# Chimney Swift Classification

Overview of Problem and Dataset

# Task Description

- Detect, localize, and track “Chimney Swift” birds in videos

- Desirable to classify different object types before/during tracking
  - Keep “Chimney Swift” objects only (shown in green)
  - Reject other kinds of moving objects (e.g. seagulls, shown in red)

# Existing Approach (Flawed)

- Background subtraction used to segment moving objects from static background scene

- Naive assumption: All segments treated as 1 Chimney Swift bird
  - Non-Chimney Swift segments (e.g. seagulls) cause false positives
  - 2+ Chimney Swift segments (overlapping) cause missed detections

# Why is this a problem?

- Example: Non-swift birds (e.g. seagulls) tend to stand and walk along edge of chimney
- This results in instances of small motion (parts of seagull captured by background subtraction)
- Without filtering, these are mistaken as Chimney Swifts

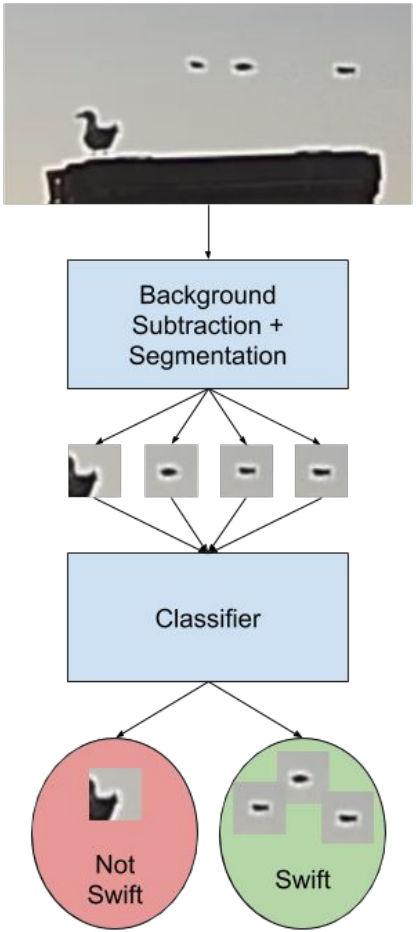
# Proposed Approach

1. Extract segment images from frames using background subtraction

2. Build dataset representative of Swifts and Non-Swifts

3. Train classifier using training subset of data
   - CNN?
   - SVM with HOG/SIFT features?
   - AdaBoost with Haar-like features?

4. Evaluate classifier on testing subset data



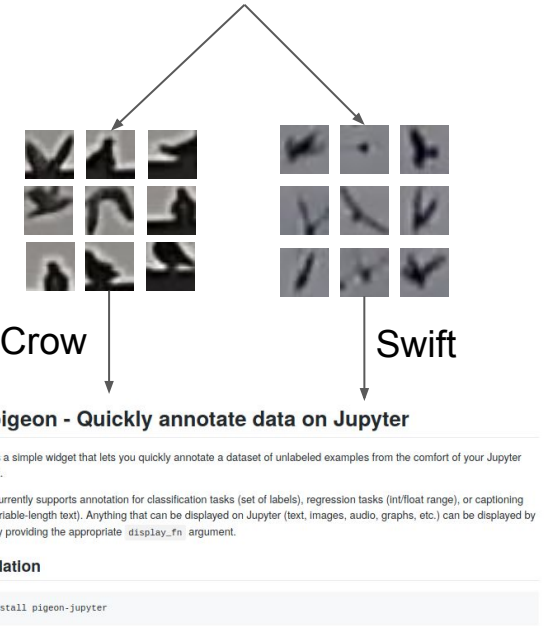
# Extract data from which videos?

1. Sault Ste. Marie, Ontario videos
   - **1 video** from 2016, **20+ videos** from 2017, **2 videos** from 2018
   - 18-30FPS, 30-90 minutes each
   - Two different cameras, differing weather conditions
2. Chalk River, Ontario videos
   - **65 videos** from 2019
   - 60FPS, 20-60 minutes each
3. User-uploaded videos on YouTube
   - **5 videos** (potentially more) from varying sources



# Extract data from which videos?

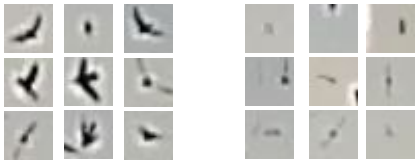
- Each video represents 10,000+ segment images.
  - Can contain 100s of swifts per video
  - Each swift appears for 10s of frames
  - Flying = rapid non-rigid deformation = many examples
- Pipeline already in place for extracting segments
  - Currently to image files
  - Considering serializing to .HDF5 due to I/O strain
- Workload primarily choosing sequences (to balance dataset) + labeling + augmentation if needed
  - Have Jupyter notebook with “Pigeon” library for labeling

# Challenges

- Objects are small and lack detail
- Varying video scale + video quality
  - Motion blur, residual “motion trail” artifacts, haloing, etc.
- “Non-Swift” class is broad and sometimes difficult to define
  - Seagulls, crows, other species of birds
  - Rapid changes in illumination causing reflections, wind causing chimney to sway
- Potentially unbalanced classes
  - “Non-swift” subjects (seagulls, crows) are unpredictable, hard to reliably locate examples within video datasets

# Gallery of Sample Images *(L: Non-swift, R: Swift)*

| | | |
|---|---|---|
| Chalk River, July 21st, 2019 |  |  |
| Sault Ste. Marie, May 2016 |  |  |
| Sault Ste. Marie, May 2018 | |  |
| Sault Ste. Marie, May 2017 |  |  |

# Next Steps

1. Choose portions of videos representative of swifts and non-swifts

2. Extract segment images from videos
    - Processing: Crop? Center? Resize?

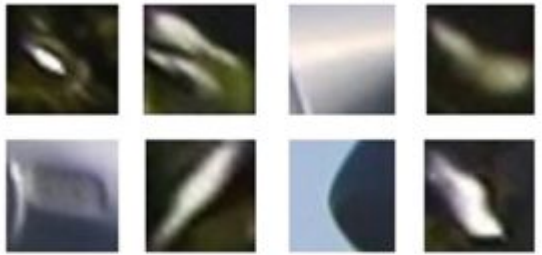
3. Label images and serialize
    - HDF5? Structure of dataset?

4. Clean/prune/prepare dataset
    - Outliers? Class balance?
    - Data augmentation?

# Aside: Wild Birds in Wind Farm Dataset

- Similar problem with bird detection in wind farms
  - Bird motion vs. non-bird motion
  - Small, low-detail objects
- Researches in Tokyo publicly released dataset
  - 32,973 bird images (hawks and crows)
  - 4,911 non-birds (airplane, helicopter, part of turbine, tree)
  - 1,907 unclear flying objects (blurred)
- Not “Chimney Swift” birds but could be useful
  - 7 different classification publications use this dataset

Birds

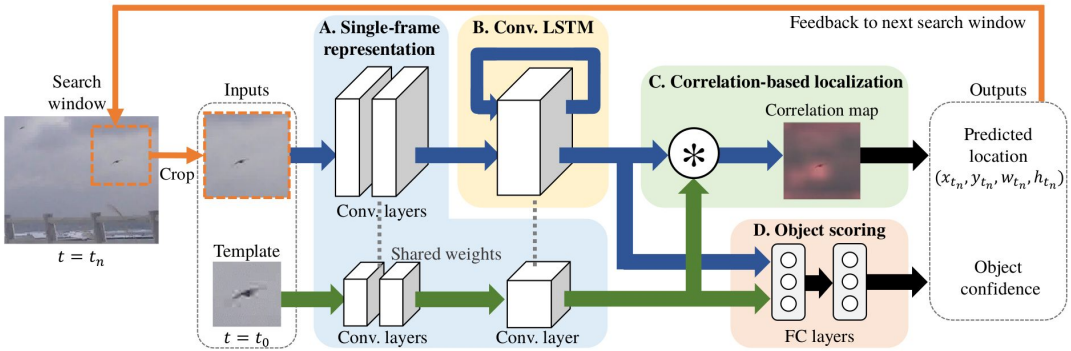


Non Birds

# Aside: Solving the Wrong Problem?

- **Current:** segmentation, classification, tracking treated as separate problems.
- **Alternative:** Combine some/all stages into joint approach?

- "Joint Detection and Tracking of Small Flying Objects" Yoshihashi et al. 2018
  - Novel CNN + LSTM detection and tracking architecture.



# Aside: Solving the Wrong Problem?

- Concern: Only January-April 2020 left for Undergraduate Honours Thesis
- Graduating soon after April 2020
- “Bird/Non-bird classifier” may be easier to produce meaningful work considering tight timeline
- Joint approaches may be better suited for “future work” recommendations