Active Learning Approaches for Deforested Area Classification

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Introduction

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INPE

Imazon

GLOBAL FOREST WATCH

forestWATCHERS .net

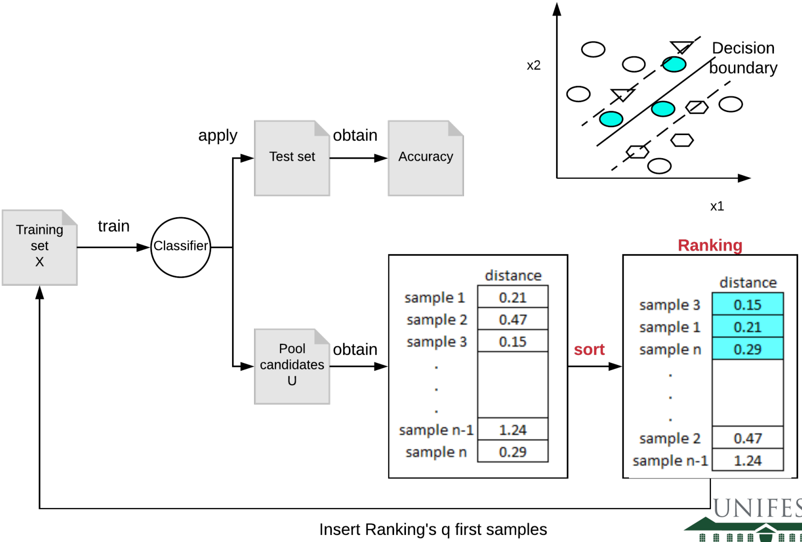
Algorithm 1 GENERAL PROCEDURE FOR ACTIVE LEARNING

Inputs : Initial training set X
Pool of training samples candidates U
Number of samples q to add at each iteration

repeat
  Train a model with current training set X.
  for *each candidate in* U **do**
    Evaluate a user-defined heuristic
  end
  Rank the candidates in U according to the score of the heuristic.
  Select the q most interesting samples.
  The user assigns a label to the selected samples.
  Add these samples to the training set X.
  Remove the samples from the pool of candidates U.
until *stop criteria is reached*;

Baseline Approaches

Margin Sampling (MS)



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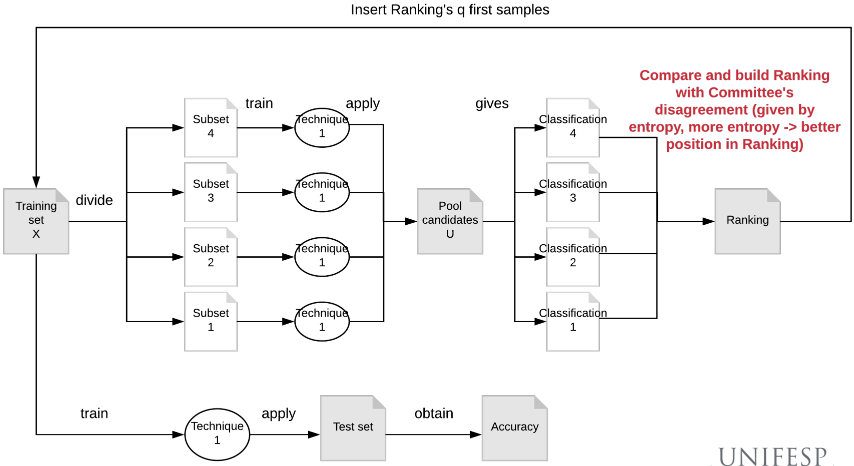
Baseline Approaches

Normalized Entropy Query-by-Bagging (nEQB)



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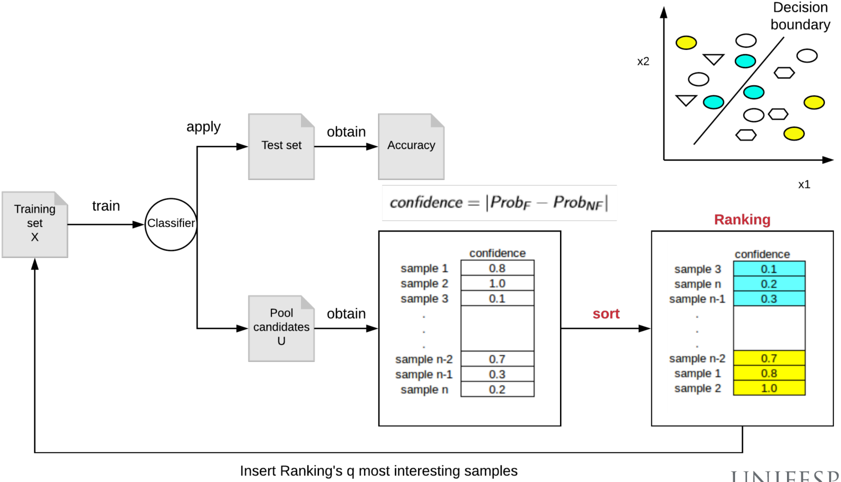
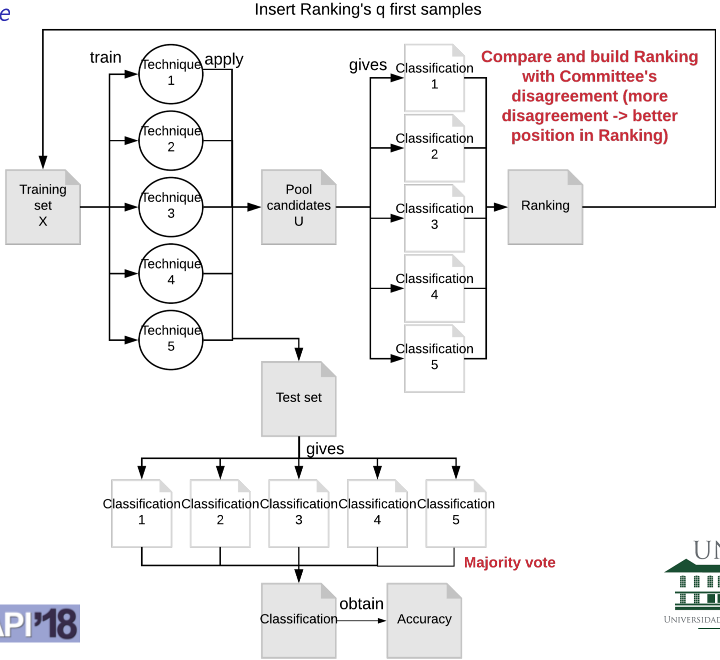
Proposed Active Learning Approaches

Confidence Heuristics: Low confidence, High confidence and Hybrid confidence





Insert Ranking's q first samples
train
apply
Technique 1
Technique 2
Technique 3
Technique 4
Technique 5
Training set X
Pool candidates U
gives
Classification 1
Classification 2
Classification 3
Classification 4
Classification 5
Compare and build Ranking with Committee's disagreement (more disagreement -> better position in Ranking)
Ranking
Test set
gives
Classification 1
Classification 2
Classification 3
Classification 4
Classification 5
Majority vote
Classification
obtain
Accuracy

Differences among Baseline and Proposed Approaches

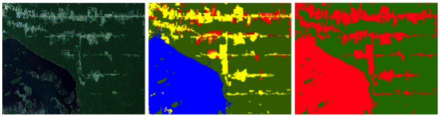
- Proposed approaches use simpler classifiers: Baseline uses Support Vector Machines (SVMs)
- Free availability: Baseline uses MATLAB
- Baseline tunes the classifier's parameters; ours don't
- Processing time
- Classifiers used in *Committee* are used to classify the test set $\rightarrow$ majority vote to decide final classification
  - Different from nEQB where SVM applied in test set is different from SVMs used in the Committee $\rightarrow$ can be costly
  - Don't need to divide the training set in subsets

- Images from Landsat-8 and PRODES (Rondônia 2016)

Cross-validation experiment

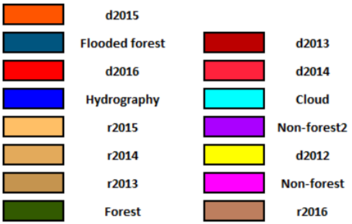
(a) Original Image. (b) PRODES Image. (c) Binary Image.

Cross-dataset experiment



(a) Original Image. (b) PRODES Image. (c) Binary Image.

Color code

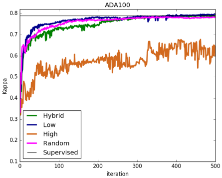


Experimental Methodology

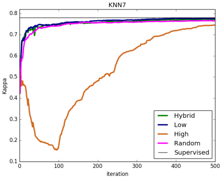
- Classifiers from Scikit-Learn: AdaBoost (ADA), Gradient Boosting Classifier (GBC), *k*-Nearest Neighbors (kNN), Multi-Layer Perceptron (MLP), Gaussian Naïve Bayes (GNB), Linear Discriminant Analysis (LDA) and Random Forest (RF);
- Baseline approaches (Margin Sampling and Normalized Entropy Query-by-Bagging) implemented by Tuia et al., 2011;
- 5-fold cross-validation with *Confidence Heuristics*, *Committee* and baseline approaches;
- Cross-dataset with best approaches from cross-validation experiment

Results (Cross-validation Scenario)

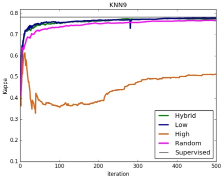
Effectiveness Analysis among Active Learning Approaches



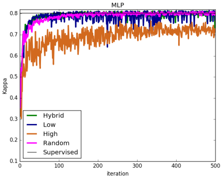
(a) ADA



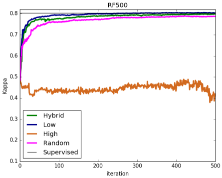
(b)kNN7



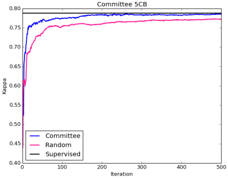
(c)kNN9



(d) MLP

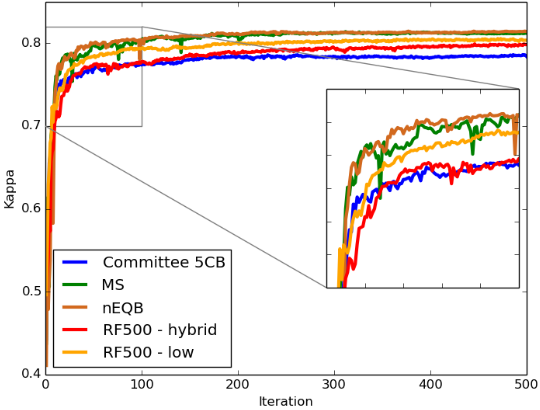


(e) RF500



(f) Committee

Results (Cross-validation Scenario)



Results (Cross-Dataset Scenario)

TABLE I
EFFECTIVENESS RESULTS AMONG THE BEST AL APPROACHES FOR A CROSS-DATASET SCENARIO. AVERAGE KAPPA INDEX MEANS THE ARITHMETIC MEAN OF THE KAPPA INDEX FOR THE FIVE TRAINING SETS.

Technique	Iteration Cut-Points (Average Kappa Index ± CI 95%)						Supervised
	10	**20**	**30**	**40**	**50**	**100**	
Committee 5CB	0,39 ±0,20	**0,60±0,24**	**0,46±0,22**	0,33±0,03	0,32±0,03	**0,37±0,16**	**0,68±0,10**
MS [3], [21], [27], [28]	**0,49±0,38**	0,57±0,30	0,16±0,17	0,26±0,28	0,03±0,12	0,12±0,34	0,03±0,21
nEQB [3], [26]	0,35±0,30	0,11±0,36	0,17±0,37	-0,06±0,26	-0,22±0,18	-0,18±0,21	
RF - hybrid	0,22±0,14	0,33±0,02	0,27±0,05	0,29±0,07	0,29±0,07	0,31±0,03	0,30±0,12
RF - low	0,48±0,26	0,33±0,05	0,36±0,02	**0,36±0,02**	**0,34±0,02**	0,35±0,02	

TABLE II
EFFECTIVENESS RESULTS AMONG THE BEST AL APPROACHES FOR A CROSS-DATASET SCENARIO. AVERAGE OA MEANS THE ARITHMETIC MEAN OF THE OA FOR THE FIVE TRAINING SETS.

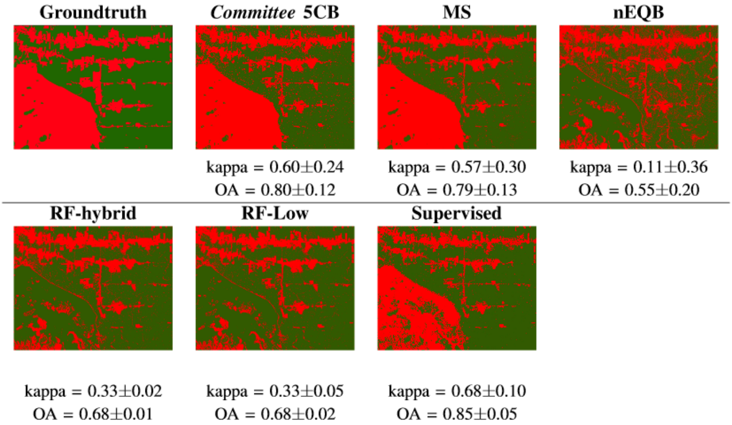
Technique	Iteration Cut-Points (Average OA ± CI 95%)						Supervised
	10	**20**	**30**	**40**	**50**	**100**	
Committee 5CB	0,70±0,09	**0,80 ±0,12**	**0,74±0,10**	0,68±0,02	0,68±0,01	0,70 ±0,07	**0,85±0,05**
MS [3], [21], [27], [28]	0,73±0,22	0,79±0,13	0,54±0,10	0,60±0,16	0,53±0,05	0,58±0,16	0,50±0,10
nEQB [3], [26]	0,68±0,15	0,55±0,20	0,57±0,20	0,43±0,15	0,35±0,08	0,38±0,12	
RF - hybrid	0,62±0,07	0,68±0,01	0,65±0,03	0,66±0,04	0,66±0,03	0,67±0,02	0,66±0,05
RF - low	**0,75±0,12**	0,68±0,02	0,70±0,01	**0,70±0,01**	**0,69±0,01**	**0,70±0,01**	

Results (Cross-Dataset Scenario)

TABLE III
CROSS-DATASET EXPERIMENT'S AVERAGES OF KAPPA INDEX AND OA.

Technique	Average Kappa Index	Average OA
Committee 5CB	0,41±0,10	0,72±0,05
MS	0,27±0,21	0,63±0,11
nEQB	0,03±0,22	0,49±0,13
RF - hybrid	0,28±0,04	0,66±0,02
RF - low	0,37±0,06	0,70±0,02

Results (Cross-Dataset Scenario)



Conclusion

- Active Learning approaches were validated for the dataset
- High confidence delivered the worst results (as expected)
- Low and Hybrid confidence had similar results than supervised learning using much fewer samples
- *Committee* and RF with 500 estimators
  - similar results than the baseline for the cross-validation experiment (without tuning classifier's parameters)
  - better results than the baseline for the cross-dataset experiment
  - better processing time and free availability in comparison with the baseline

Future Work

- More images to improve the cross-dataset experiment
- Study the dataset's noise
- Use of Citizen Science instead of specialists to classify the pixels
  - Prototype being made at Zooniverse, a Citizen Science web portal (`www.zooniverse.org/projects/dallaqua/foresteyes`)
- Study of semantic segmentation with deep learning to be used in an Active Learning procedure with volunteer's classification

Acknowledgment

CAPES

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