Do You Need Experts in the Crowd?

A case study in image annotation for marine biology

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An image labeling problem that requires specialists' knowledge

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What is in the picture?

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What is in the picture?

- A fish

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What is in the picture?

- A fish

Which species is it?

An image labeling problem that requires specialists' knowledge

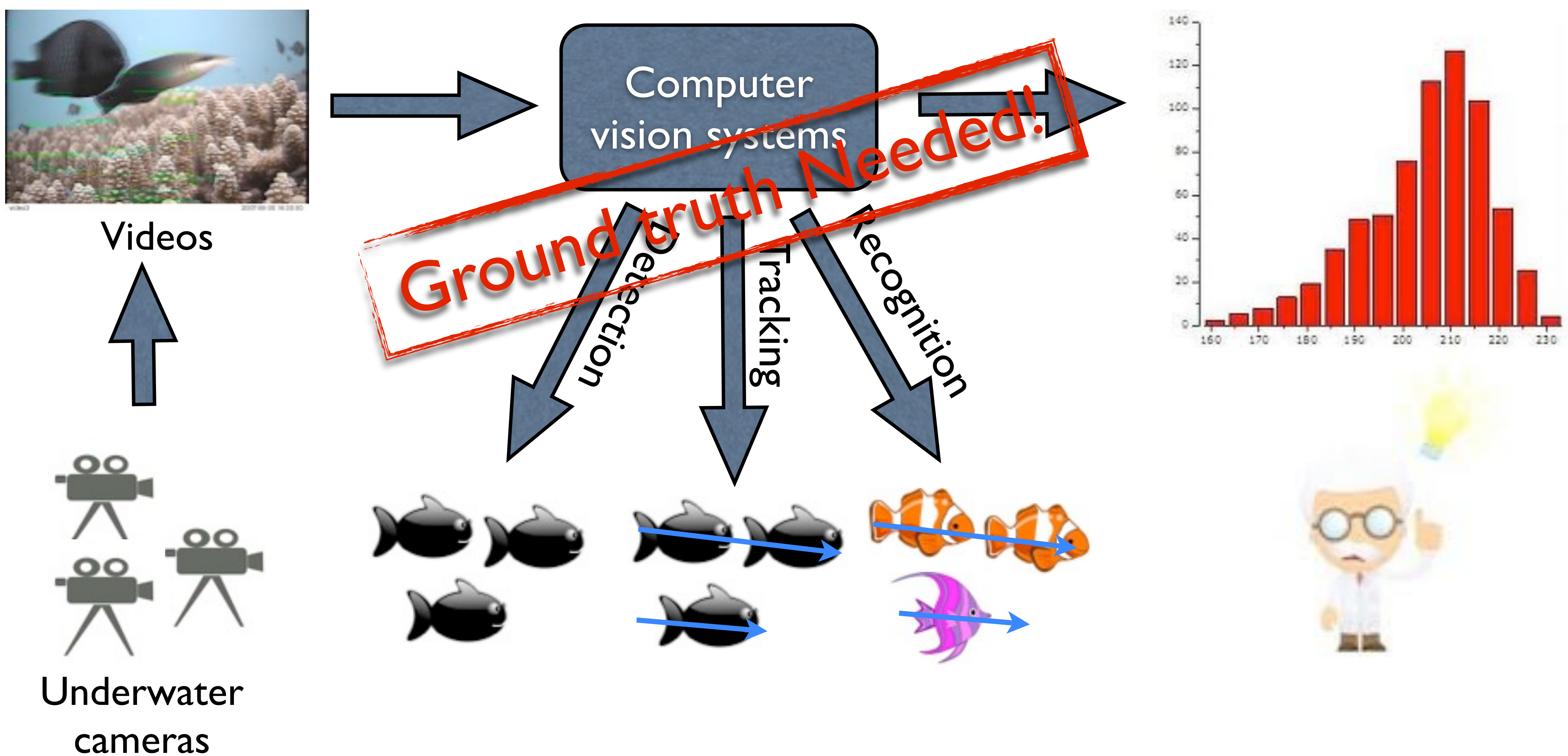
What is in the picture?

- A fish

Which species is it?

- Chaetodon trifascialis

Some background



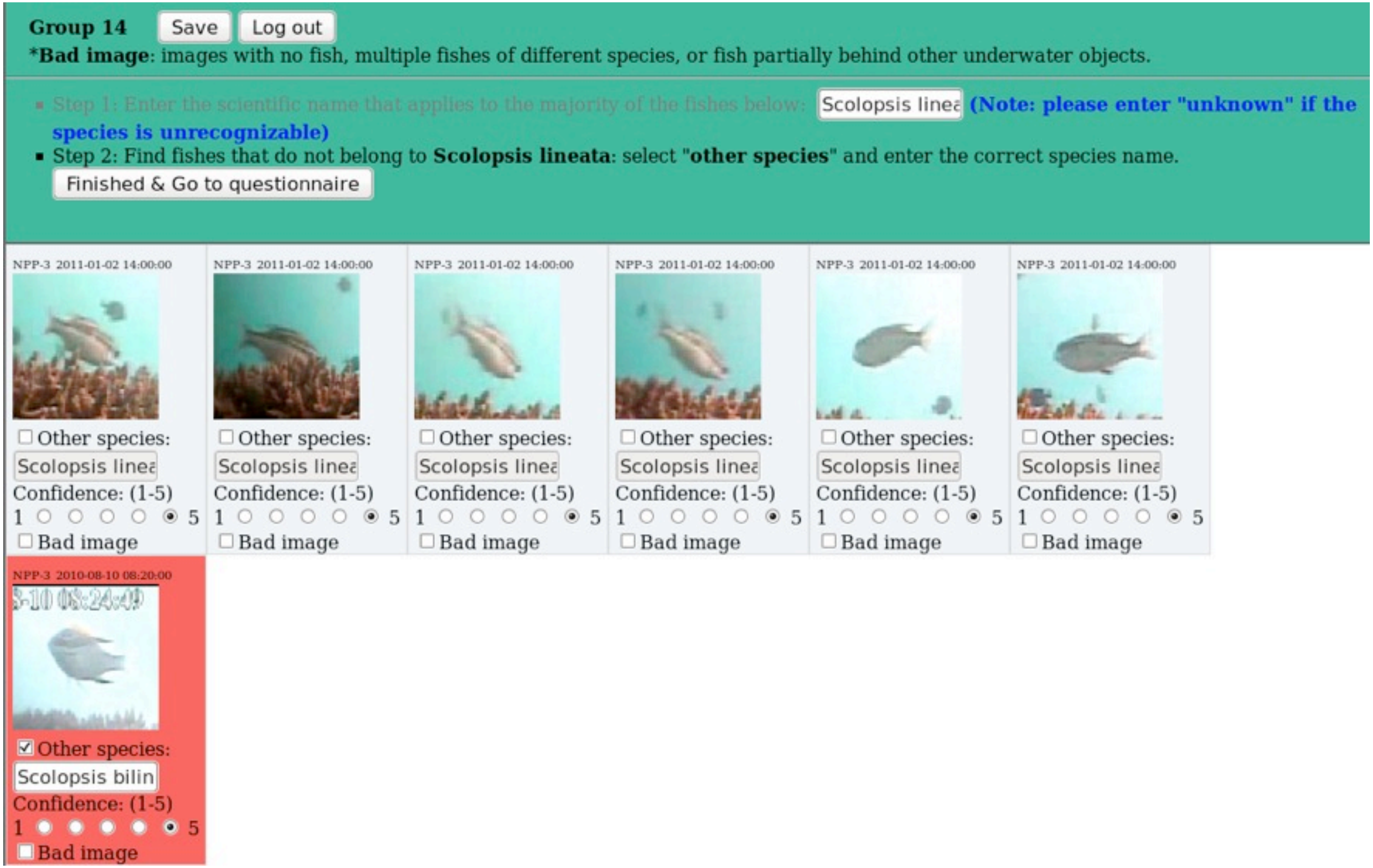
Fish species recognition

- Large set of labeled images/videos needed
- Expert knowledge needed
  - Non-experts often lack the knowledge needed to recognize a fish
  - Non-experts may not be able to map the common name of a fish to its scientific name
- Experts are expensive, rare resources
  - Even experts can have their expertise in different types of fish or fish in different areas

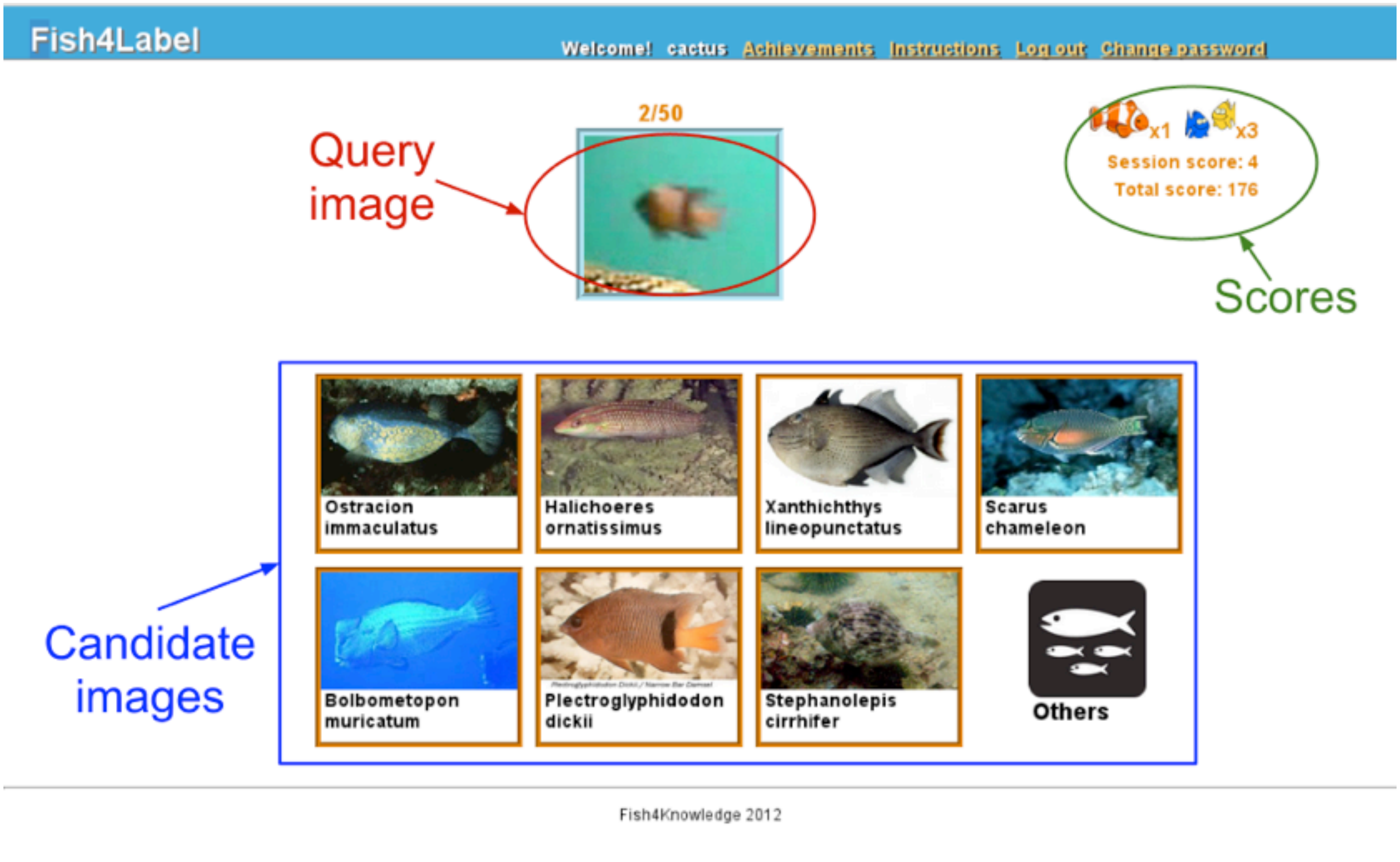
What can non-experts (not) do?

- Assumptions
  - Non-experts are not able to actively name fish species
  - But may able to passively judge if two fish are visually similar
- Possible tasks
  - Manual clustering
  - Classification with textbook images as category labels

An interface to support fish recognition with experts - collecting ground truth



An interface to support fish recognition with non-experts



Experts vs. non-experts

	Candidate source	Verification source
Experts	From their knowledge	Text book
Non-experts	Given by the system	System feedback

A study of non-expert annotators

- Can non-experts effectively separate similar species given the current setup?
- Can non-experts learn during the labeling process, e.g., from the system feedback?

A study of non-expert annotators

- Controlled experiments
  - 190 expert labeled images
  - 3 experts provided ground truth
  - 2 simulated labeling conditions

Exp	Candidate type	#Users	# Labels/image
1	True label is present together with similar but incorrect labels	22	19
2	In 25% of the cases, true labels were removed, while similar but incorrect labels are present	32 (28 +4)	13

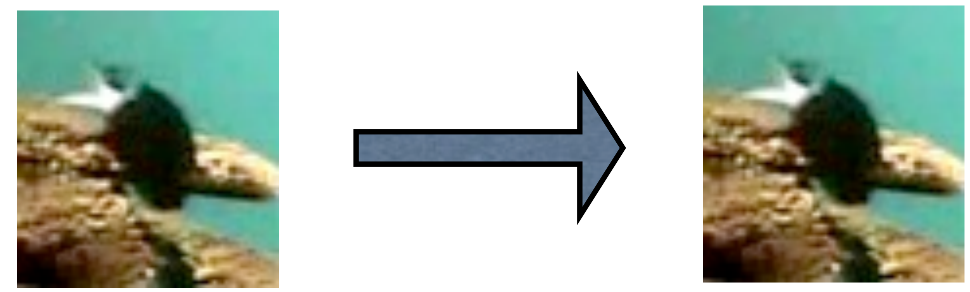
Reliability of non-expert labels

- Compared to expert labels
  - agreement in terms of Cohen's kappa;
  - non-experts labels aggregated by simple majority voting

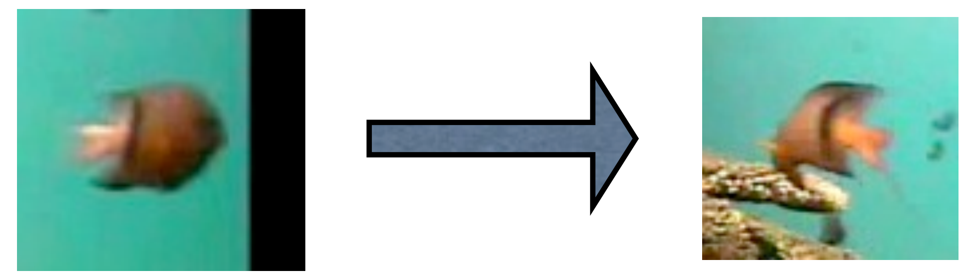
Expr.	Expert vs.	Species level	Family level
-	expert	0.55~0.67	0.75~0.85
1	non-experts	0.55~0.65	0.72~0.83
2	non-experts (new)	0.45~0.65	0.68~0.73
2	non-experts (old)	0.53~0.68	0.74~0.80

Do non-experts learn?

- Two types of learning
  - Memorization



  - Generalization



Exp.	Memorization			Generalization		
labels	1	2	3	1	5	10
1	0.30	**0.38**	**0.46**	0.42	**0.51**	**0.59**
2 (new)	0.30	**0.4**	**0.44**	0.37	**0.58**	**0.62**
Average user scores that are normalized by the maximum score one can achieve at each label						

CWI

Conclusions

- Converting an active labeling task to a passive image comparing task allows non-expert users to perform image labeling task that requires highly specialized knowledge
  - In ideal case, non-experts can achieve an agreement with experts comparable to that achieved between experts
  - In the more confusing case, novice non-experts are more likely get confused compared to experienced users
- Non-expert users are able to learn in terms of both memorization and generalization

CWI

Reliability of non-expert labels

- Accuracy of aggregated labels
  - Novice users are likely to be confused when correct labels are not present

Expr.	User type	Species level		Family level	
		ndcg@1	ndcg@5	ndcg@1	ndcg@5
1	22 new users	0.84	0.88	0.93	0.94
2	28 new users	0.72(<)	0.77(<)	0.86(<)	0.94
2	4 old users	0.88	0.86	0.91	0.94

Main findings

- When expert feedback is available
  - In ideal case, non-experts can achieve an agreement with experts comparable to that achieved between experts
  - In the more confusing case, novice non-experts are more likely get confused
  - Implication: It's important to select good candidates
- When expert feedback is not available
  - Can aggregation on noisy feedback generate reasonable results?
  - If not:
    - More sophisticated aggregation method
    - More users - reach sufficient confidence
    - Training session with expert feedbacks before labeling

Main findings (2)

- Non-experts learn while playing the game
  - memorizing - performance on same image improves
  - generalization - performance on same species improves
- When there is no feedback (3 users)
  - 3 users set the initial labels for the peer-agree runs - work independently
  - User score with experts:
    - each judgement gets 0, 1, 2, 3 points if agree with 0, 1, 2, or 3 experts
    - 50 images per session
  - Users seem to be able to improve without feedback (Need more evidence), to what limit?

user	session 1	session 2	session 3	session 4
1	92	99	116	101
2	69	94	90	99
3	83	81	93	90

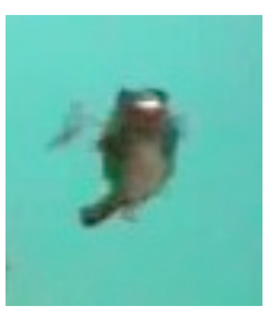
Some images are more confusing than others

- Let clarity score = #majority vote/#vote
- Per image clarity score in Experiment 1

4/23 votes

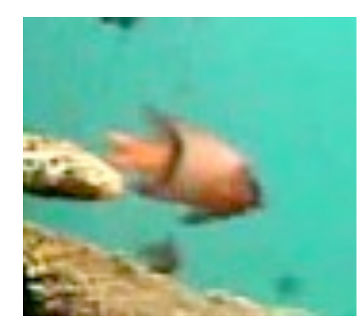
4/23 votes

4/22 votes



25/25 votes

24/24 votes



24/24 votes