HappyWalrus: A Computer Vision App that Helps Parents Identify and Mitigate Kitchen Hazards

Product Audience:

Expectant parents and those of children ages 0 to 4

Group 1:

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Unmet Need for Simple Tools to Help Parents Babyproof Homes

- Injuries give rise to 1.4 million ER visits each year (8.5% of children ages 0-4)
- Currently available apps are cumbersome checklists
- Parents and caregivers are overwhelmed and may not be cognizant of all hazards

HappyWalrus identifies kitchen hazards in user photos to make babyproofing easy and accessible

What Core Functionalities Did Our Prospective Users Want HappyWalrus to Possess?

Users wanted HappyWalrus to:

- Identify a variety of objects
- Provide both object-specific and general safety guidance
- Be mobile friendly

HappyWalrus exhibits all of these features!

Application Demonstration

Data Pipeline Produces Annotated Images to Train Model that Backs Our Web App

1

Data Pipeline

- Acquisition
- Engineering
- Object Annotation

Model Development

- Model Training
- Image Augmentation
- Error Analysis
- Model Tuning

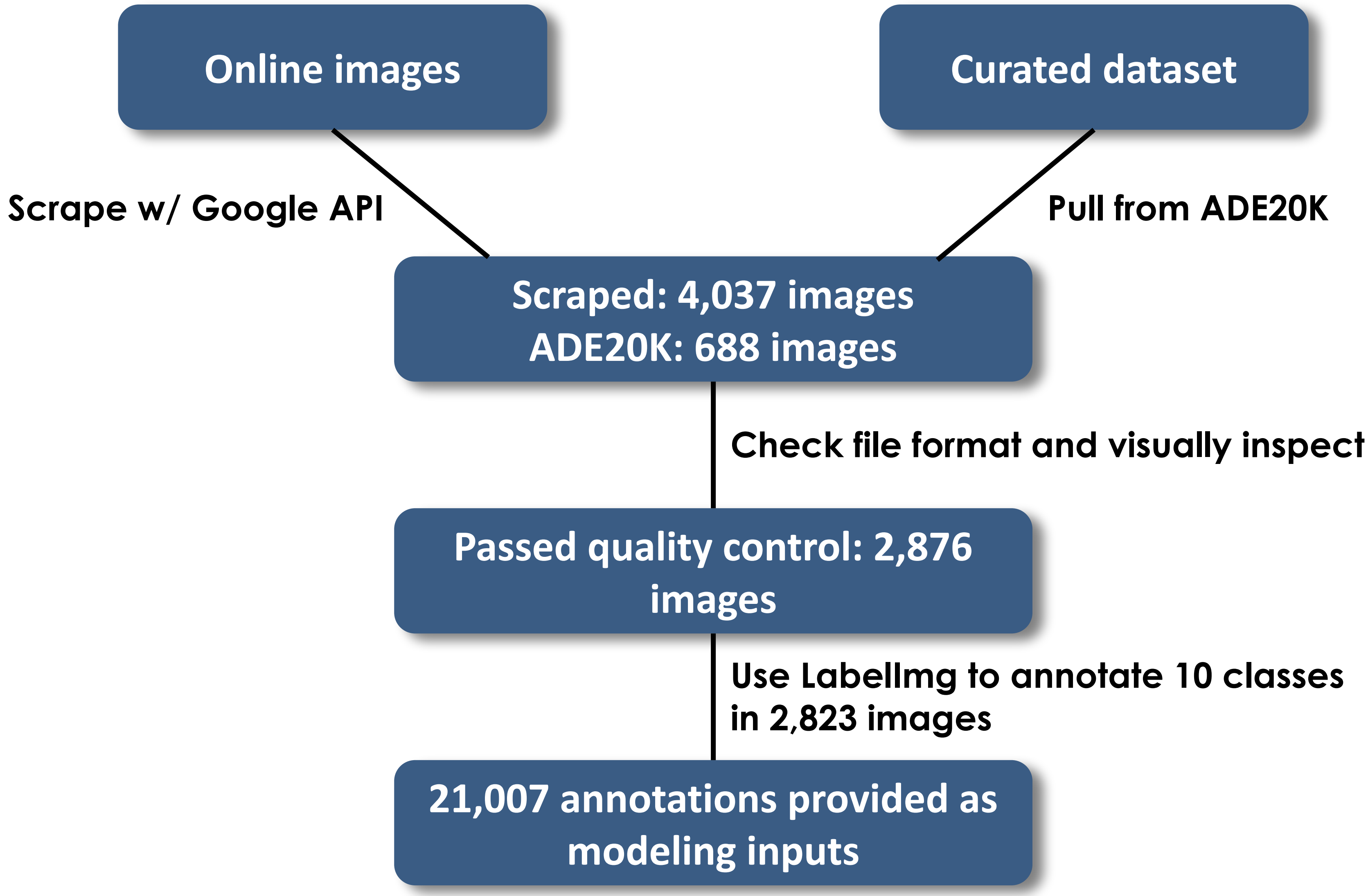
2

3

Web Application

- Model Deployment
- Web Development
- User Experience

Our Data Acquisition and Annotation Pipeline Yielded 2,823 images



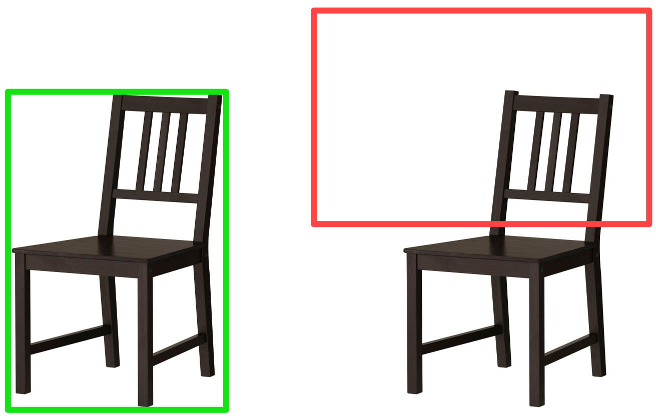
Annotated Objects = Major Sources of Unintentional Injury (Falls, Struck by, Burns, Poisoning)

Object	Instances
countertop	5,140
cabinet	3,875
chair	2,999
outlet	2,582
stove	2,216
pots, pans, kettles	1,600
oven	1,071
stool	763
dishwasher	649
sofa	112
Total	**21,007**

These sources are the #1, #2, #8, and #10 causes of injury—together account for >69% of total

Not Just a Classifier: Mean Average Precision (mAP) Accounts for an Object Detector's Dual Functions

1. Localizing objects with as tight a bounding box as possible



✔ Tight, localized

X Loose, mislocalized

2. Correctly classifying objects

✔ Chair

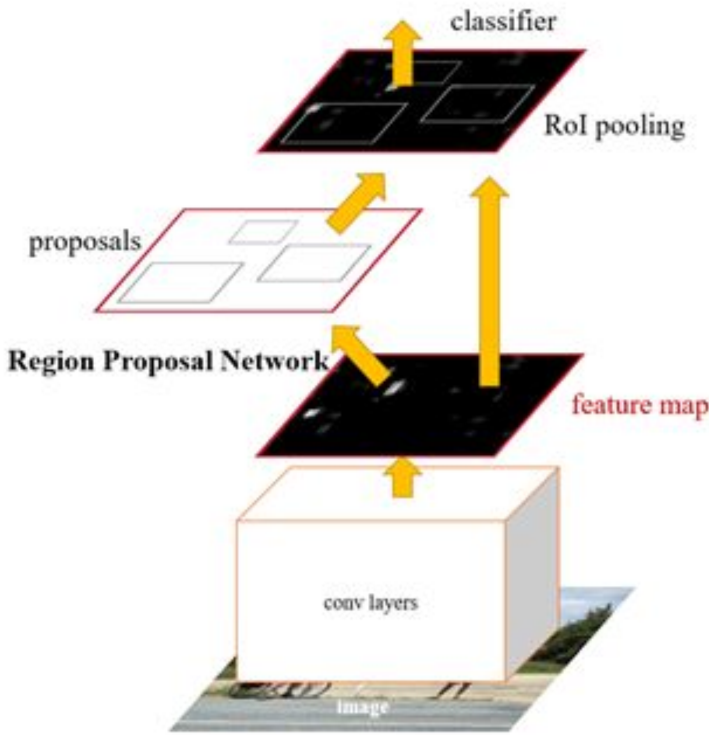
X Dishwasher

X Pot

mAP balances false positives against false negatives—all things being equal, a larger mAP (closer to 1) is better

Faster R-CNN with a ResNet101 Feature Extractor Gave a High mAP and Low Inference Time

Faster R-CNN architecture



We employed TensorFlow's Object Detection API to quickly experiment with different configurations

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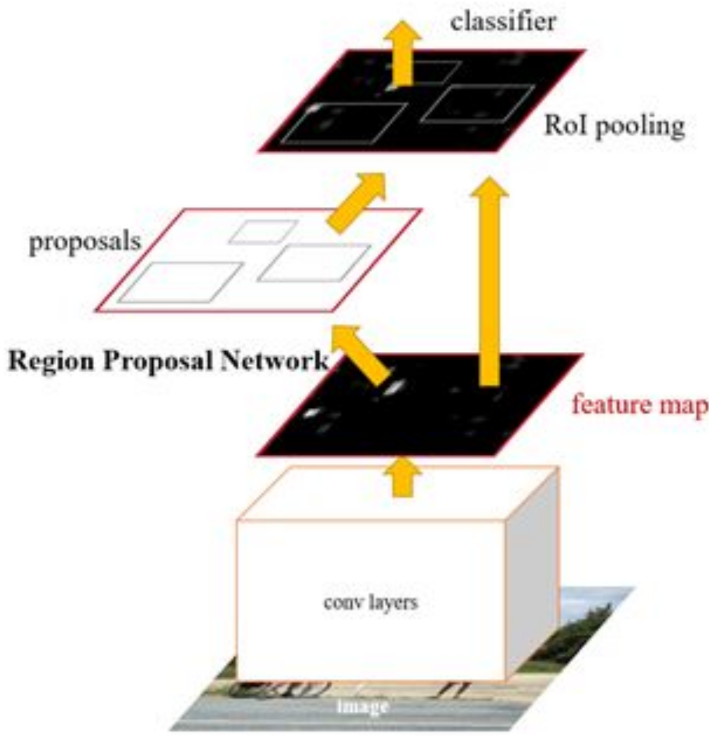

CNN (training set)	mAP	Inference (s)
Inception v2 (COCO)	0.52	0.4
ResNet101 (COCO)	0.53	1.6
Inception ResNet v2 Atrous (COCO)	0.57	5.7
Inception ResNet v2 Atrous (OIDV4)	0.56	5.8
NASNet (COCO)	0.59	23.4

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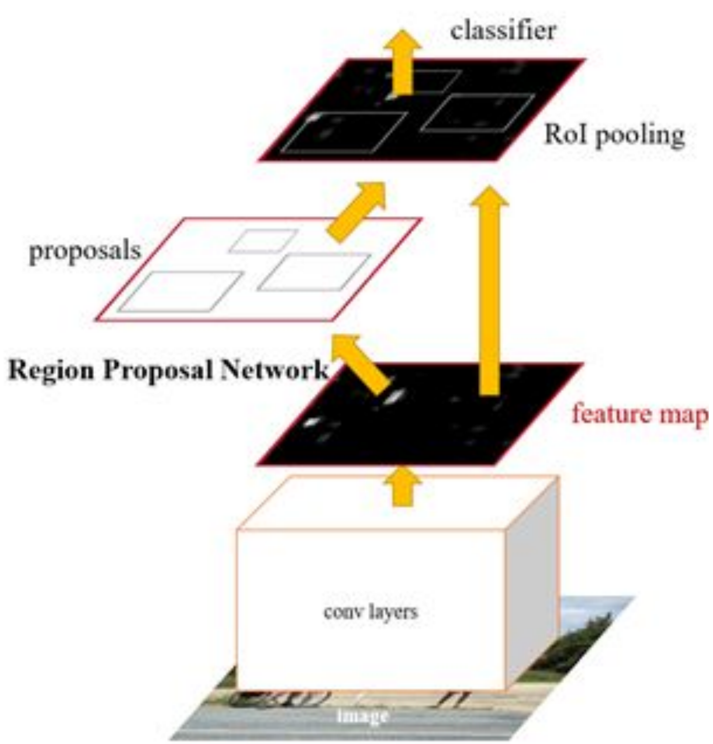

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Google Brain's Suggestions outperformed alternative augmentation policies

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Custom	0.47	1.6
Horizontal flip	0.48	1.6
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Horizontal flip

Some augmentations (e.g., brightness) likely improve the app's ability to process inputs from different users

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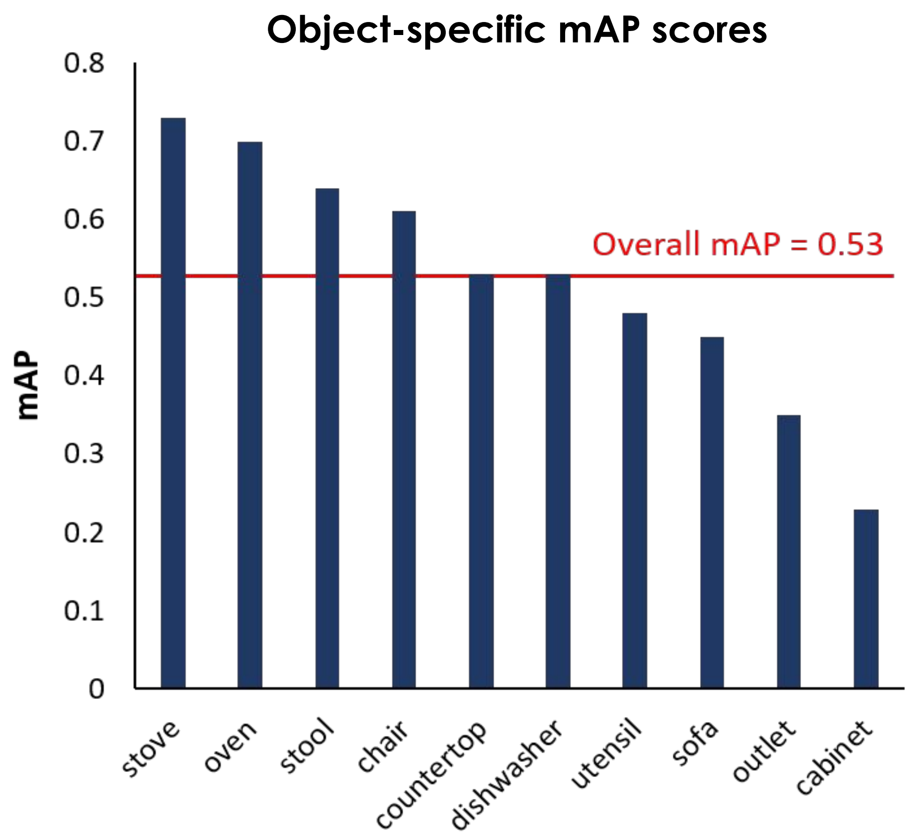
Can Label More Cabinets, but Outlets Could Just Be Hard for the Model to Identify in Widefield Images



Did not label all cabinets

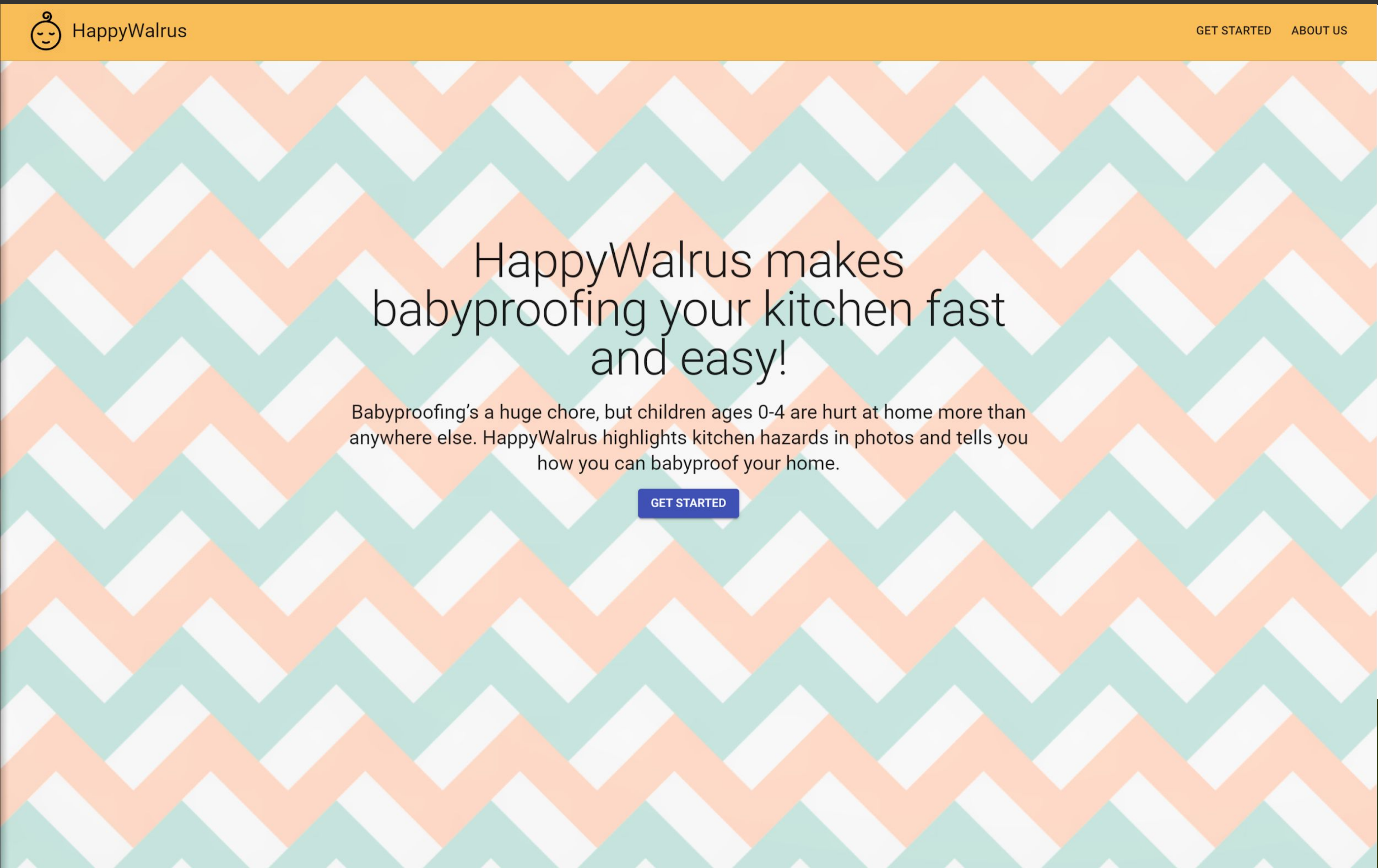
Outlets are very small features

Of the 10 objects we annotated, our model most easily identifies stoves and ovens

Our MVP Provides a Solid Foundation for Additional Refinements and a Blueprint to Expand

- Increase dataset's breadth (more search terms) and depth (more images per search term)
- Annotate additional classes
- Highlight easy-to-reach objects
- Expand to address other rooms
- Incorporate user feedback on model's performance
- Package as mobile app (works on mobile web right now!)

HappyWalrus Will Help Parents Identify Kitchen Hazards to Reduce Injury Rates



Questions?

Performance per class

	map	map0_5	cabinet	chair	countertop	dishwasher	outlet	oven	sofa	stool	stove	utensil
autoaugm_inceptionv2	0.28	0.52	0.28	0.61	0.50	0.57	0.23	0.69	0.36	0.71	0.72	0.49
autoaugm_resnet101	0.29	0.53	0.23	0.61	0.53	0.53	0.35	0.70	0.45	0.64	0.73	0.48
autoaugm_inception_resnet_v2_atrous_coco	0.34	0.57	0.27	0.68	0.56	0.66	0.43	0.73	0.34	0.69	0.79	0.58
autoaugm_inception_resnet_v2_atrous_oidv4	0.33	0.56	0.32	0.66	0.52	0.59	0.44	0.71	0.30	0.73	0.77	0.57
autoaugm_nas	0.36	0.59	0.23	0.72	0.53	0.67	0.47	0.71	0.48	0.69	0.79	0.63
custaugm_resnet101	0.28	0.47	0.16	0.60	0.48	0.47	0.26	0.63	0.27	0.64	0.70	0.48
hflip_resnet101	0.28	0.48	0.20	0.62	0.49	0.50	0.29	0.67	0.28	0.63	0.72	0.42
noaugm_resnet101	0.27	0.47	0.14	0.61	0.48	0.44	0.27	0.65	0.39	0.65	0.68	0.43