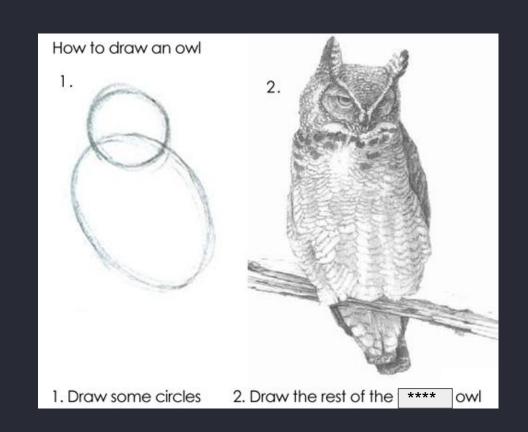
Before I train the model...:

Three adventures in developing ML systems for coastal geomorphology

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Acknowledgements:

Eli Lazarus & Hannah Williams (Southampton)

Dan Buscombe & Sharon Fitzpatrick (USGS contr.)

Jacob Stasiewicz (UNCW)

(Many other colleagues)
My Family



MOTIVATION

- ML is 🔥 right now

MOTIVATION

- ML is 🔥 right now

"Everyone wants to do the model work, not the data work": Data Cascades in High-Stakes Al

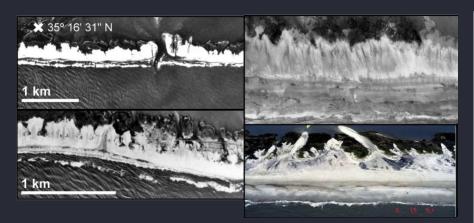
Nithya Sambasivan, Shivani Kapania, Hannah Highfill, Diana Akrong, Praveen Paritosh, Lora Aroyo

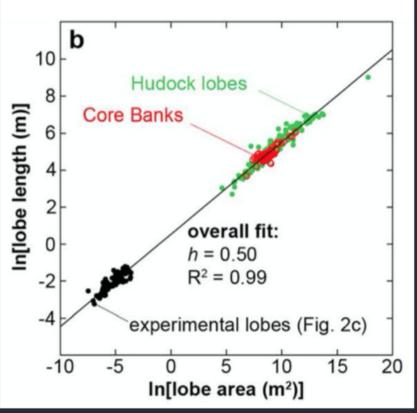
> [nithyasamba,kapania,hhighfill,dakrong,pkp,loraa]@google.com Google Research Mountain View, CA

Ex. I: Labeling images to study barrier island overwash (process) & washover (deposit)

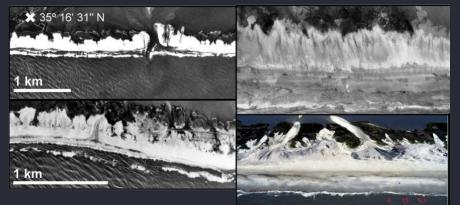


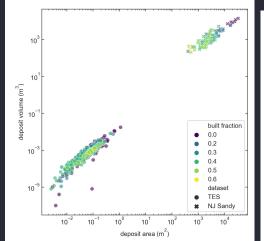
Ex. I: Labeling images to study barrier island overwash (process) & washover (deposit)

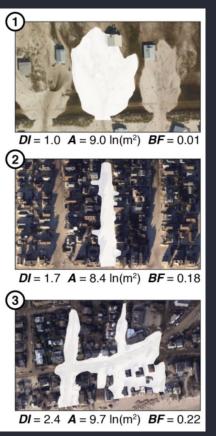




Ex. I: Labeling images to study barrier island overwash (process) & washover (deposit)

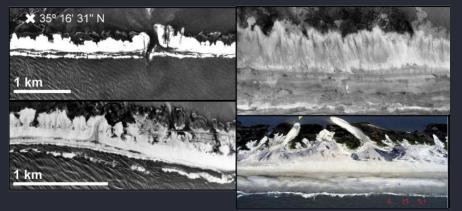


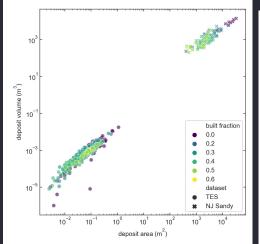




Lazarus et al (2020, 2022)

Ex. I: Labeling images to study barrier island overwash (process) & washover (deposit)

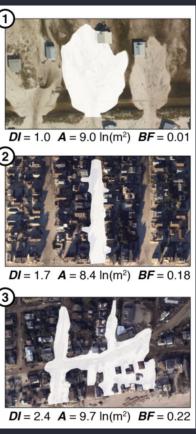






Hurricane Florence 2018: 29k images, 7.7Mb each (!!!)

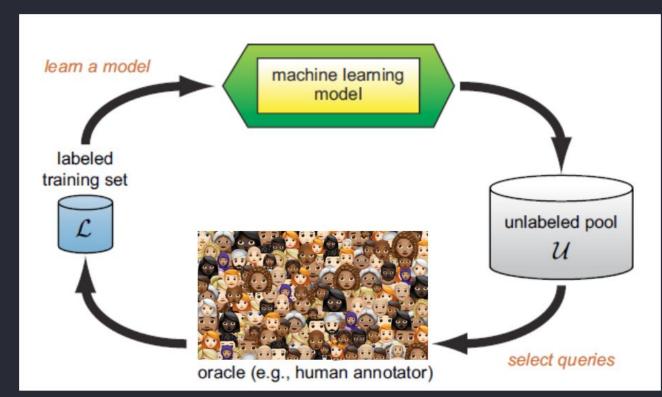
>140k images over 12 storms



Lazarus et al (2020, 2022)

We need labeled data

- Experts? Expensive
- Active learning



System described in Goldstein et al., Al for Earth NeurlPS workshop, 2020

Coastal Image Labeler:

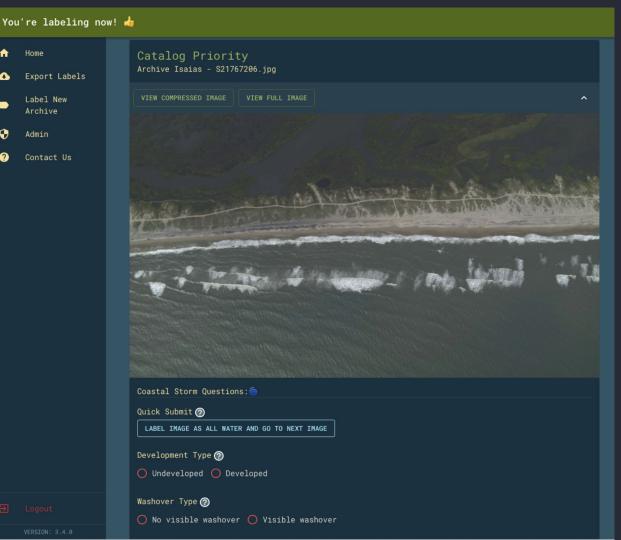
Label New Archive Admin Contact Us

Public-facing, deployed via Azure VM from 2020-2023

31 people

10.2k labels for 4250 images

https://doi.org/10.5281/zenodo.4272063



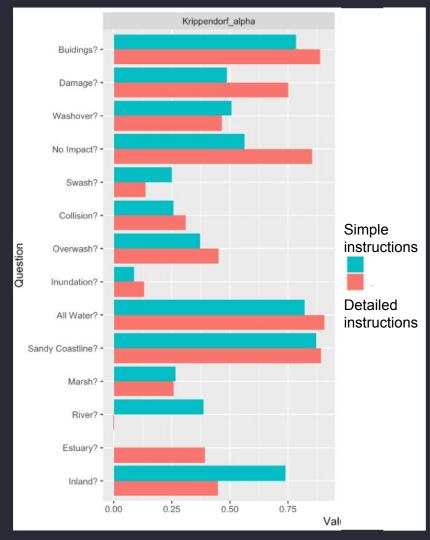
Inter-rater agreement

Poor	Slight	Fair	Moderate	Substantial	Almost perfect
0.0	.20	.40	.60	.80	1.0

Creating labeled data is challenging - & the 'labeled' data is not even clean, unbiased, or error free.

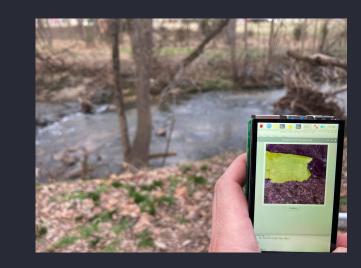
Some objects/definitions are not as clear as we think.



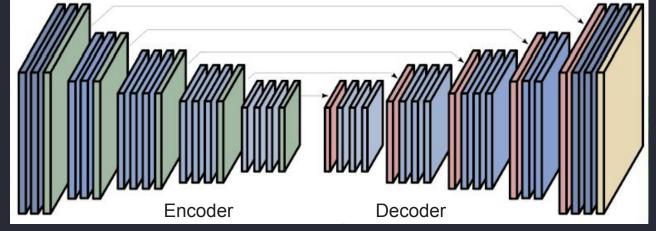


Ex. 2: Developing a generic geoscience segmentation tool

Dan Buscombe: end-to-end solution for labeling & modeling



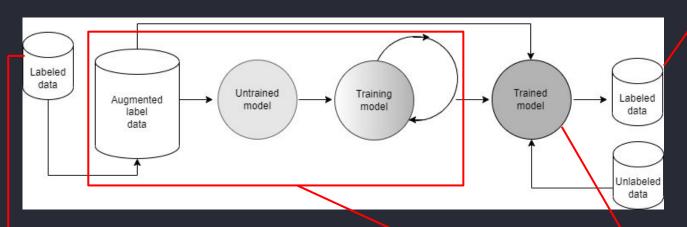






Doodleverse

Coast Train



Buscombe et al. 2023

"A 1.2 Billion Pixel Human-Labeled Dataset for Data-Driven Classification of Coastal Environments."



Buscombe et al. (2021) "Human-in-the-Loop Segmentation of Earth Surface Imagery." Earth and Space Science



Buscombe and Goldstein (2022) "A Reproducible and Reusable Pipeline for Segmentation of Geoscientific Imagery."
Earth and Space Science



Library of trained models.. In progress!

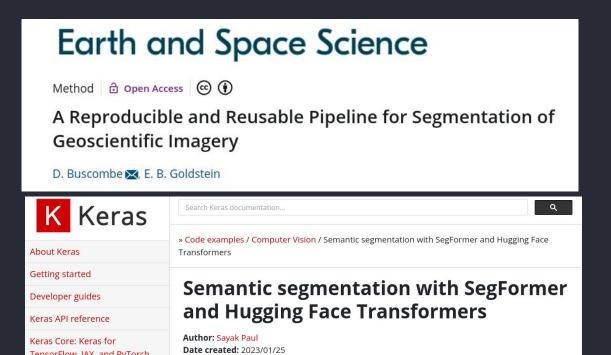


https://github.com/Doodleverse

There will always be a better model...

Sept 2022

January 2023



Quickly incorporated because of open datasets.

We need more (cleaned, labeled) data and to really value people who share (FAIR-ly)

Ex. 3: EdgeML for instant grain size

grain size variability is

wild





- Small (cm) & fast (sec.) scales.
- Spatio-temporal data sparsity
- Measuring is onerous
- Models can use distributions, but most people use D50

Decades of work on instant grain size measurements





Sedimentary Geology 202 (2007) 402-408



Underwater microscope for measuring spatial and temporal changes in bed-sediment grain size

David M. Rubin ^{a,*}, Henry Chezar ^b, Jodi N. Harney ^{a,1}, David J. Topping ^c,
Theodore S. Melis ^c, Christopher R. Sherwood ^d

^a U.S. Geological Survey, 400 Natural Bridges Dr., Santa Cruz, CA 95060, USA
^b U.S. Geological Survey, 345 Middlefield Rd., Menlo Park, CA 94025, USA

^c U.S. Geological Survey, 2255 N. Gemini Dr., Flagstaff, AZ 86001, USA
^d U.S. Geological Survey, 384 Woods Hole Road, Woods Hole, MA 02543, USA





Sedimentary Geology 201 (2007) 180-195



www.elsevier.com/locate/sedgeo

Field test comparison of an autocorrelation technique for determining grain size using a digital 'beachball' camera versus traditional methods

Patrick L. Barnard a,*, David M. Rubin a, Jodi Harney a, Neomi Mustain b

^a United States Geological Survey, Coastal and Marine Geology Team, Pacific Science Center, 400 Natural Bridges Drive, Santa Cruz, CA 95060, United States

b Department of Earth and Planetary Sciences, University of California, Santa Cruz, 1156 High Street, Santa Cruz, CA 95060, United States

Received 27 June 2006; received in revised form 18 May 2007; accepted 22 May 2007

A SIMPLE AUTOCORRELATION ALGORITHM FOR DETERMINING GRAIN SIZE FROM DIGITAL IMAGES OF SEDIMENT

DAVID M. RUBIN

U.S. Geological Survey, Santa Cruz, California 95060, U.S.A. e-mail: drubin@usgs.gov

EARTH SURFACE PROCESSES AND LANDFORMS Earth Surf. Process. Landforms 34, 1811–1821 (2009) Copyright © 2009 John Wiley & Sons, Ltd. Published online in Wiley InterScience (www.interscience.wiley.com) DOI: 10.1002/esp.1877

Cobble cam: grain-size measurements of sand to boulder from digital photographs and autocorrelation analyses[†]

Jonathan A. Warrick, David M. Rubin, Peter Ruggiero, Jodi N. Harney, Amy E. Draut and Daniel Buscombe

- US Geological Survey, Coastal and Marine Geology, Santa Cruz, CA, USA
- Oregon State University, Geosciences Department, Corvallis, OR, USA
- 3 Coastal & Ocean Resources Inc., Sidney, BC, Canada

 Cameras and methods exist, but requires <u>calibration</u> and <u>hand-off</u> (i.e., off-device processing)

LIMNOLOGY and OCEANOGRAPHY: METHODS

Limnol. Oceanogr.: Methods 12, 2014, 390–406
© 2014, by the American Society of Limnology and Oceanography, Inc.

Autonomous bed-sediment imaging-systems for revealing temporal variability of grain size

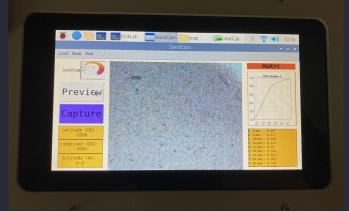
Daniel Buscombe^{1*}, David M. Rubin², Jessica R. Lacy², Curt D. Storlazzi², Gerald Hatcher², Henry Chezar², Robert Wyland², and Christopher R. Sherwood³

United States Geological Survey, Flagstaff, Arizona, USA

²United States Geological Survey, Santa Cruz, California, USA
 ³United States Geological Survey, Woods Hole, Massachusetts, USA

Instagrain









- Image regression on RPi using TF lite
- Multi-output: D2 to D98
- 2 sec. / obs. (mostly I/O)
- 15% MAPE on D50

**Only worked as co-designed system



Wrap Up

- 'Labeled' data is not as clean, unbiased, or error-free as we hope. Objects/definitions are not as clear as we think.
- There will always be a new, potentially better model. (Open data helps you quickly test new models.)
- On the edge, solutions likely require hardware + software + ML co-design.

Thank you for the invitation to speak and thanks for listening!