# Query Learning for Fish Identification

Gaoang Wang[1], Jenq-Neng Hwang[1], Farron Wallace[2], Craig S. Rose[2]

[1]University of Washington

[2]National Oceanic and Atmospheric Administration

ELECTRICAL ENGINEERING

UNIVERSITY of WASHINGTON

NOAA

# Outline

- Introduction and Overview
  - Fish Identification
  - Query Learning
- Query Learning with Diversity Constraint
- Combine Semi-Supervised Learning
- Results

# Fish Identification

- Want to know the species of the fish given input images [1].

[1] Wang, G., Hwang, J. N., Williams, K., Wallace, F., & Rose, C. S. (2016, December). Shrinking Encoding with Two-Level Codebook Learning for Fine-Grained Fish Recognition. In *Computer Vision for Analysis of Underwater Imagery (CVAUI), 2016 ICPR 2nd Workshop on* (pp. 31-36). IEEE.

# Fish Identification Results

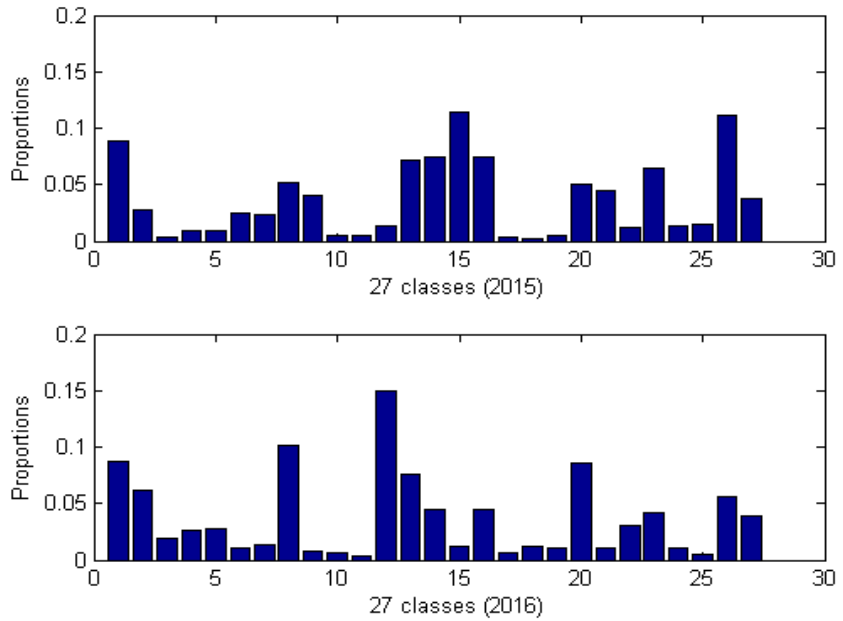
- Datasets
  - 2015 chute data (8835 images with 27 classes)
  - 2016 chute data (5032 images with 27 classes)
- Same dataset split into training and testing

| Training Data | Testing Data | Cross Validation | Accuracy (%) |
|---|---|---|---|
| 2015 | 2015 | 10-fold | 96.1 |
| 2016 | 2016 | 10-fold | 98.5 |
| 2015+2016 | 2015+2016 | 10-fold | 96.9 |

# Some Problems with Supervised Learning

- If large difference exists between training and testing datasets
  - Different camera distortions
  - Different colors
  - Different distributions of species

Species Distributions



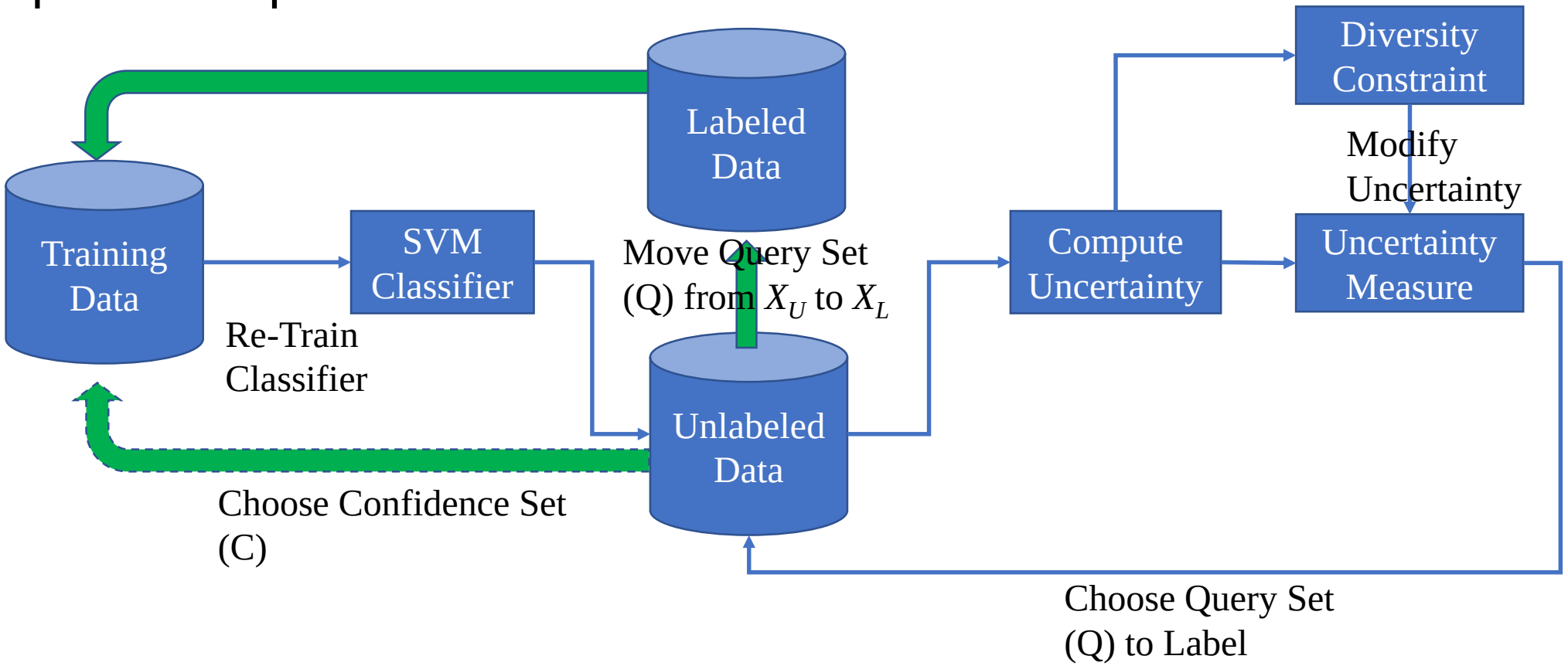

| Fish ID | Fish Name |
|---|---|
| 1 | Arrowtooth Flounder |
| 2 | Atka Mackeral |
| 3 | Bathymaster Signatus |
| 4 | Berryteuthis Magister |
| 5 | Blackspotted Rockfish |
| 6 | Dover Sole |
| 7 | Dusky Rockfish |
| 8 | Flathead Sole |
| 9 | Giant Grenadier |
| 10 | Gorgonocephalus Eucnemis |
| 11 | Harlequin Rockfish |
| 12 | Northern Rock Sole |
| 13 | Northern Rockfish |
| 14 | Pacific Cod |
| 15 | Pacific Halibut |
| 16 | Pacific Ocean Perch |
| 17 | Pacific Octopus |
| 18 | Paragorgia Arborea |
| 19 | Prowfish |
| 20 | Rex Sole |
| 21 | Sablefish |
| 22 | Shortraker Rockfish |
| 23 | Shortspine Thornyhead |
| 24 | Strongylocentrotus sp |
| 25 | Sturgeon Poacher |
| 26 | Walleye Pollock |
| 27 | Yellow Irish Lord |

- Comparison with across-year datasets

| Training Data | Testing Data | Acc (%) |
|---|---|---|
| 2015 dataset (5%) | 2015 dataset (95%) | 83.9 |
| 2016 dataset (5%) | 2016 dataset (95%) | 86.6 |
| 2015 dataset (100%) | 2016 dataset (100%) | 69.5 |
| 2015 dataset+2016 dataset (5%) | 2016 dataset (95%) | 88.1 |

# Query Learning (Active Learning)

- Goal: iteratively select informative samples for human labeling to improve the performance of the classifier.



# Uncertainty Measure

- **Best vs. Second Best (BvSB)** Strategy:
  - Predictions from multi-class SVM classifier

    $p = [p_1, p_2, \ldots, p_K]$ for $K$ classes.

    $p_k$ is the likelihood of the sample $x$ belongs to $k$-th class.

  - Define the uncertainty by

    $f(x) = \max\left(1 + p_{k_2} - p_{k_1}, 0\right) \in [0, 1].$

$k_1, k_2$: the first two most likely predicted classes.
$x$ : arbitrary unlabeled sample.
$f$: uncertainty score

# Query Learning with Diversity Constraint

- Motivation: choose large uncertain samples with large diversity.

Fast greedy search:

1. Choose the top 1 most uncertain sample $x_k$ to the query set.

$$k^t = \arg\max_i f_i^{t-1}$$

2. Decrease the uncertainty of all samples $x_i$ using a Gaussian kernel, like

$$f_i^t = f_i^{t-1} - f_k^{t-1} \exp\left(-\frac{\| x_i - x_k \|^2}{\sigma^2}\right), \forall i$$

where $f_i$ and $f_k$ are the uncertainty scores of $x_i$ and $x_k$.

3. Go to step 1 until we select enough samples.

$x$: unlabeled samples.
$f$: uncertainty score.
**Red**: large uncertainty sample.
**Green**: small uncertainty sample.
**Black**: selected sample.

Unlabeled samples

# Query Learning with Diversity Constraint

- Motivation: choose large uncertain samples with large diversity.

Fast greedy search:

1. Choose the top 1 most uncertain sample $x_k$ to the query set.

$$k^t = \arg\max_i f_i^{t-1}$$

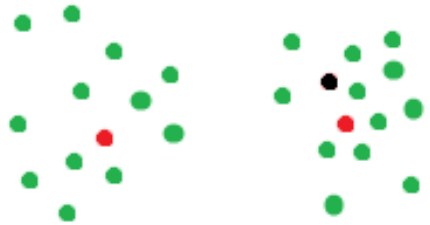
2. Decrease the uncertainty of all samples $x_i$ using a Gaussian kernel, like

$$f_i^t = f_i^{t-1} - f_k^{t-1} \exp\left(-\frac{\| x_i - x_k \|^2}{\sigma^2}\right), \forall i$$

where $f_i$ and $f_k$ are the uncertainty scores of $x_i$ and $x_k$.

3. Go to step 1 until we select enough samples.

$x$: unlabeled samples.
$f$: uncertainty score.
**Red**: large uncertainty sample.
**Green**: small uncertainty sample.
**Black**: selected sample.



Unlabeled samples

# Query Learning with Diversity Constraint

- Motivation: choose large uncertain samples with large diversity.

Fast greedy search:

1. Choose the top 1 most uncertain sample $x_k$ to the query set.

$$k^t = \arg\max_i f_i^{t-1}$$

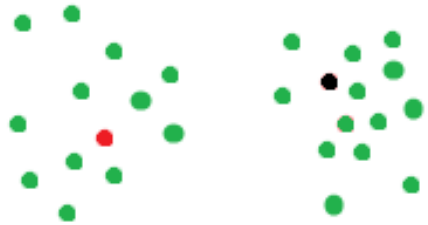
2. Decrease the uncertainty of all samples $x_i$ using a Gaussian kernel, like

$$f_i^t = f_i^{t-1} - f_k^{t-1} \exp\left(-\frac{\| x_i - x_k \|^2}{\sigma^2}\right), \forall i$$

where $f_i$ and $f_k$ are the uncertainty scores of $x_i$ and $x_k$.

3. Go to step 1 until we select enough samples.

$x$: unlabeled samples.
$f$: uncertainty score.
**Red**: large uncertainty sample.
**Green**: small uncertainty sample.
**Black**: selected sample.



Unlabeled samples

# Query Learning with Diversity Constraint

- Motivation: choose large uncertain samples with large diversity.

Fast greedy search:

1. Choose the top 1 most uncertain sample $x_k$ to the query set.

$$k^t = \arg\max_i f_i^{t-1}$$

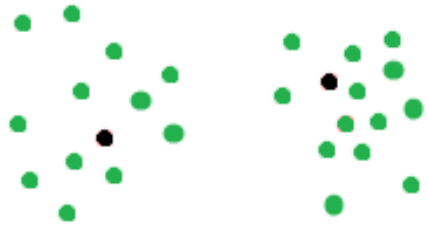
2. Decrease the uncertainty of all samples $x_i$ using a Gaussian kernel, like

$$f_i^t = f_i^{t-1} - f_k^{t-1} \exp\left(-\frac{\| x_i - x_k \|^2}{\sigma^2}\right), \forall i$$

where $f_i$ and $f_k$ are the uncertainty scores of $x_i$ and $x_k$.

3. Go to step 1 until we select enough samples.

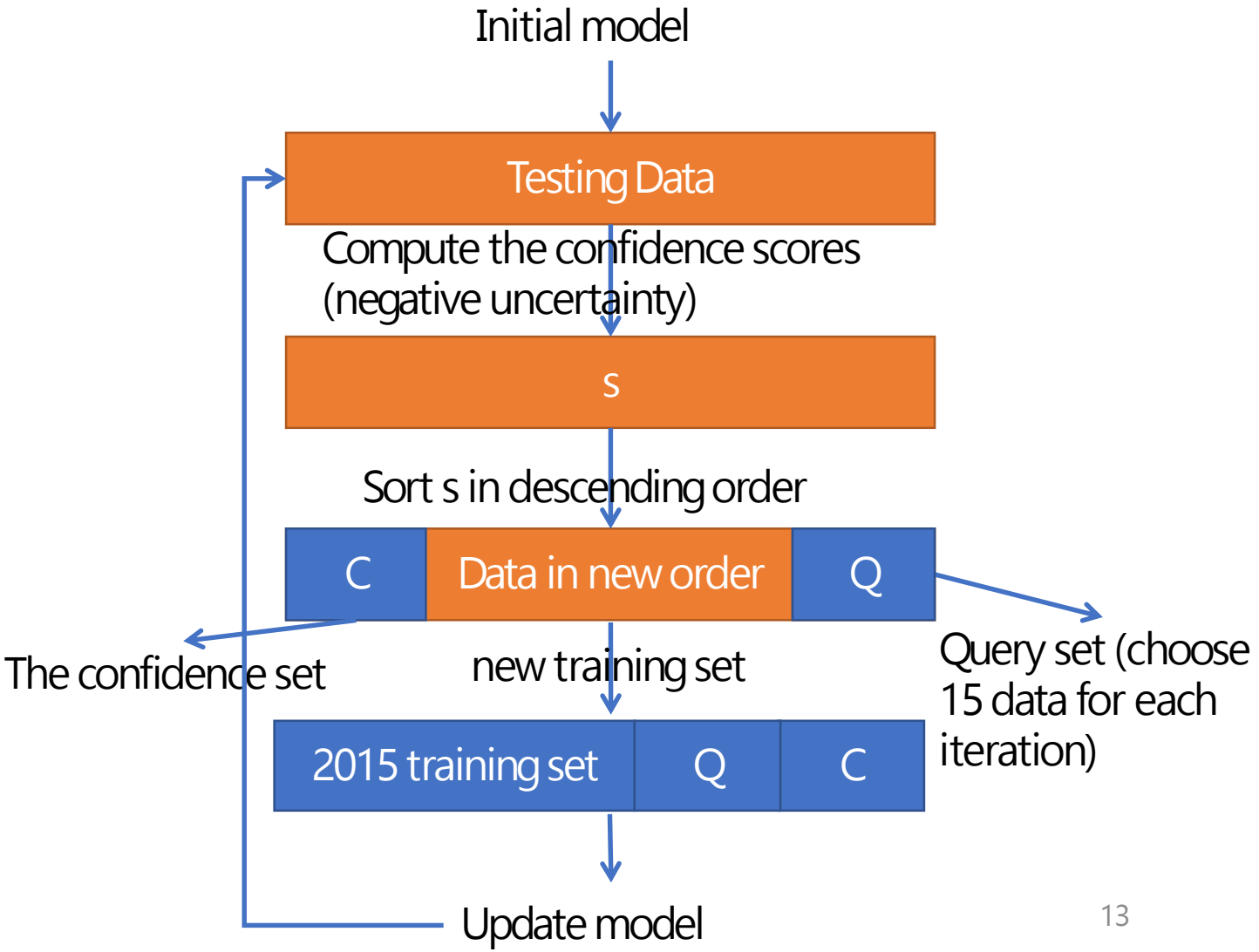
$x$: unlabeled samples.
$f$: uncertainty score.
**Red**: large uncertainty sample.
**Green**: small uncertainty sample.
**Black**: selected sample.



Unlabeled samples

# Combine Semi-Supervised Learning

- Train the classifier based on 2015 dataset.
- Test the classifier on 2016 dataset. For each testing data, define a confidence score based on the uncertainty measure.
- Select 15 samples using query learning with diversity constraint for human labeling at each iteration. (Stop human labeling if the labeled set achieves 5% of the testing data.)
- Adaptively re-train the classifier.

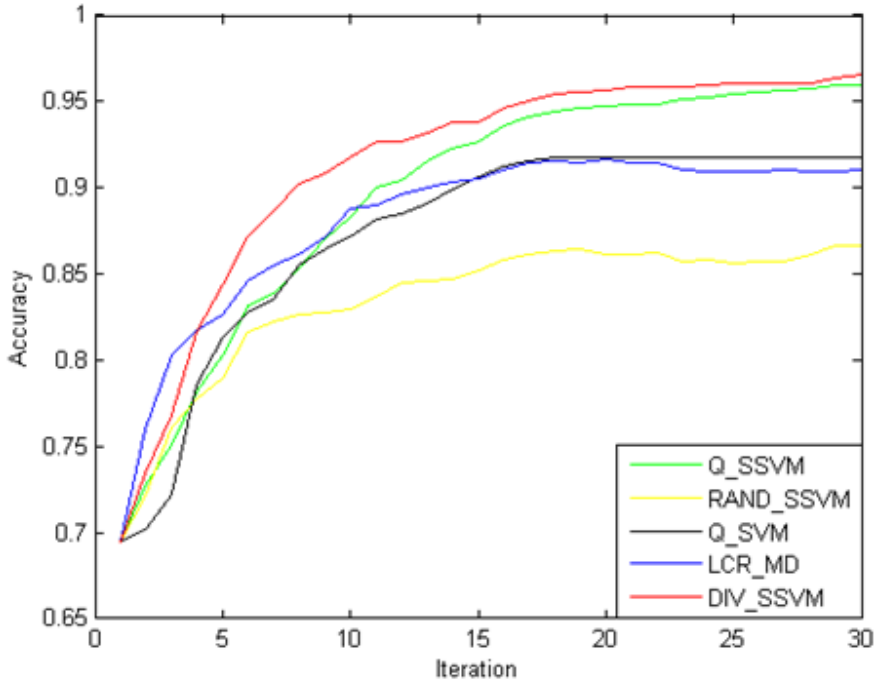


# Summary of Query Learning

- Some Properties:
  - 1. Iteratively select informative samples for human labeling.
  - 2. Consider uncertainty and diversity in the selection.
    - Uncertainty: ambiguity of unlabeled data.
    - Diversity: data with large dissimilarity.
  - 3. Combine semi-supervised learning.
    - Add very confident unlabeled data to the training set.
  - 4. Update training samples and re-train the classifier for each iteration.

# Results

- Training set: 2015 dataset+2016 dataset (5%)
- Accuracy: 96.8% (88.1% to 96.8%)




Q_SSVM: Query learning with semi-supervised learning without diversity constraint.
RAND_SSVM: Query learning based on random sample selection.
Q_SVM: Query learning without semi-supervised learning.
LCR_MD: (Leng et al. 2013).
DIV_SSVM: Query learning with both semi-supervised learning and diversity constraint.

*Thank you!*

# Q & A