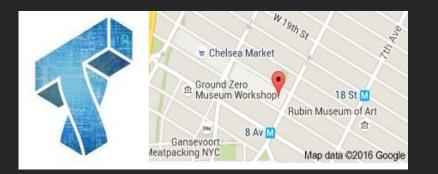
Fine Grained Visual Category Recognition and Perceptual Embedding

Serge Belongie

TECH



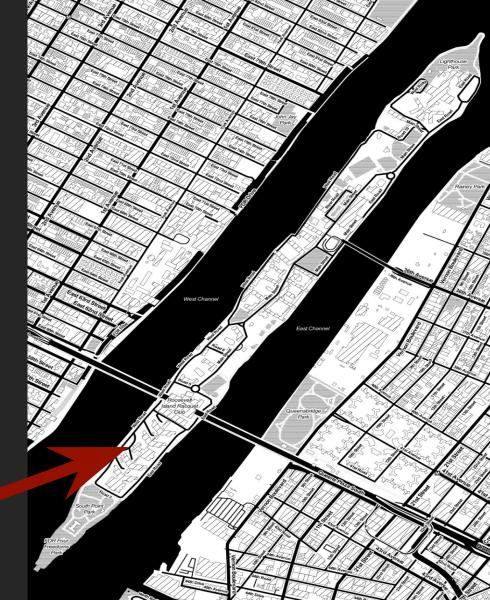




Cornell Tech is the technology-focused campus of Cornell University

Founded in 2012

Future Location

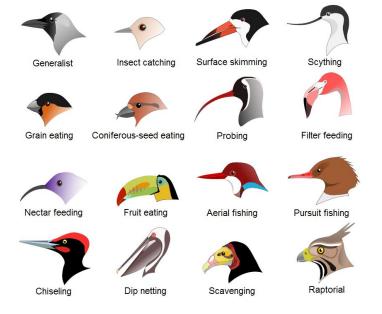


FUTURE CAMPUS (2017)

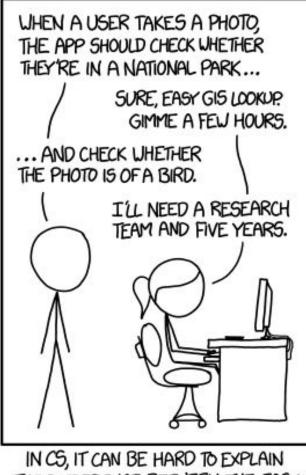
Part I Fine Grained Category Recognition with Humans in the Loop

What Is Visipedia?

- A user-generated encyclopedia of visual knowledge
- An effort to associate articles with large quantities
 of well-organized, intuitive visual concepts



http://en.wikipedia.org/wiki/Bird



IN CS, IT CAN BE HARD TO EXPLAIN THE DIFFERENCE BETWEEN THE EASY AND THE VIRTUALLY IMPOSSIBLE.

http://xkcd.com/1425



Posted on October 20, 2014 by Rob Hess, Clayton Mellina, and Friends

← Previous

Introducing: Flickr PARK or BIRD



tl;dr: Check it out at parkorbird.flickr.com!

Motivation

- People will willingly label or organize certain images if:
 - They are interested in a particular subject matter
 - They have the appropriate expertise



Ring-tailed lemur



Thruxton Jackaroo

A DUBIOUSLY ACCURATE 233 YEAR HISTORY OF CYCLING

posted by Saris - September 4, 2013 - 5pm EDT



While we're not particularly certain about some of the claims in this bicycle family tree (e.g. freeride bikes spawned downhill bikes, which gave birth to 29ers?), we're certain you'll appreciate the artwork. You can head to their website to buy your own copy and laugh at the implication that big wheels evolved into recumbents for only \$22.

[BikeRumor.com]

COMMENTS

1

Ben - 09/04/13 - 5:44pm

This is so completely out of order. Why the hell would you pay 22 dollars for a poster that doesn't make any sense?

Gillis - 09/04/13 - 6:00pm

I like how the track bike sits in between the randonneur and touring bikes. And a modern looking TT bike some how comes before Boardman's Lotus, which both come after fixie's.

This is junk.

D

Walter - 09/04/13 - 6:09pm

So triathlon bikes gave birth to fixies and early eighties long wheel base recumbents came from modern high racers. These folks are creationists.

NotAMachinist - 09/04/13 - 6:20pm

It's sort of cool looking until you really look at it. For instance how does a randonneur differ from a touring or trekking bike? How did cyclocross spawn BMX? The cycling family tree is far more incestuous.

Joe - 09/04/13 - 6:22pm

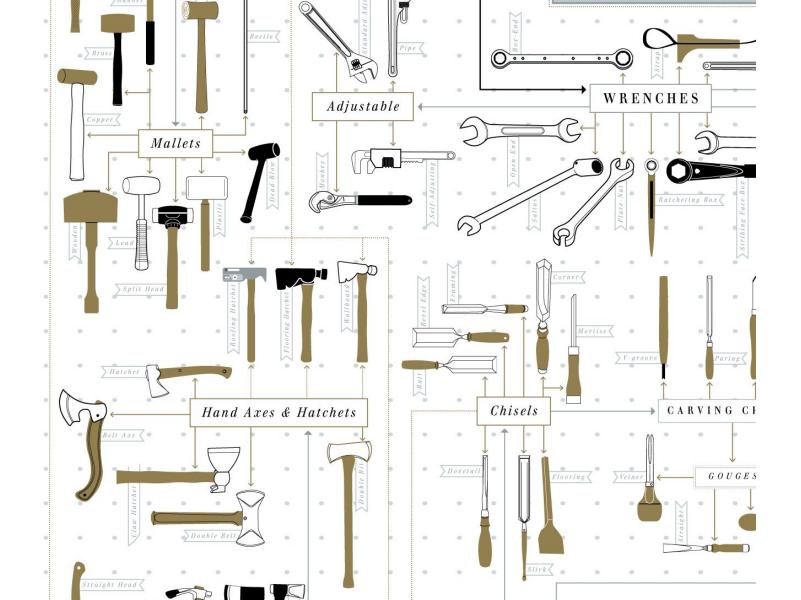
Cyclocross to 20" Dirt, Street, Park to Racing to Freestyle and Flatland????? Not a one of these is right....the whole chart is a nice piece of wallpaper art but that's it.

2

88888888888

Keith D - 09/04/13 - 6:46pm It's pretty much rubbish.

(~)-(~





(A) Easy for Humans





Chair? Airplane? ...

(B) Hard for Humans (C) Easy for Humans





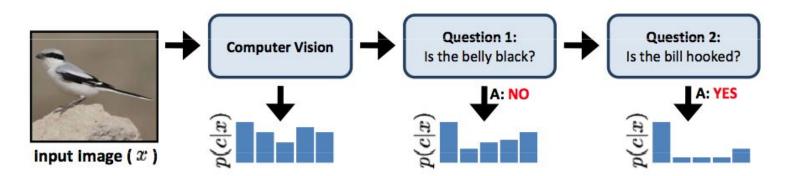
Finch? Bunting?...





Yellow Belly? Blue Belly? ...

Visual 20 Questions



Algorithm 1 Visual 20 Questions Game 1: $U^0 \leftarrow \emptyset$ 2: for t = 1 to 20 do 3: $j(t) = \max_k I(c; u_k | x, U^{t-1})$ 4: Ask user question $u_{j(t)}$, and $U^t \leftarrow U^{t-1} \cup u_{j(t)}$. 5: end for 6: Return class $c^* = \max_c p(c | x, U^t)$

antedeepluvian

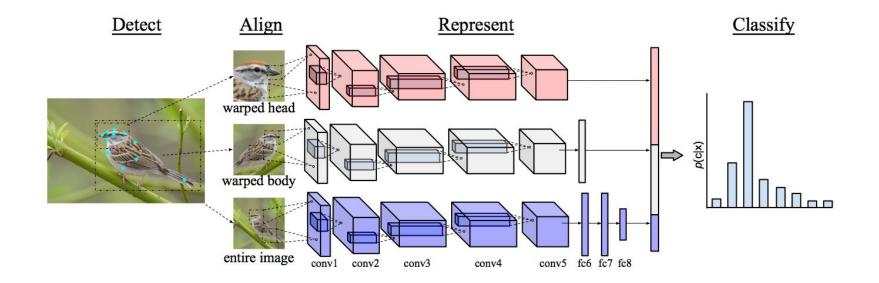
an·te·deep·lu·vi·an

an(t)ēdēp'loovēən/

adjective

- 1. before the flood of deep learning papers
- 2. "Histograms of vector quantized filter responses are *antedeepluvian* features."

Pose Normalized Deep ConvNets



[Van Horn, Branson, Perona, Belongie BMVC 2014]

Try out on a new dataset for fine-grained recognition, featuring 550 of North America's most common birds. The full dataset will be available in the fall. Join the competition today and download the "taster" dataset!

http://birds.cornell.edu/nabirds

CCUB NABirds includes:

- More than 700 visual categories, organized taxonomically
- · Photos curated in collaboration with domain experts
- Data organized in a researcher-friendly, widely-used PASCAL VOC format

CCUBNABirds

700

For more information contact: Ryan Farrell (farrell@eecs.berkeley.edu)



Visipedia Backend

Storage and collaboration infrastructure to support visual search applications.

Storage Cloud storage and access for your image datasets and annotations.

Collaborate

Divide and conquer your data collection and curation tasks by sharing your data with collaborators.

Deploy

Integrate Vibe storage functionality into your app or website for easy image upload and annotation by your users.

Annotate

Organize

Build a hierarchical representation of your domain and

use it to organize your images.

Use our annotation templates to create your custom annotation tasks.

Analyze

Hook Vibe into your classification pipeline to analyze how images are being classified.



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> Flamingos :						
Shearwaters, Petrels, Albatross, and Allies				3 N.V.		
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> Frigatebirds, Boobies, Cormorants, Darters, a		13	1000		- Alexandre	
> Pelicans, Herons, Ibises, and Allies :			11-1-		cae .	13t
Hawks, Kites, Eagles, and Allies						and the second se
Caracaras and Falcons :						
Cranes and Rails						
> Plovers, Sandpipers, and Allies :		MO			2000	
Skuas and Alcids :			ANT T	1		
Gulls, Terns, and Allies						
> Pigeons and Doves :				·····		
>Parrots :			Mar all	(AND) / (1998)		
Cuckoos :				P	-	
>Owls :		N			The second	and a second
Nightjars :						
Swifts and Hummingbirds :		(
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➤Kingfishers and Allies :				80 03		
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	Fulvous Whistling-Duck Greater White-fronted Goose	44		162									
	Snow Goose (White morph)			177									
	Snow Goose (Blue morph)		118										
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	Cackling Goose			166									
	Canada Goose		- 15	3									
	Mute Swan			2	205								
	Trumpeter Swan			171									
	Tundra Swan			190									
	Muscovy Duck		91										
	Wood Duck (Breeding male)					261							
	Wood Duck (Female/Eclipse male)			186									
	Gadwall (Breeding male)				226								
	Gadwall (Female/Eclipse male)		109										
	American Wigeon (Breeding male)			190									
	American Wigeon (Female/Eclipse male)		109										
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	Blue-winged Teal (Female/Juvenile)		121										
	Cinnamon Teal (Male)				211								
	Cinnamon Teal (Female/juvenile)		108										
	Northern Shoveler (Breeding male)				28	50							
	Northern Shoveler (Female/Eclipse male)		150		-								

Have a bird photo? Help us test Merlin Bird Photo ID



Start Bird Photo ID >

The Cornell Lab of Ornithology and Visipedia are collaborating to develop computer vision technology to identify birds in photos. Help test our new tool!

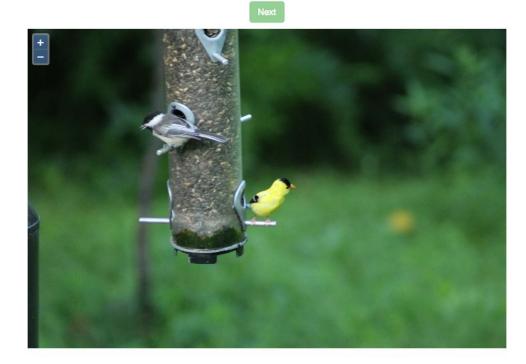
Note: Merlin Bird Photo ID does not work on tablets or mobile devices at this time. For best results, please use a computer with a recent version of Chrome or Safari.

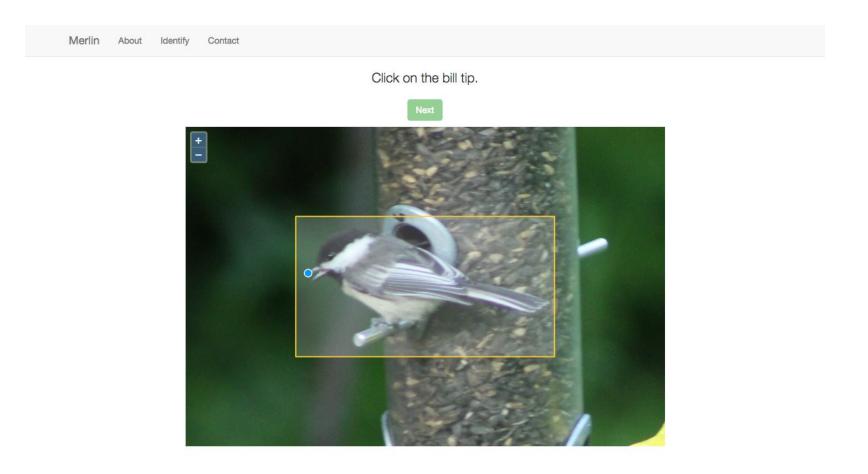
http://merlin.allaboutbirds.org/photo-id

Select your photo.



Crop the bird by clicking and dragging a box.

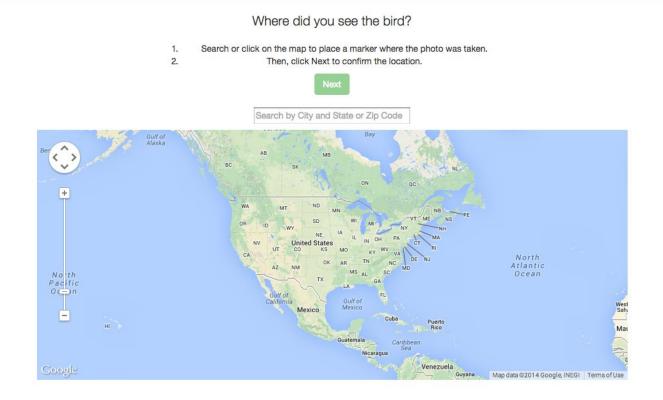




Click on the eye. If both eyes are visible, click on the side of the head that is more visible.







Merlin About Identify Contact

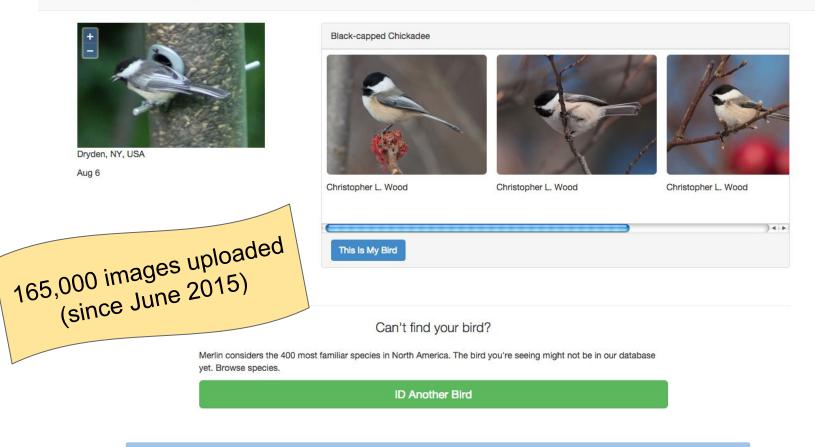
When did you see the bird?



Merlin About Identify Contact

Creating list of possible birds...





http://merlin.allaboutbirds.org/photo-id

*

Part II Learning about Similarity from Human and Machine Expertise

Our goals:

We want to **pull out** humans' intuitive notion of **perceptual similarity!**



How can we combine machine and human expertise? How can we efficiently ask humans about their knowledge?

[Wilber et al. ICCV 2015]

We can't directly measure similarity





"These two foods taste similar." Disagree 1 2 3 4 5 Agree

We can't directly measure similarity





"These two foods taste similar." Disagree 1 2 3 5 Agree

We can't directly measure similarity

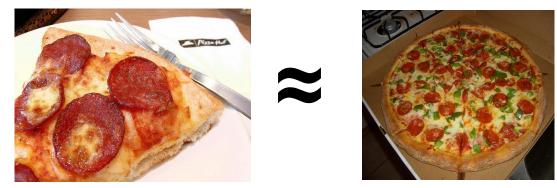




"These two foods taste similar." Disagree 1 2 3 4 5 Agree

How could we learn how humans perceive taste?

"Pepperoni pizza tastes similar to other pizza"



"Pepperoni pizza tastes different from coffee"



Our design: Grid questions

To collect constraints efficiently, we ask: "Please select the **four foods** that taste similar to the one on the left."





Our design: Grid questions

To collect constraints efficiently, we ask: "Please select the **four foods** that taste similar to the one on the left."





Our design: Grid questions

Selected points are more similar to the reference food than unselected points.



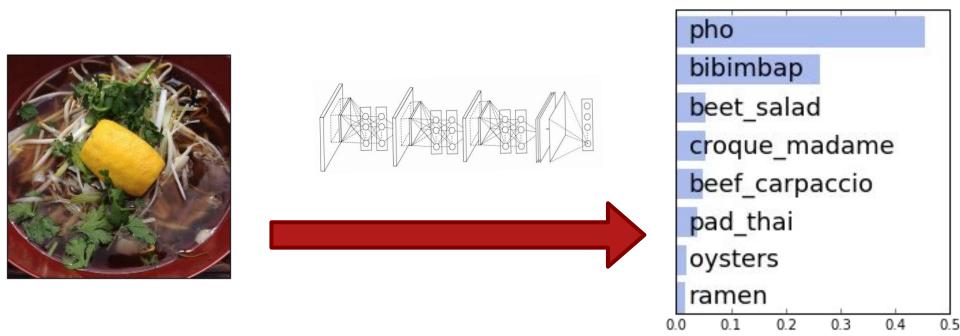




Far

Machine similarity: Recognition is not enough.

Current **deep learning** approaches are great at recognizing objects, but they can't understand food taste without help.



Machine similarity: Recognition is not enough

Both of these are **pepperoni pizzas**, but they taste very different!



Machine similarity: Recognition is not enough

Is this **guacamole** or **wasabe**? This is not apparent from visual appearance.



Machine similarity: Taxonomies may be imprecise

This is a **wasabi Kit-Kat bar**. Where does it fit into the food taxonomy?

A perfect model can't help us.



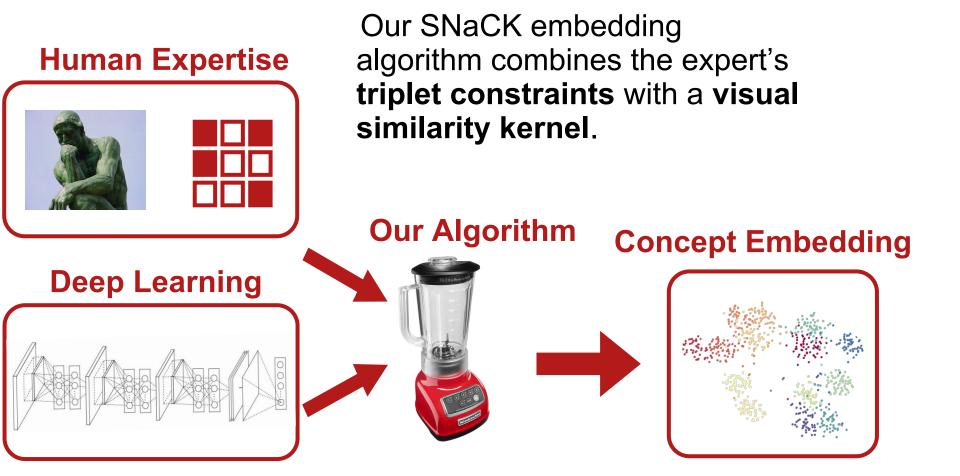


Machine similarity: Taxonomies may be imprecise

This is a **Berliner**. Berliner hobbyists will refuse to call this a "Jelly Doughnut", because it does not have a hole.



Stochastic Neighbor and Crowd Kernel (SNaCK)



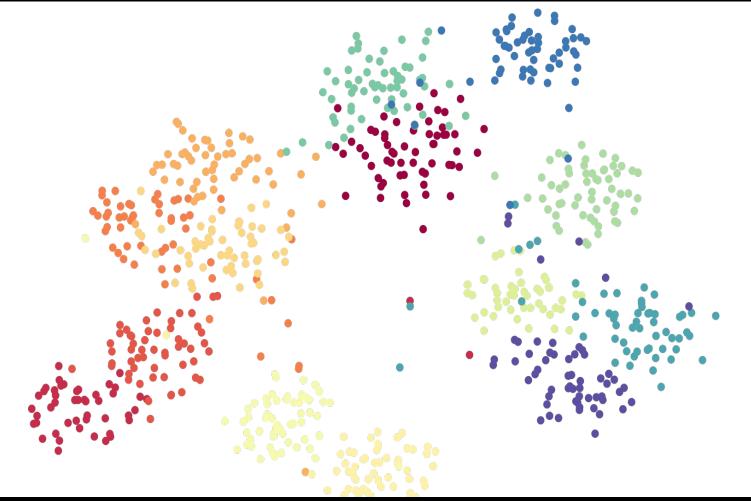
Embedding example: Food-10k



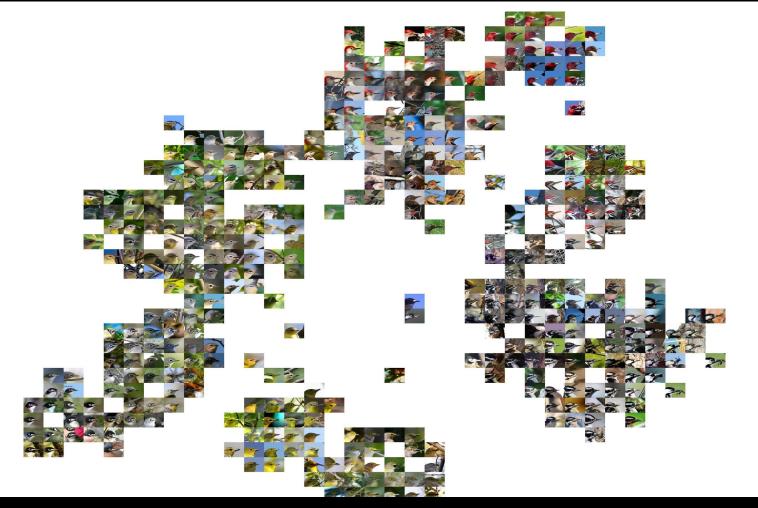
Embedding example: Food-10k



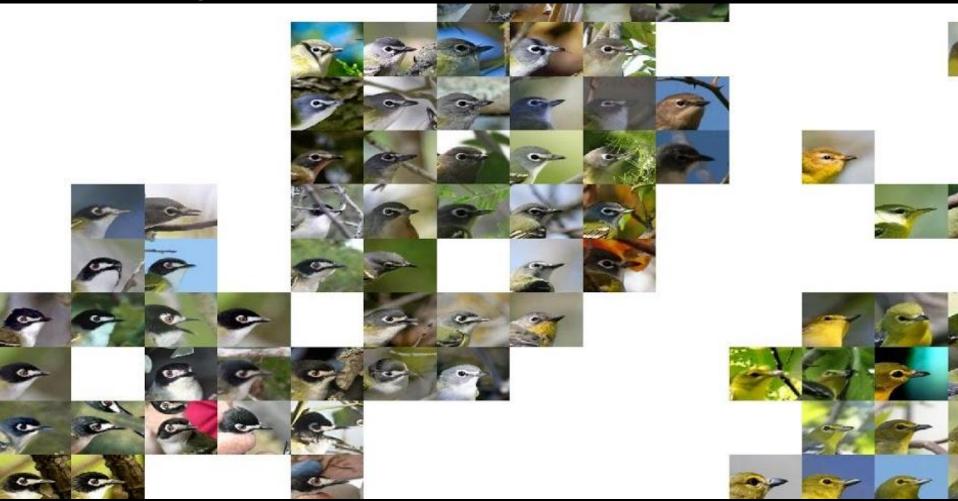
Embedding example: CU Birds 200 "Birdlets" subset



Embedding example: CU Birds 200 "Birdlets" subset



Embedding example: CU Birds 200 "Birdlets" subset

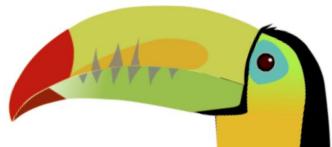


What's Next for Visipedia?

- More taxa: flowers, trees, terrestrial mammals, amphibians, seashells, mushrooms, bugs, ...
- Partnership with Macaulay Digital Archive
- Visipedia.org Schema & Data Sharing Best Practices
- Suite of digital field guide apps
- CV/ML research for the most challenging taxa
- FGVC workshops: datasets and competitions

Thank You

- Cornell: Michael Wilber, Jessie Barry, Scott Haber
- UCSD: Iljung Sam Kwak, David Kriegman
- Caltech: Steve Branson, Grant Van Horn, Pietro Perona
- BYU: Ryan Farrell
- Google Focused Research Award
- Jacobs Technion-Cornell Institute



RESEARCH

Security and Privacy (Shmatikov, Juels, Pass, Ristenpart)

Computer Vision (Belongie, Snavely, Zelnik, Zabih)

Social/Mobile Computing (Estrin, Naaman, Dell)

tech.cornell.edu/programs

PhD (CS, ECE, InfoSci...) Postdocs **Runway Postdocs** Masters: **Connective Media** Health Tech MBA (1 year) CS MEng (1 year) LLM (1 year) ORIE (1 year)