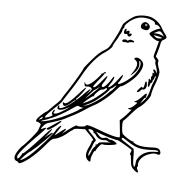
# Reducing confounding factors in automatic acoustic recognition of individual birds

#### Dan Stowell

Machine Listening Lab Centre for Digital Music

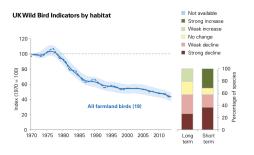


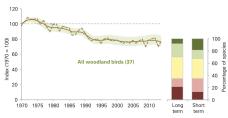




versus

## Machine listening and bird sounds - why?





## Machine listening and bird sounds - why?

- Changes in populations, in migration patterns -monitoring is important
- Intrusive vs. passive monitoring —behavioural impact of catching/ringing birds
- Many birds are most easily observed by sound
  - ▶ Manual (volunteer) monitoring common, but not scalable

#### In this talk...

#### Classification-based approaches to:

- 0. Bird species recognition
- 1. Bird sound detection (presence/absence)
- 2. Bird individual ID

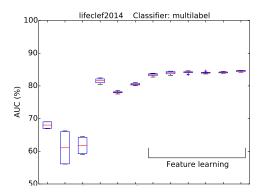
(By the way: we do more than just classification!)



## Species classification of bird sounds

In 2014: feature-learning approach to bird sound recognition

Dataset	Location	Total duration	Num items	Num classes	Labelling
lifeclef	Brazil	77.8 hours (12M frames)	9688	501	singlelabel



## Bird species classification: Warblr



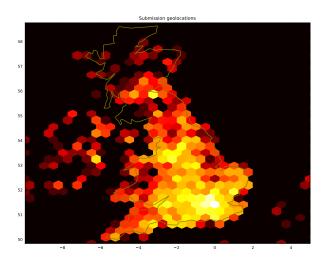


'Warblr' app - for Android and iOS



## Bird species classification: Warblr

Over 45,000 recordings submitted to our database ( $\approx 80/\text{day}$ )





Some of our users...



#### Some of our users...



## Part 1: Bird Audio Detection challenge

Many projects need reliable *detection* of bird sounds e.g. in long unattended recordings



But existing methods are not robust, not general-purpose enough, and need lots of manual tweaking/post-processing

## Bird Audio Detection challenge

#### We designed the Bird Audio Detection challenge

Dev set 1: 10k items, crowdsourced audio from around the UK (Warblr phone app)

Dev set 2: 7k items, crowdsourced audio from misc field recordings





Testing set: 10k items, remote monitoring, Chernobyl Exclusion Zone



## Bird Audio Detection challenge

- Training/testing sets differ in:
  - location
  - recording eqpt
  - species
  - class balance
  - background sounds
  - time of day
  - ▶ time of year
  - weather
  - **.**..
- How is a classifier meant to work in such mismatched conditions???



## Bird Audio Detection challenge: outcomes

- 30 teams submitted
- Strong results (up to 89% AUC)

User	Preview Score ili \$	Final Score <sub>i</sub> lı	Classifier	Domain adaptation	Ensembling \$
bulbul	88.9 %	88.7 %	CNN	Pseudo-labelling	Model averaging
cakir	88.3 %	88.5 %	CRNN	no	no (for strongest submission); Model averaging
topel	88.8 %	88.2 %	CNN-DenseNet	Pseudo-labelling	Multi-epoch, Model averaging(geom)
MarioElias	88.5 %	88.1 %	CNN, ExtraTreesRegressor	no	Model averaging (over 2 diverse methods)
adavanne	88.2 %	88.1 %	CRNN	Test mixing	no
Elias	88.0 %	88.0 %	CNN	no	Model averaging
kdrosos	86.1 %	85.8 %			

- Domain adaptation strategies
  - Pseudo-labelling, test mixing
  - Though not always needed



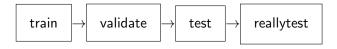
## So why do we evaluate using matched conditions?

- ▶ To study the classifier's behaviour
- Sometimes a practical application is in matched conditions
- Pragmatic reasons: only one dataset available; free choice of bootstrap/n-fold crossvalidation
- ...because our algorithms aren't good enough at avoiding confounds?

## Machine learning workflow



## Machine learning workflow



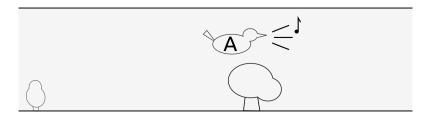
## Part 2: Identifying individual bird ID

Motivation: reduce intrusive monitoring (capturing/tagging/ringing)

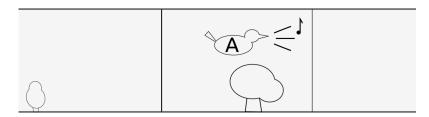
Many birds do have individual signature



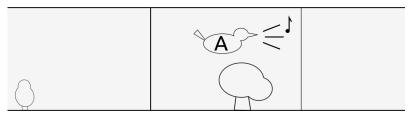
#### Data collection:



#### Data collection:

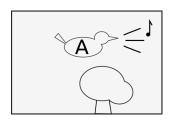


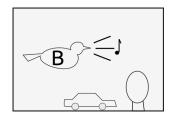
#### Data collection:

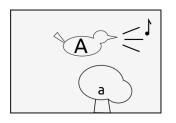


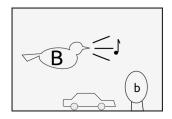
Bird ID: categorical label.

Is this the "same" task as species classification?

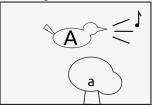


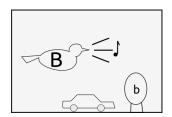




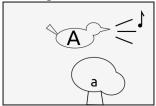


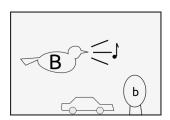
## Training set:



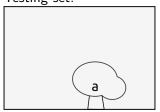


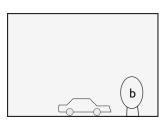
## Training set:

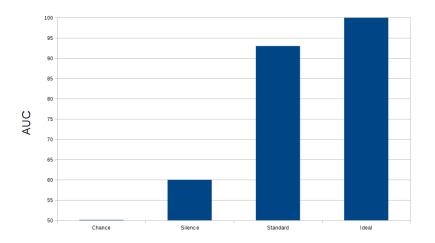




#### Testing set:

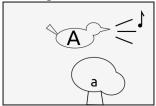


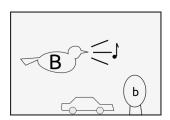




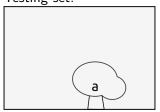


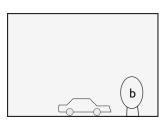
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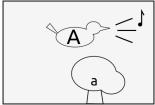


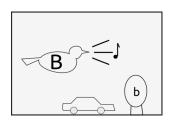
#### Testing set:



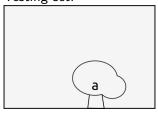


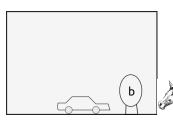
## Training set:





#### Testing set:





Training set: Express Yourself





Training set:

Express Yourself



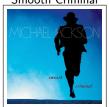


Testing set:

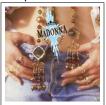
Like a Prayer





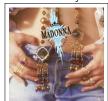


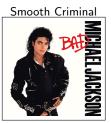
Training set: Express Yourself





Testing set: Like a Prayer





Training set:
\_Express Yourself



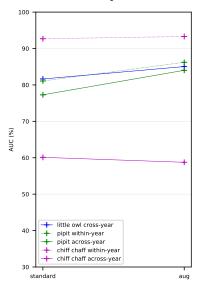


Testing set: Like a Prayer





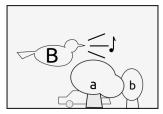
## Territorial birds: the territory is the 'album'



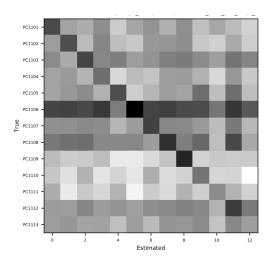


Data augmentation of the TESTING set (adversarial)

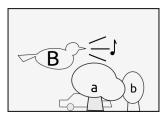
Measure the 'distractability' of the classifier when mismatched silence is added

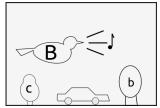


Measure RMSE in classifier decisions



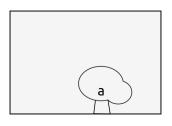
#### Data augmentation of the TRAINING set

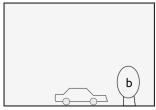




Each item gets new versions with added silence from each class

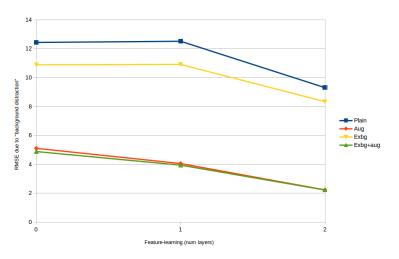
Finally we can add a new wastebasket class





NB not using the a/b labels here

#### Results



Plus silence-test result: 50% AUC



#### Conclusions

#### Outdoor bird sound recognition is tricky:

- The sounds (classes) are highly variable
- Many potential confounding factors for black-box ML
- 1. Bird Audio Detection Challenge:
  - Good detection, even in strongly mismatched conditions
  - Adaptation methods useful—though, not always needed?
- 2. Recognising individual bird ID:
  - Strong recognition possible (depending on species)
  - Silence is surprisingly useful for sound recognition!

Generally: make more use of mismatched-condition testing



## Thank you

#### Collaborators:

- Bird Audio Detection Challenge:
   Mike Wood (U of Salford), Yannis Stylianou (U of Crete),
   Hervé Glotin (U of Toulon), IEEE Signal Processing Society
- Recognising individual bird ID: Pavel Linhart (Adam Mickiewicz U / Praha U)

#### Machine Listening Lab:

