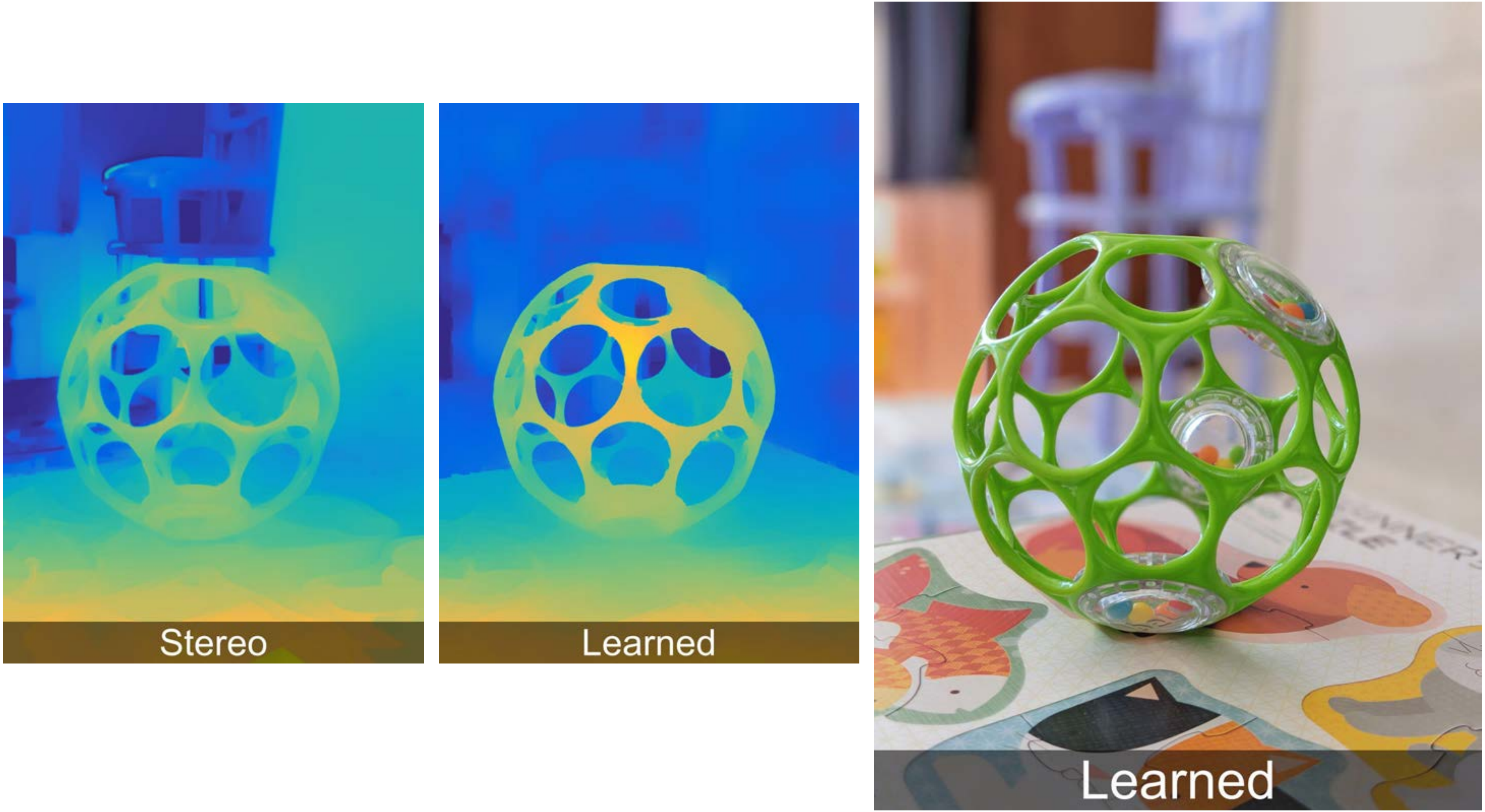



Stereo
Learned
Learned


Stereo


Learned

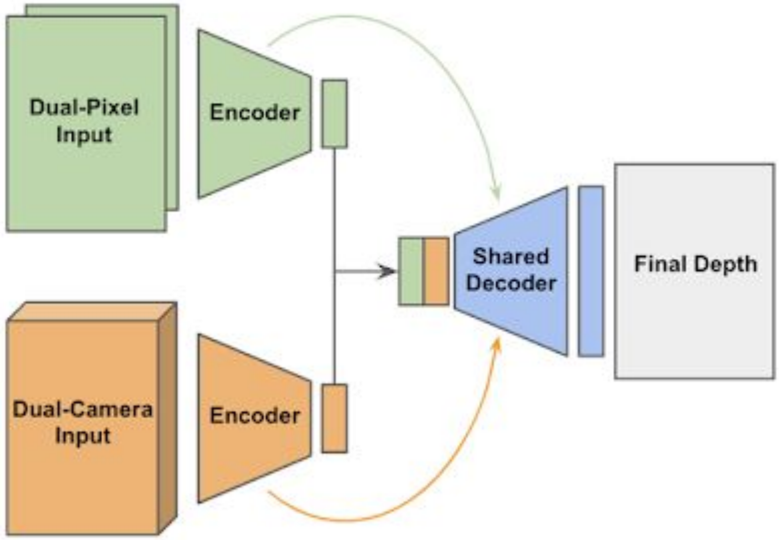

Learned


Stereo
Learned
Learned

# Dual Cameras are Complementary to Dual-Pixels


Left: Dual-pixel views. Right: Dual-camera views. The dual-pixel views have only a subtle vertical parallax in the background, while the dual-camera views have much greater horizontal parallax. While this makes it easier to estimate depth in the background, some pixels to the man's right are visible in only the primary camera's view making it difficult to estimate depth there.

# Depth from Dual Cameras and Dual-Pixels




Our network to predict depth from dual-pixels and dual-cameras. The network uses two encoders, one for each input and a shared decoder with skip connections and residual blocks.

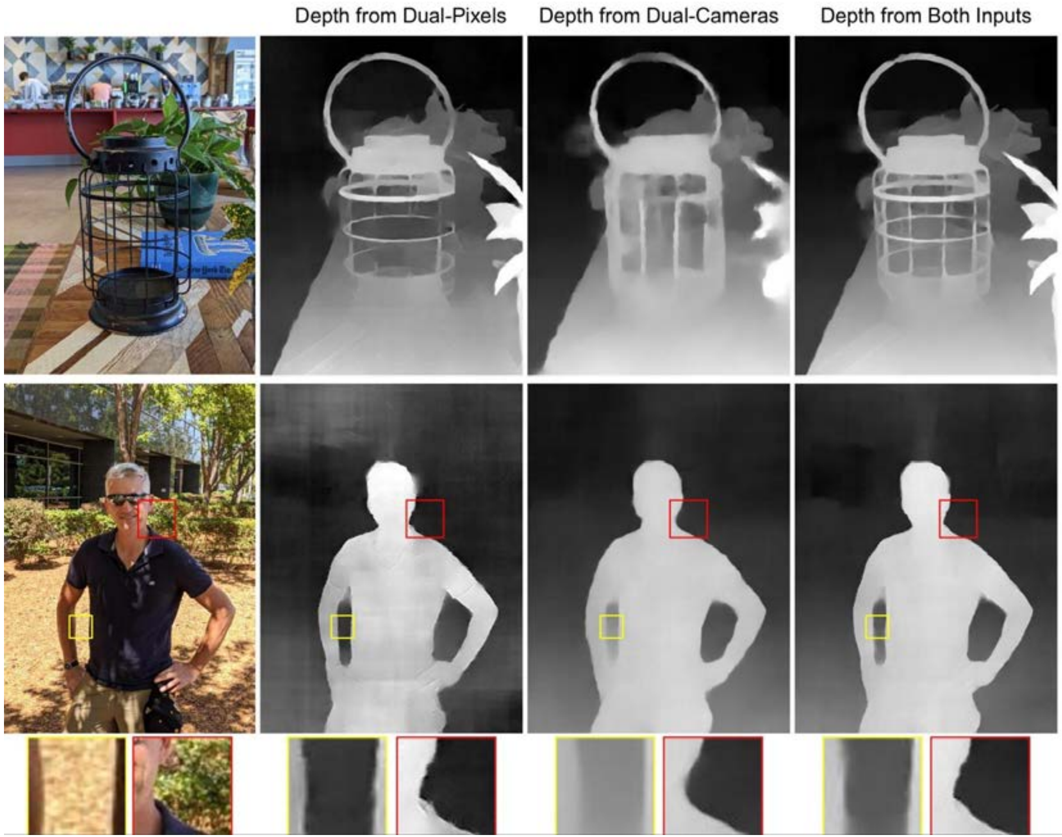
# Depth from Dual Cameras and Dual-Pixels

Depth maps from our network where either only one input is provided or both are provided.

Top: The two inputs provide depth information for lines in different directions.

Bottom: Dual-pixels provide better depth in the regions visible in only one camera, emphasized in the insets.

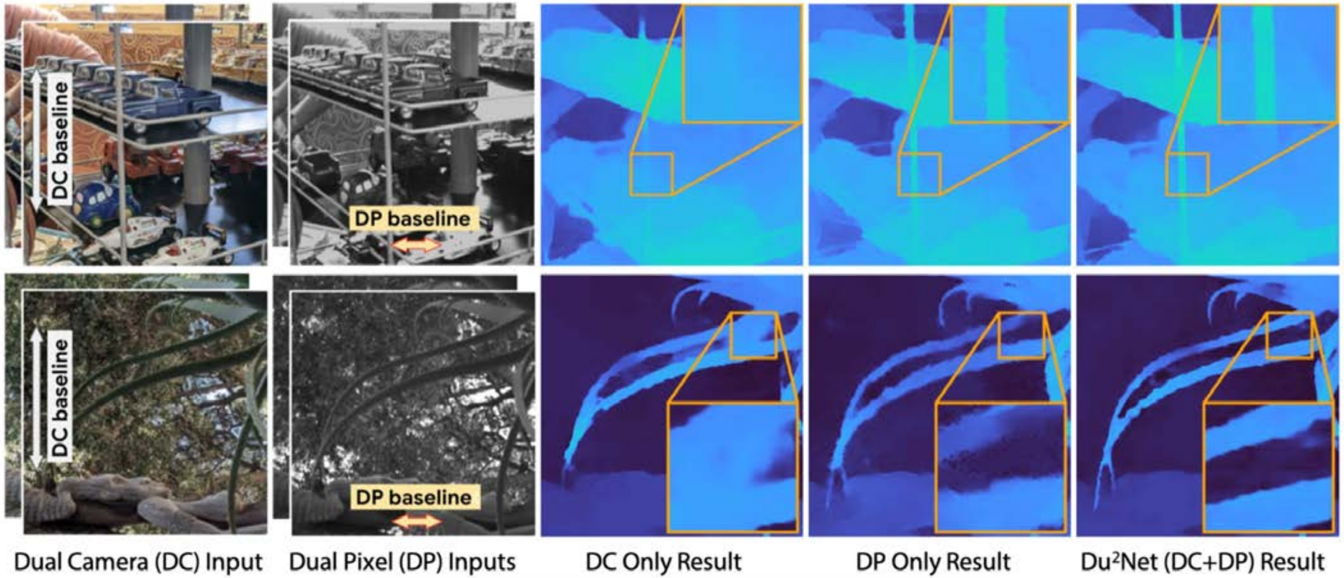
Dual-cameras provide better depth in the background and ground.



# Du$^2$Net: Learning Depth Estimation from Dual-Cameras and Dual-Pixels

Yinda Zhang Neal Wadhwa Sergio Orts-Escolano Christian Häne Sean Fanello Rahul Garg

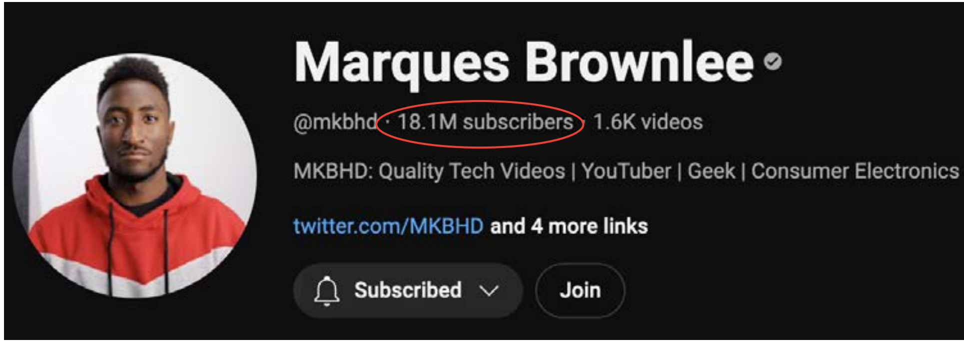
Google Research




ECCV 2020

# All this computational photography stuff matters!






[The blind smartphone camera test, 1/8/2024]

# All this computational photography stuff matters!

Tested:

- Daylight
- Low light
- Portrait

Blind study from viewers (sxs photos, pick the best one)

Exact same photo from 20 devices

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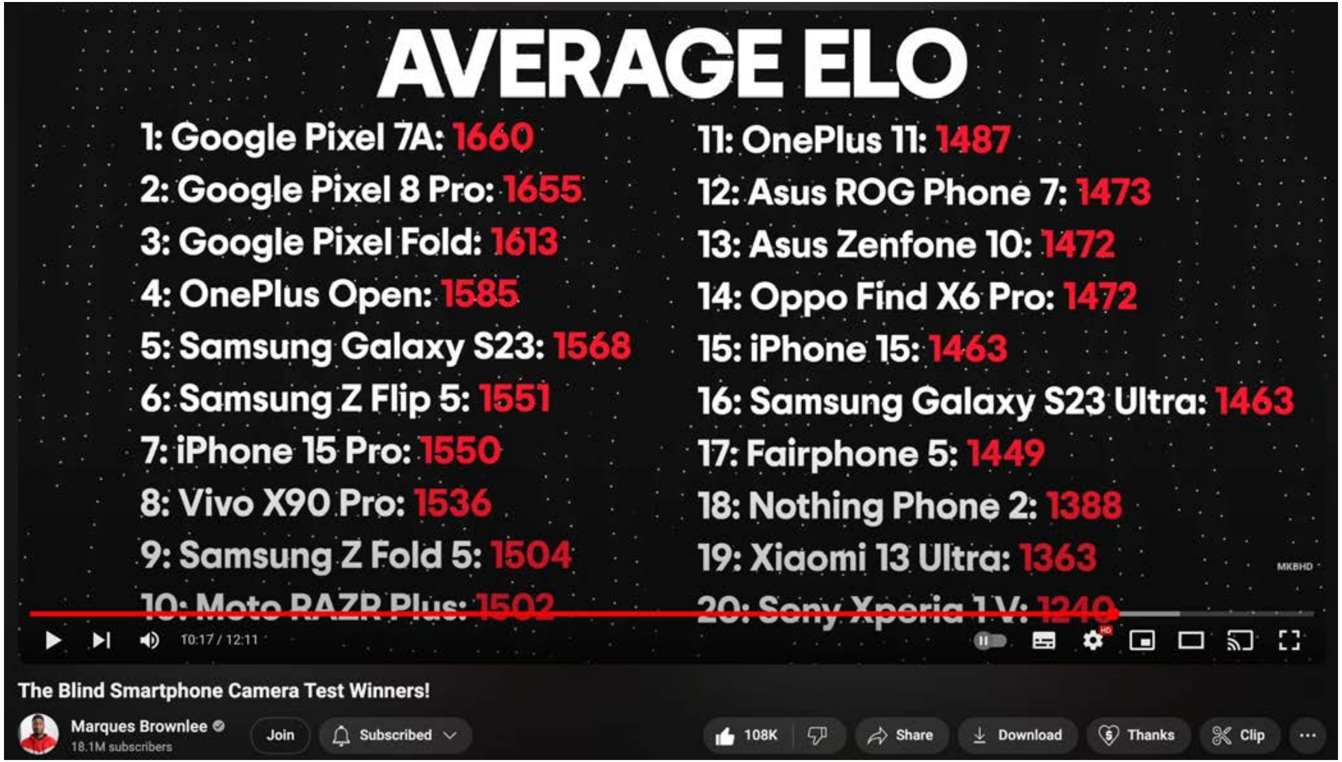

# Giving the camera superpowers!

~~Capture the moment as it is~~

Create the photo that represents the moment as we want to remember it

Or… Tell an entirely new story

# 2020: ML-based monocular depth

Cinematic Memories
(View Synthesis)

Google AI

# The Technology Behind Cinematic Photos

Tuesday, February 23, 2021

Posted by Per Karlsson and Lucy Yu, Software Engineers, Google Research

# 2021: Magic Eraser

# 2021: Magic Eraser

Google

# Magic Eraser: Automatically detect and remove bystanders and powerlines

# Magic Eraser: Manually select and remove distractors


Google

# 2023: On-device GenAI inpainting, using MaskGit

# 2023: Server-side Magic Editor

Segment, erase, change the composition, sky effects, and more

# 2023: Best Take

Choose the best faces from a series of photos

# Thank you!

# References and Further Reading


Papers

- Hasinoff, Sharlet, Geiss, Adams, Barron, Kainz, Chen, Levoy “Burst photography for high dynamic range and low-light imaging on mobile cameras”, SIGGRAPH Asia 2016
- Neal Wadhwa, Rahul Garg, David E. Jacobs, Bryan E. Feldman, Nori Kanazawa, Robert Carroll, Yair Movshovitz-Attias, Jonathan T. Barron, Yael Pritch, Marc Levoy, “Synthetic Depth-of-Field with a Single-Camera Mobile Phone.” SIGGRAPH 2018.
- Orly Liba, Kiran Murthy, Yun-Ta Tsai, Tim Brooks, Tianfan Xue, Nikhil Karnad, Qiurui He, Jonathan T. Barron, Dillon Sharlet, Ryan Geiss, Samuel W. Hasinoff, Yael Pritch, Marc Levoy, “Handheld mobile photography in very low light.” SIGGRAPH Asia 2019.
- Liba, Orly, Longqi Cai, Yun-Ta Tsai, Elad Eban, Yair Movshovitz-Attias, Yael Pritch, Huizhong Chen, and Jonathan T. Barron. "Sky Optimization: Semantically Aware Image Processing of Skies in Low-Light Photography." In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops, pp. 526-527. 2020.
- Chen, et al. "Learning to see in the dark." Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 2018.
- Wronski B, Garcia-Dorado I, Ernst M, Kelly D, Krainin M, Liang CK, Levoy M, Milanfar P . “Handheld multi-frame super-resolution”, SIGGRAPH 2019.

Google AI blog:

- https://ai.googleblog.com/2017/10/portrait-mode-on-pixel-2-and-pixel-2-xl.html
- https://ai.googleblog.com/2018/11/learning-to-predict-depth-on-pixel-3.html
- https://ai.googleblog.com/2019/12/improvements-to-portrait-mode-on-google.html
- https://ai.googleblog.com/2021/02/the-technology-behind-cinematic-photos.html
- https://ai.googleblog.com/2018/11/night-sight-seeing-in-dark-on-pixel.html
- https://ai.googleblog.com/2019/11/astrophotography-with-night-sight-on.html