FINDING THE (AD)OPTIMAL CAT PHOTO

MILESTONE 2 PRESENTATION

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PROBLEM

- About 6.5M dogs and cats each year enter animal shelters, according to the ASPCA
- But approximately 1.5M of these are put down

That's 1 in 4 pets.

THE QUALITY OF THE PHOTO OF A PET IS CORRELATED TO ITS LIKELIHOOD OF BEING ADOPTED

GOALS

increase adoption rates

decrease euthanasia for shelter cats

SPONSOR: AUSTIN PETS ALIVE!

- Animal shelter based in Texas
- No-kill shelter
- Saved over **70,000 animal lives** since 2008

Austin Pets Alive! is not your average animal shelter. We pioneer innovative lifesaving programs designed to save the animals most at risk of euthanasia.

Adopt

Looking for a furry friend to add to the family? We have thousands of animals that would love to be part of your home.

Foster

Open your heart and home to a pet in need, and be the bridge to a dog or cat's forever home.

Volunteer

Our volunteers make lifesaving possible – become a volunteer today!

SPONSOR: ADOPTIMIZE

- Software company
- Primary goals
  - Increase adoption
  - Decrease euthanasia
  - Increase shelter engagement
- Algorithm that optimizes image taking
  - For the best chance of adoption

Increases Adoption Rates

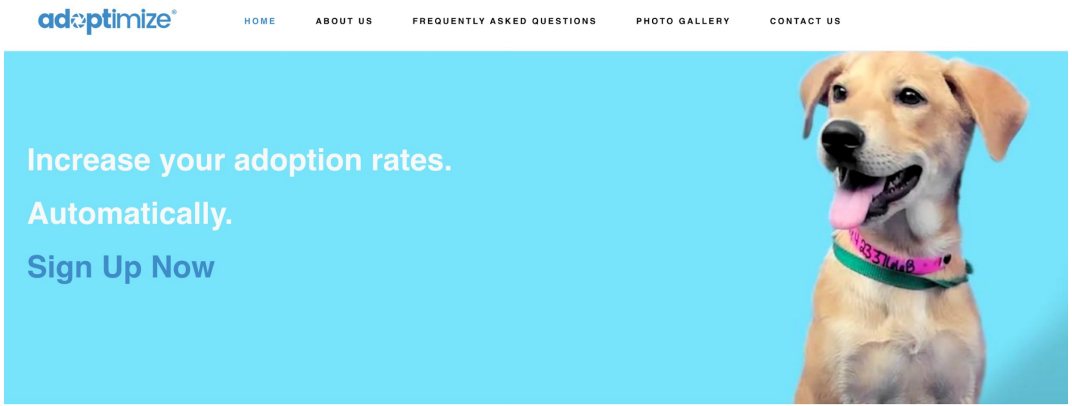
Saves Lives

Increases Online Engagement

SPONSOR: ADOPTIMIZE

Dog model process

- Takes in **video** of animal
- Selects **optimal shot**
- Automatically **edits** image
- Outputs **enhanced optimal** image



IMPACT

124% increase in adoption
41% reduction in euthanasia

27% increase in adoption
56% reduction in euthanasia

SCOPE OF WORK

In scope

- Model taking cat videos and outputting best frame
  - Length: <60s
  - Unobstructed view of a single cat
- Functional web app for mobile devices

Out of scope

- Stylized front-end
- Measuring adoption rates

CHALLENGES

Behavior	Video Quality
○ Fur covering face ○ Not facing camera	○ Unstable camera ○ Camera quality (phone vs. laptop)
Dataset	**Limitations**
○ Small number of cat videos ○ No labeled data	○ Environment ○ Equipment

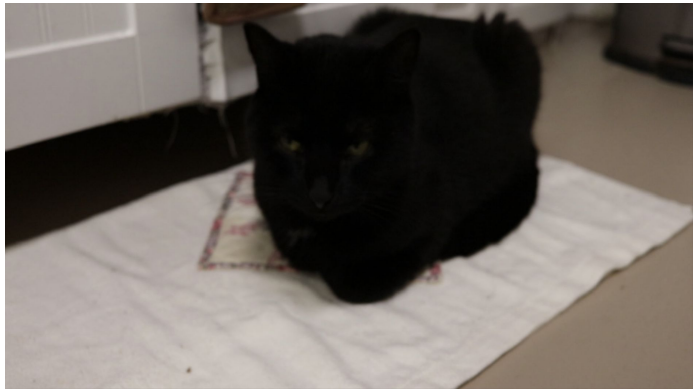
The data poses some **challenges...**

THE DATA

The Good

- Full body visible
- Looking directly at camera
- Clear, high quality image
- Good lighting

The Bad



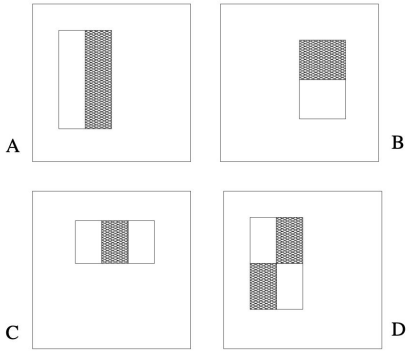
- Full body not visible
- Can’t distinguish facial features
- Looking away from camera
- Blurry image
- Darker area

HEURISTICS

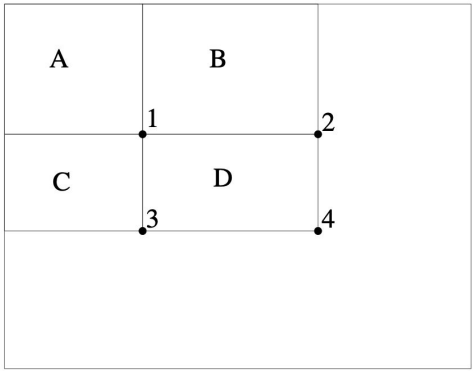
- Detection of Cat Features
- Variance of Laplacian
- Relative Size of Cat Head

LITERATURE REVIEW: VIOLA-JONES

- *Rapid Object Detection using a Boosted Cascade of Simple Features*
- Haar-like Features
  - Pre-Compute Integral Image
- AdaBoost on Decision Stumps
- Cascade
- Sliding Windows



Haar-like Features



After post-processing, rectangle features can be calculated with array lookups as opposed to sums

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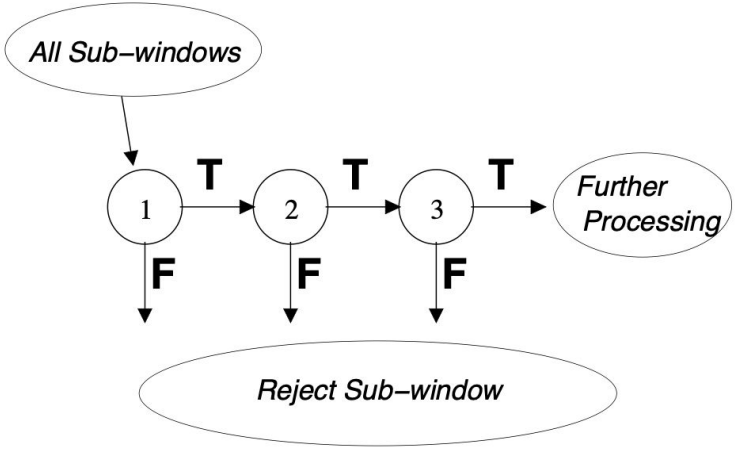
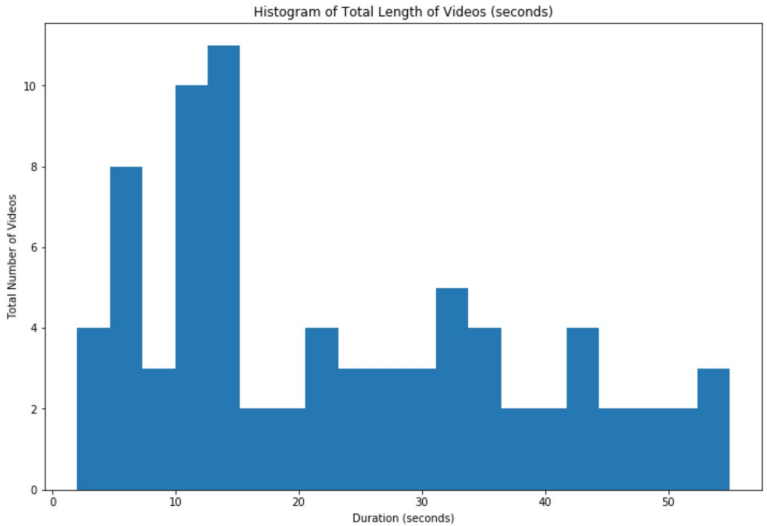


High-level view of cascade approach

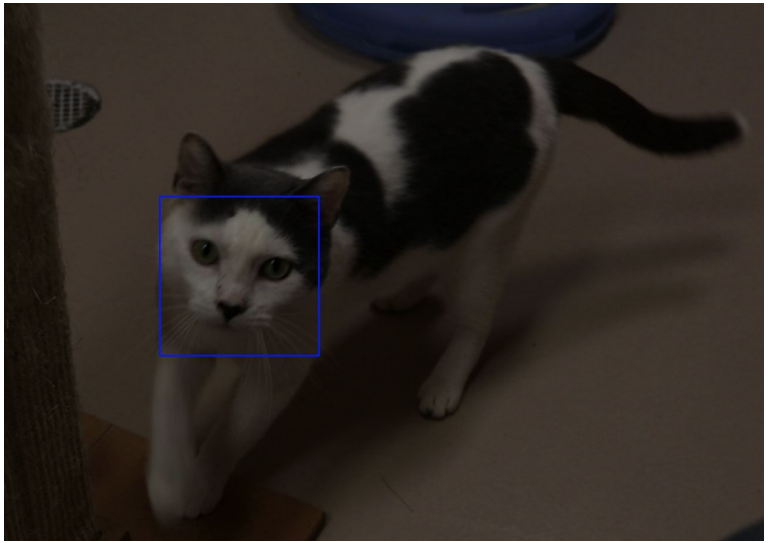
EDA: GENERAL DATA SENSE

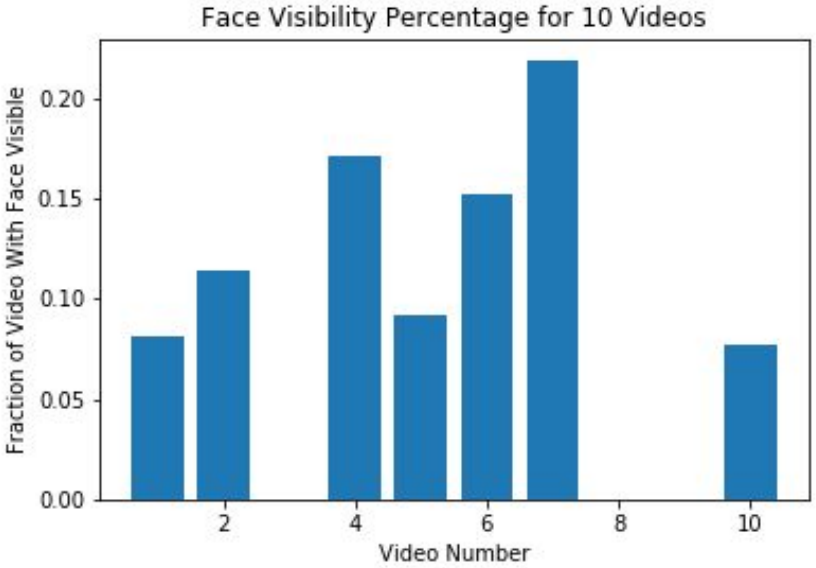
- Initial data cleaning yielded 80 videos
- Duration: Avg: 23 seconds. Min 2 seconds. Max 55 seconds



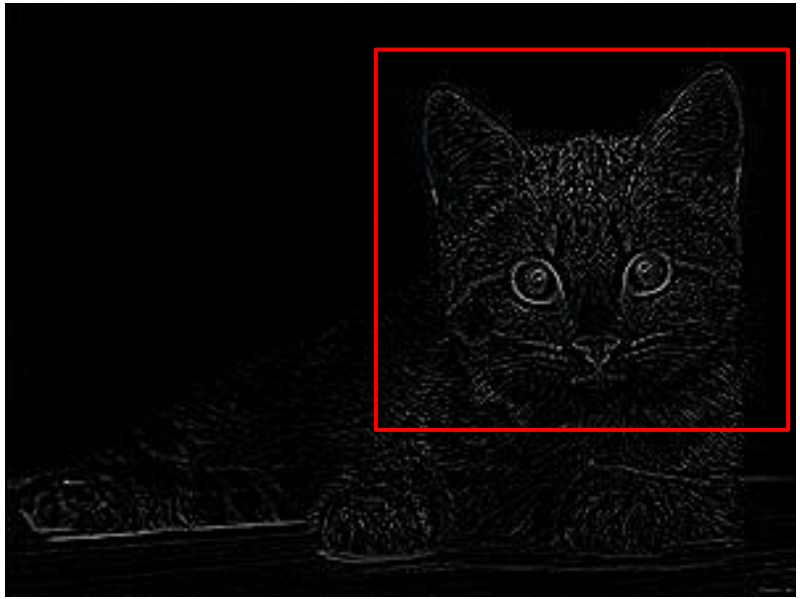
EDA: CAT FACE DETECTION

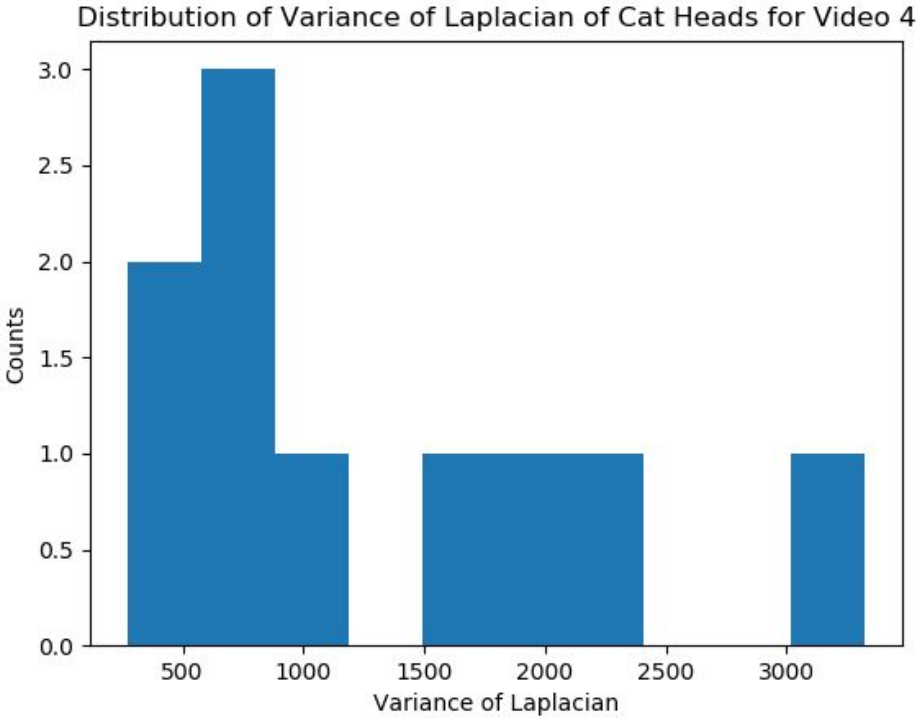
- Ran cat face detection using Haar Cascade
- Subsample of 10 videos
- Every 10th frame per video



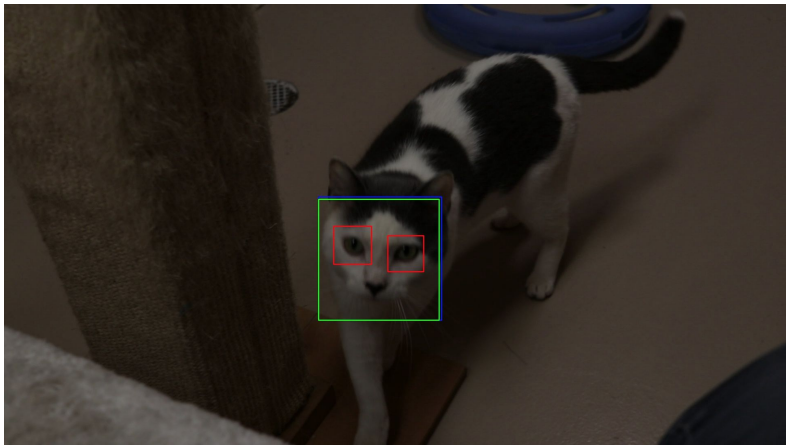


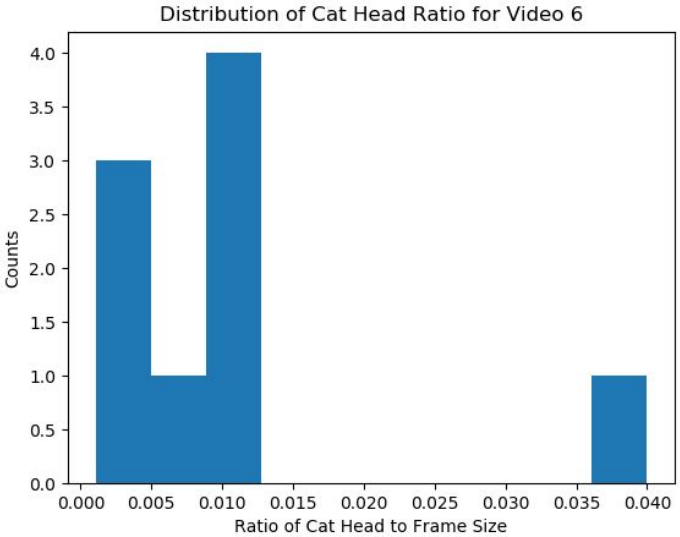
EDA: MEASURES OF SHARPNESS





EDA: HEAD SIZE RATIOS





BASELINE VS. DEVELOPED MODEL

baseline

random image selected from set of frames with cat head detected

developed

image selected from set of frames with cat head detected, with highest combined scores of sharpness and best cat head ratio

TESTING THE MODELS

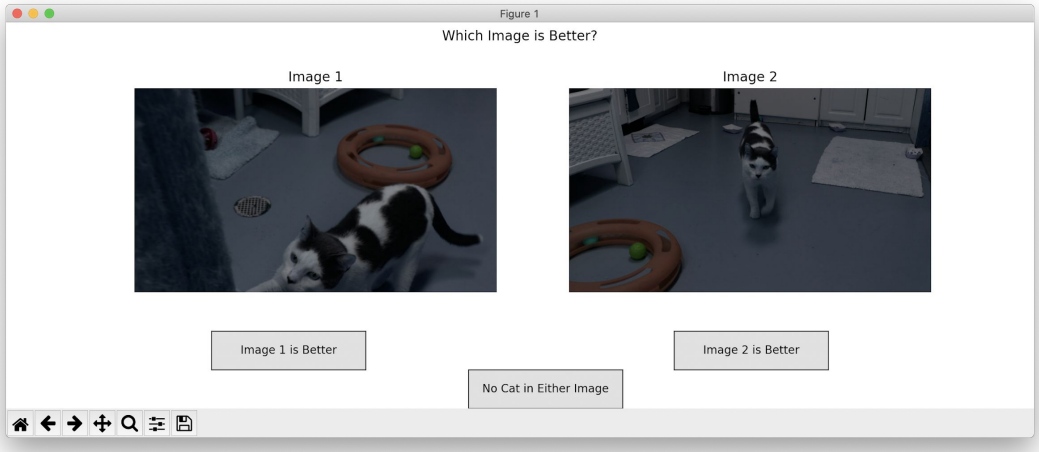
Implementation

Blind A/B testing: baseline vs. developed output

Results

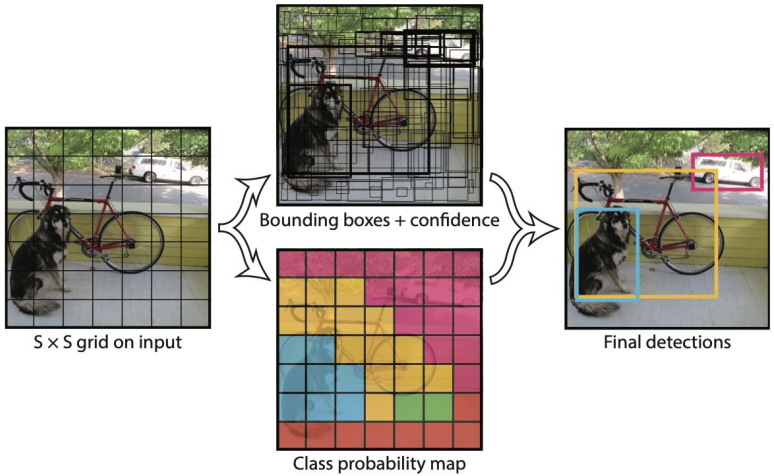
64% of the time developed model produced “better” image

Testing interface



LITERATURE REVIEW: YOLO

- *You Only Look Once: Unified, Real-Time Object Detection*
- Simultaneous Box and Class Proposal
- Simplicity: CNN
- Optimized for Speed



Each grid cell is responsible for producing exactly *B=2* bounding boxes representing existence of any object with center in the cell

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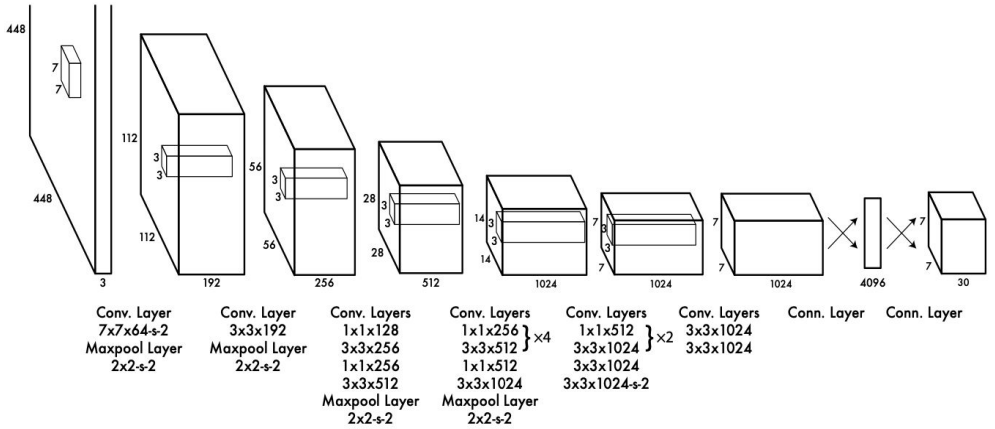
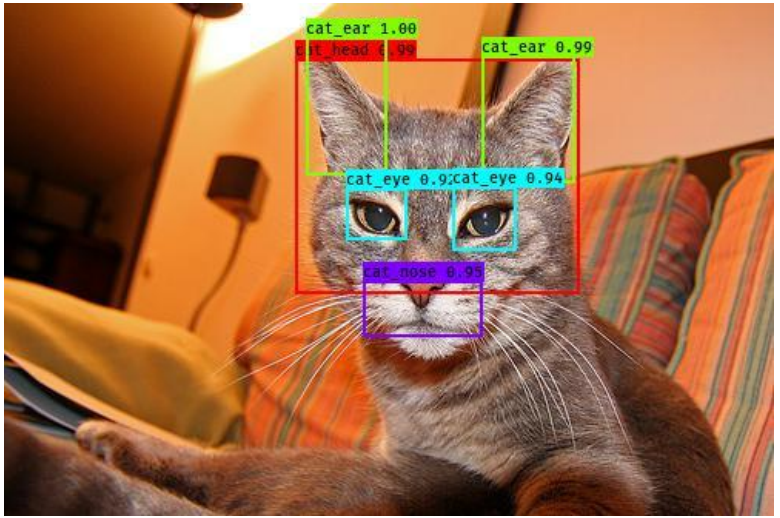


YOLO architecture; note only convolutional and fully connected layers

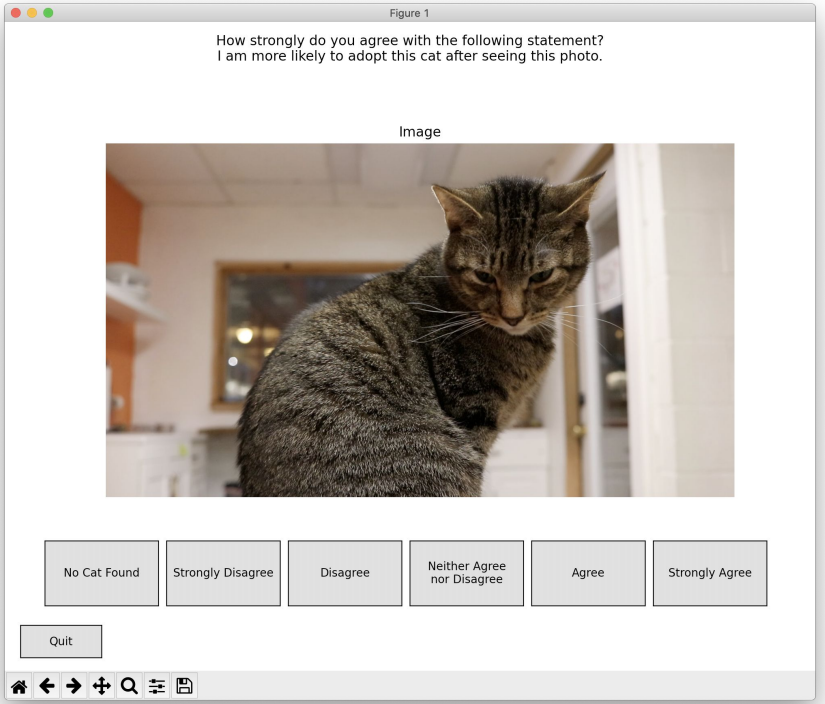
TRAINING YOLO

- YOLO vs Haar Cascade
- 4 Features
  - Eyes, Nose, Ears, Head
- 100 Training Examples
- AWS EC2 g3s.xlarge
  - NVIDIA Tesla M60 GPU
- mAP: 71.96%

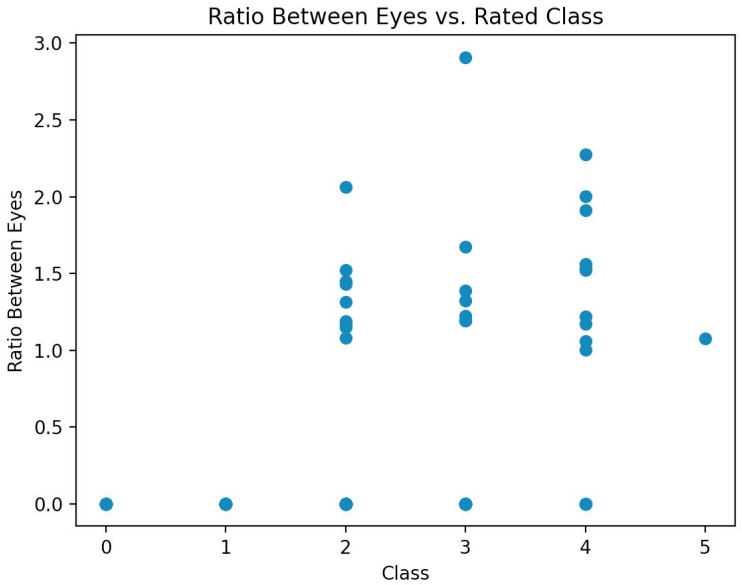


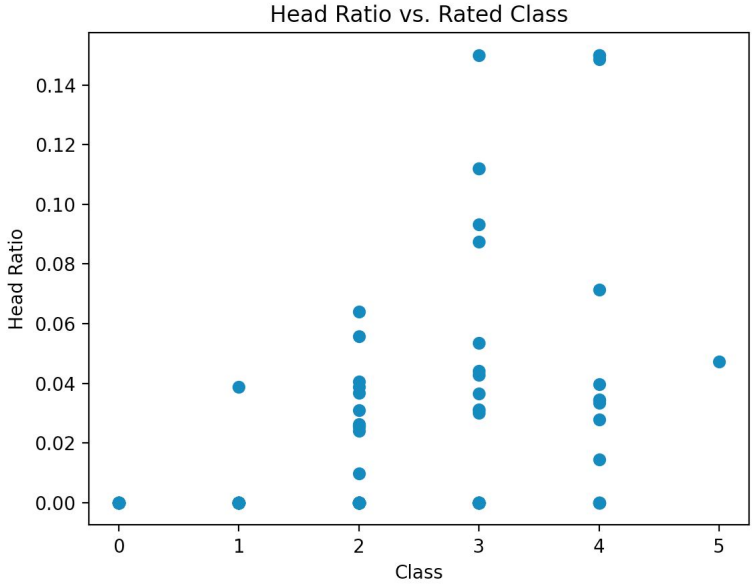
REGRESSION: LABELING

- Data-driven approach to weighting features
- Likert scale
  - Resulting in classes 1-5 (excluding images without cats) that would serve as the ‘y’-values to fit the regression model



REGRESSION: EDA ON PREDICTORS





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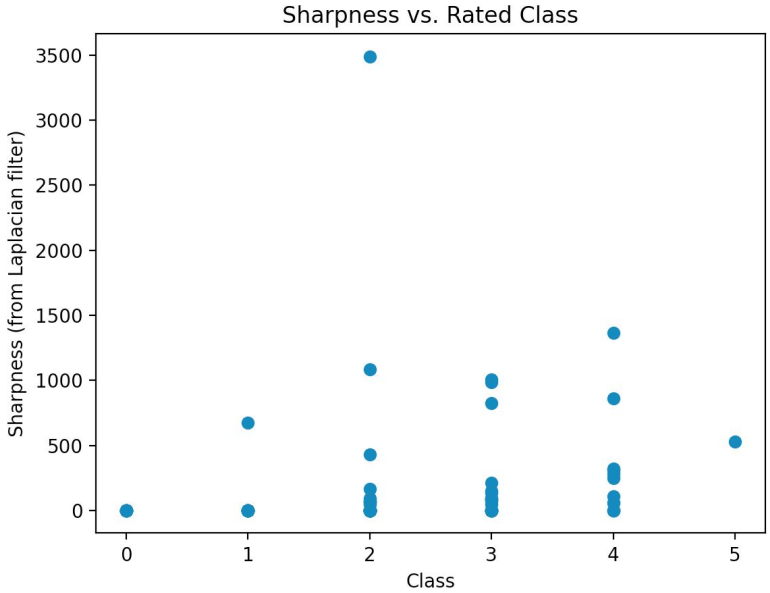
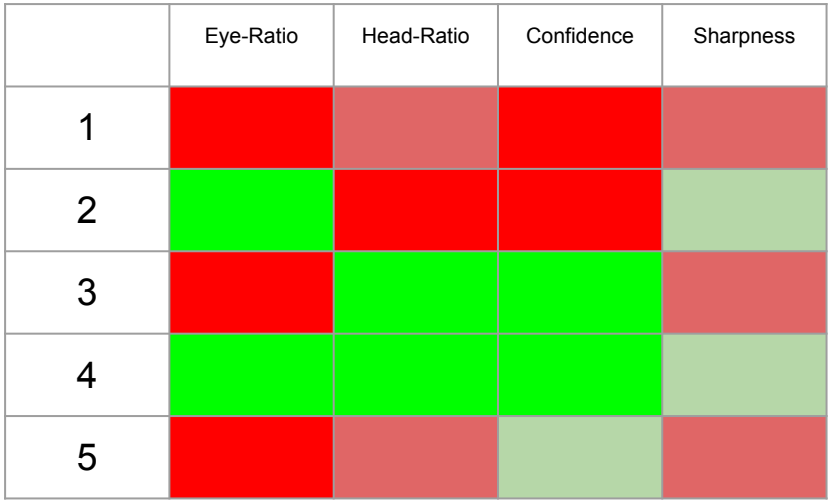
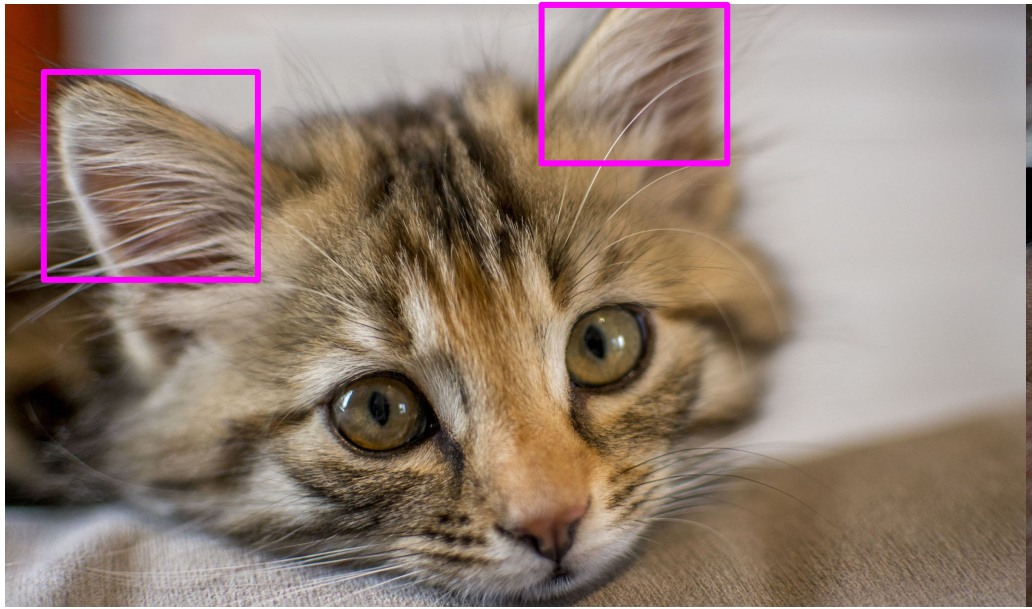


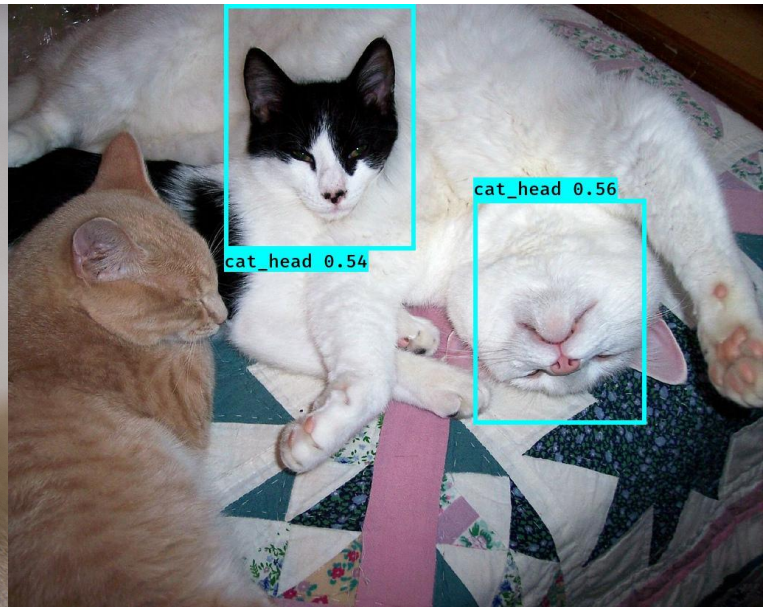
REGRESSION: RESULTS

- Used ‘out-of-box’ sklearn Logistic Regression for Python
- Need to fine-tune model on more data, some of the metrics we had didn’t perform as we would have liked to



NEXT STEPS: REFINING MODEL

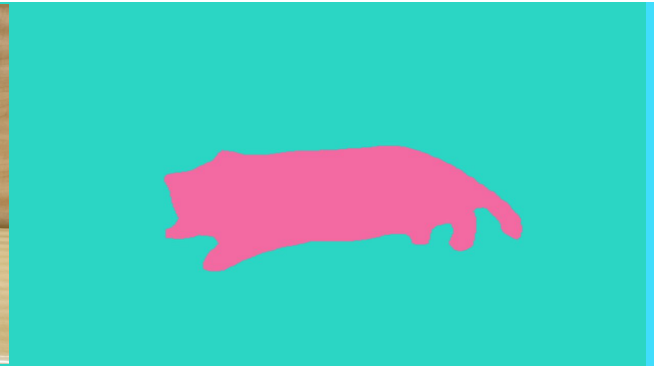
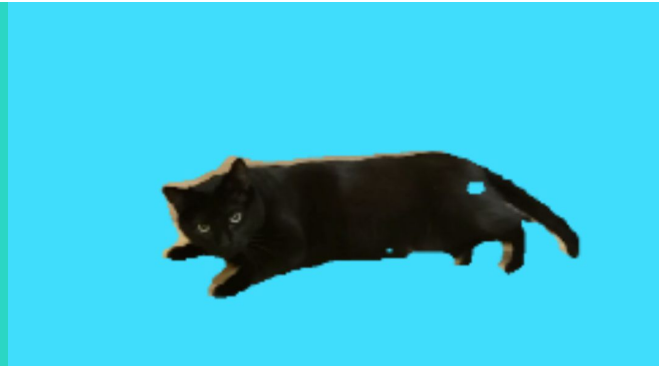




NEXT STEPS: BACKGROUND SUBTRACT





NEXT STEPS: WEB INTERFACE

THANK YOU

Questions?