

Ensemble Approaches

for classification and Regression

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Overview

1. Introduction to Ensemble approaches

- key ideas

2. Approaches

- 1. Voting

- 2. Mixture of Experts, Stacking

- 3. Bagging, Boosting, Cascade

3. Case Study

- 1. NDSB - Classification

- 2. Liberty Mutual - Regression

Before we go....

Termonology

1. Training set
2. Validation set
3. Testing set
4. Features
5. Underfit and Overfit



class->	A	B	C
y_i	0.7	0.1	0.2

What is Ensemble ?

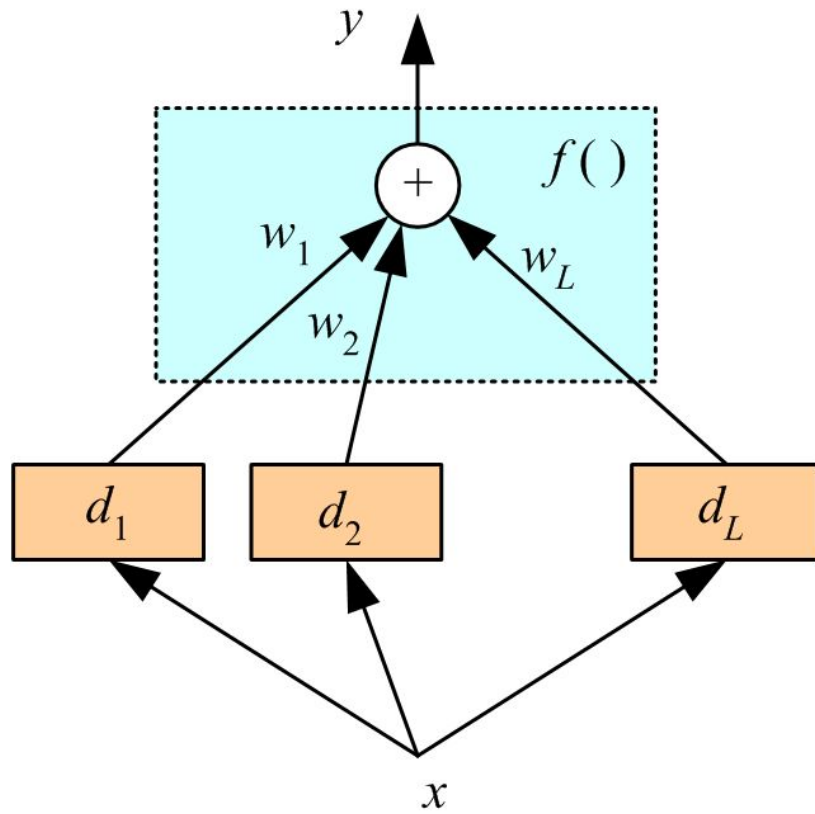
Combining multiple models, learners or Estimators

- What models to combine?
- How to combine?

Key Ideas

1. Combine different Learners/Estimators/Models
 - Average, weighted Average etc
 - **Voting**
 - **Mixture of experts**
 - **Stacking**
2. **NOT** to combine strong or very accurate (should be complement)
 - different base learners/estimators
 - different hyperparameters of same learners/estimators
3. Different learners/estimators/modals with different set of features
4. Different learners/estimators/modals with different training sets
 - **Bagging, Boosting, Cascading**

Voting



$$y_i = \sum_j w_j d_{ji} \text{ where } w_j \geq 0, \sum_j w_j = 1$$

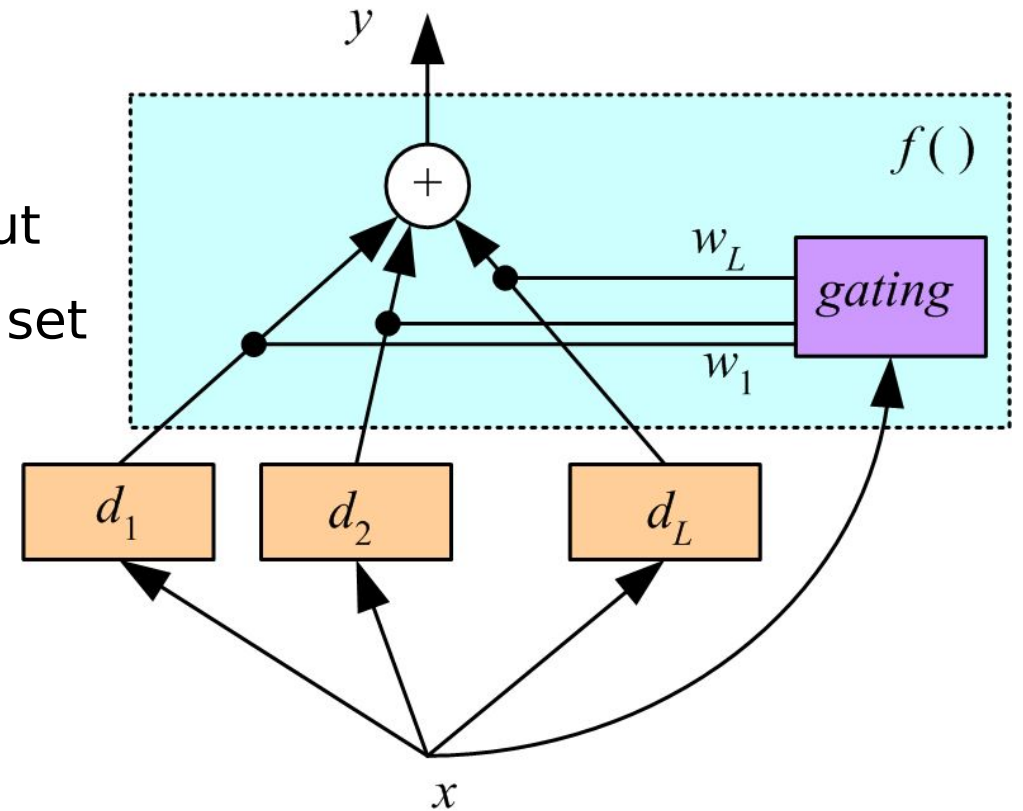
Rule	Fusion function $f(\cdot)$
Sum	$y_i = \frac{1}{L} \sum_{j=1}^L d_{ji}$
Weighted sum	$y_i = \sum_j w_j d_{ji}, w_j \geq 0, \sum_j w_j = 1$
Median	$y_i = \text{median}_j d_{ji}$
Minimum	$y_i = \min_j d_{ji}$
Maximum	$y_i = \max_j d_{ji}$
Product	$y_i = \prod_j d_{ji}$

Mixture of Experts

(Jacobs et al., 1991)

- Experts or gating can be nonlinear
- Weights may be different for different input
- Each learner become experts of different set of inputs

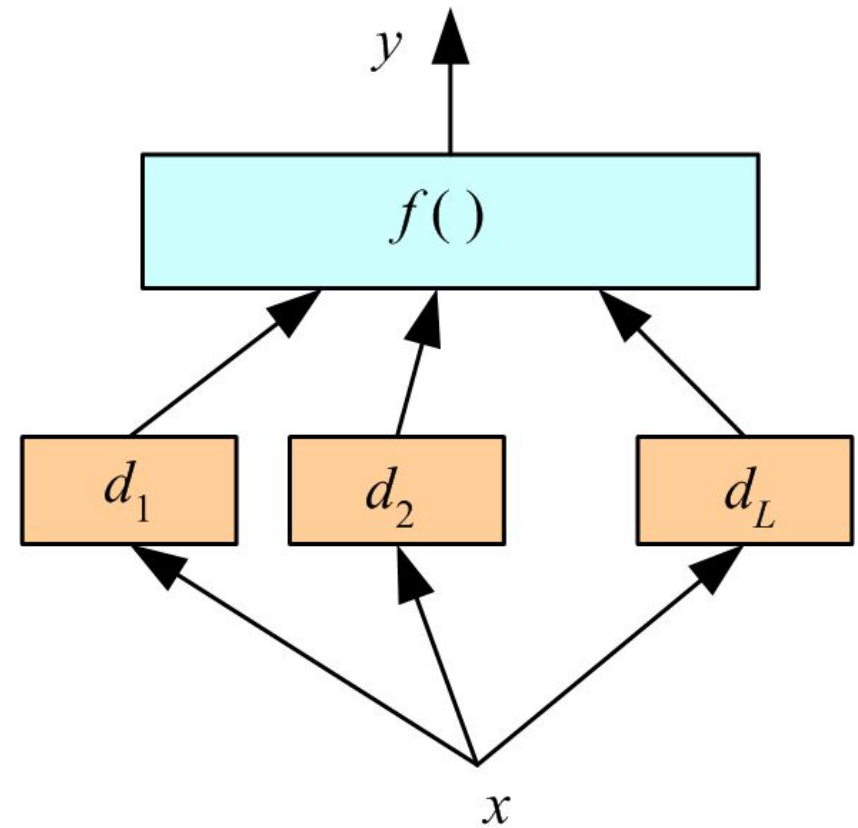
$$y = \sum_{j=1}^L w_j(x) d_j$$



Stacking

(Wolpert, 1992)

- Combiner $f(\cdot)$ is also learner
- $f(\cdot)$ may not be even linear
- Need to be trained on non-training data



Bagging

(Breiman 1996)

- L learner are trained with slightly different L training sets
- $X^1, X^2 \dots \dots X^L \subseteq X$
- Done by bootstrap
- Some sample might be many times and some might not be at all
- All sets of samples X^i almost similar, but slightly different
- For large training set, simple approach is to divide with overlapping sets
- Works better when learning algo is unstable (sensitive to small change)

Boosting – Adaboost

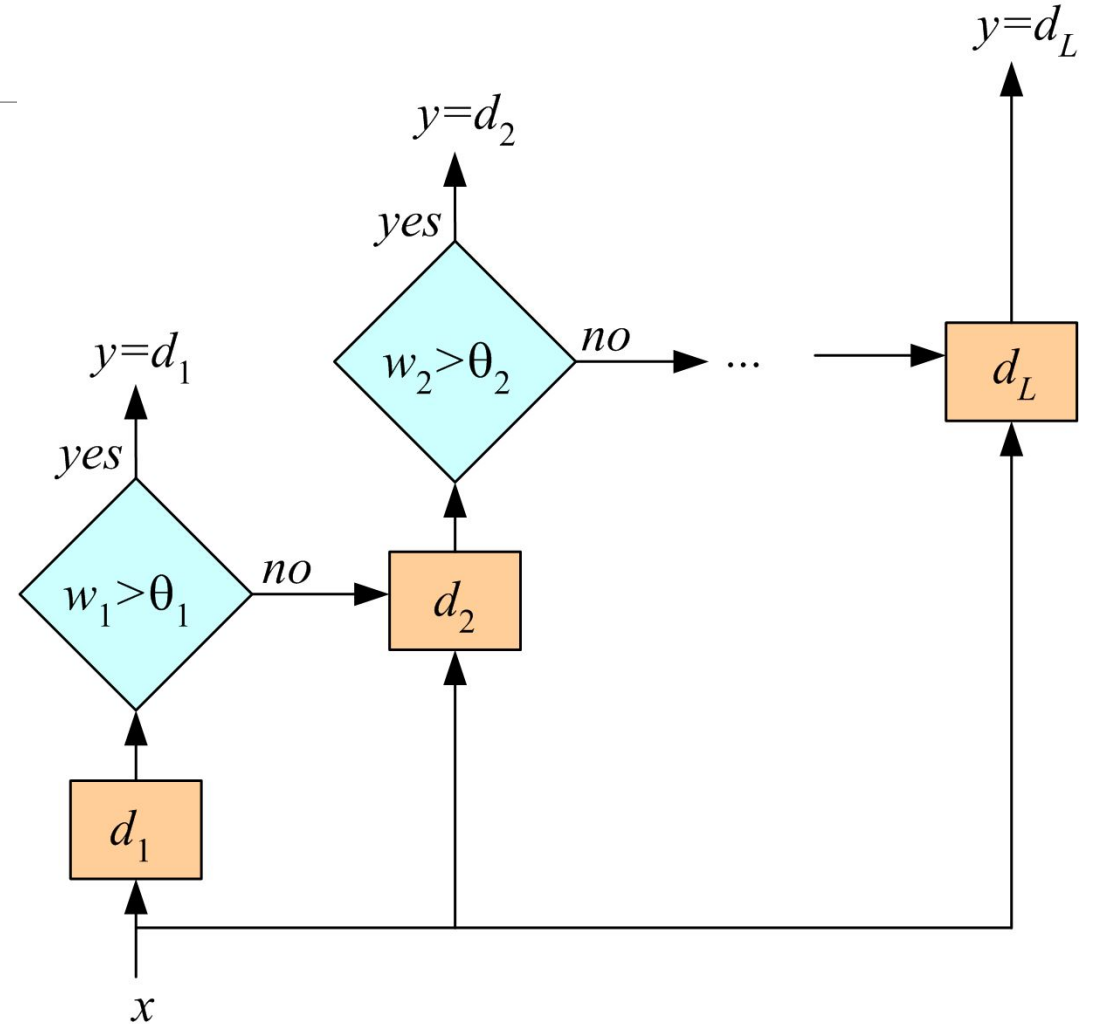
Original Idea - (Schapire 1990), Adaboost - (Freund and Schapire 1996)

- In Bagging - learners being complementary depends on chances
- In Boosting, complementary learners are actively generated
- L Learners: $d_1 d_2 \dots d_L$
- d_{j+1} focus on instance more which was misclassified by d_j

Cascading

(Kaynak and Alpaydın 2000)

- Almost same idea as boosting
- Only difference is next model is trained when previous model was not confident enough (unlike misclassifies)



Case Study

1. NDSB – Classification



(<http://www.datasciencebowl.com/>)

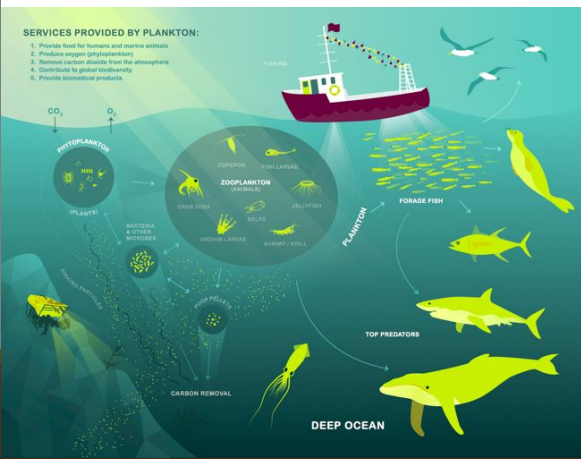
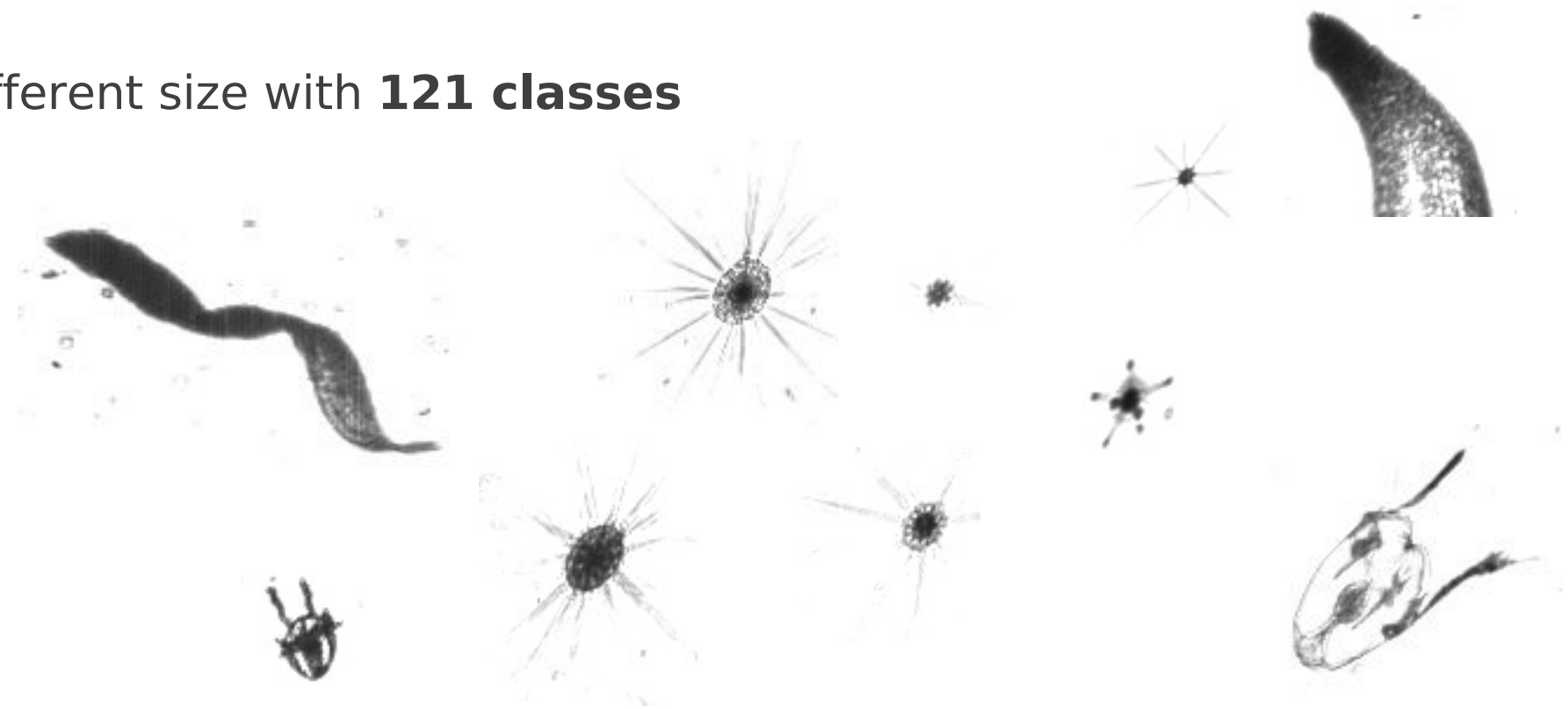
Goal : Classify images of plankton ([kaggle](#))

Training data :

30K images of different size with **121 classes**

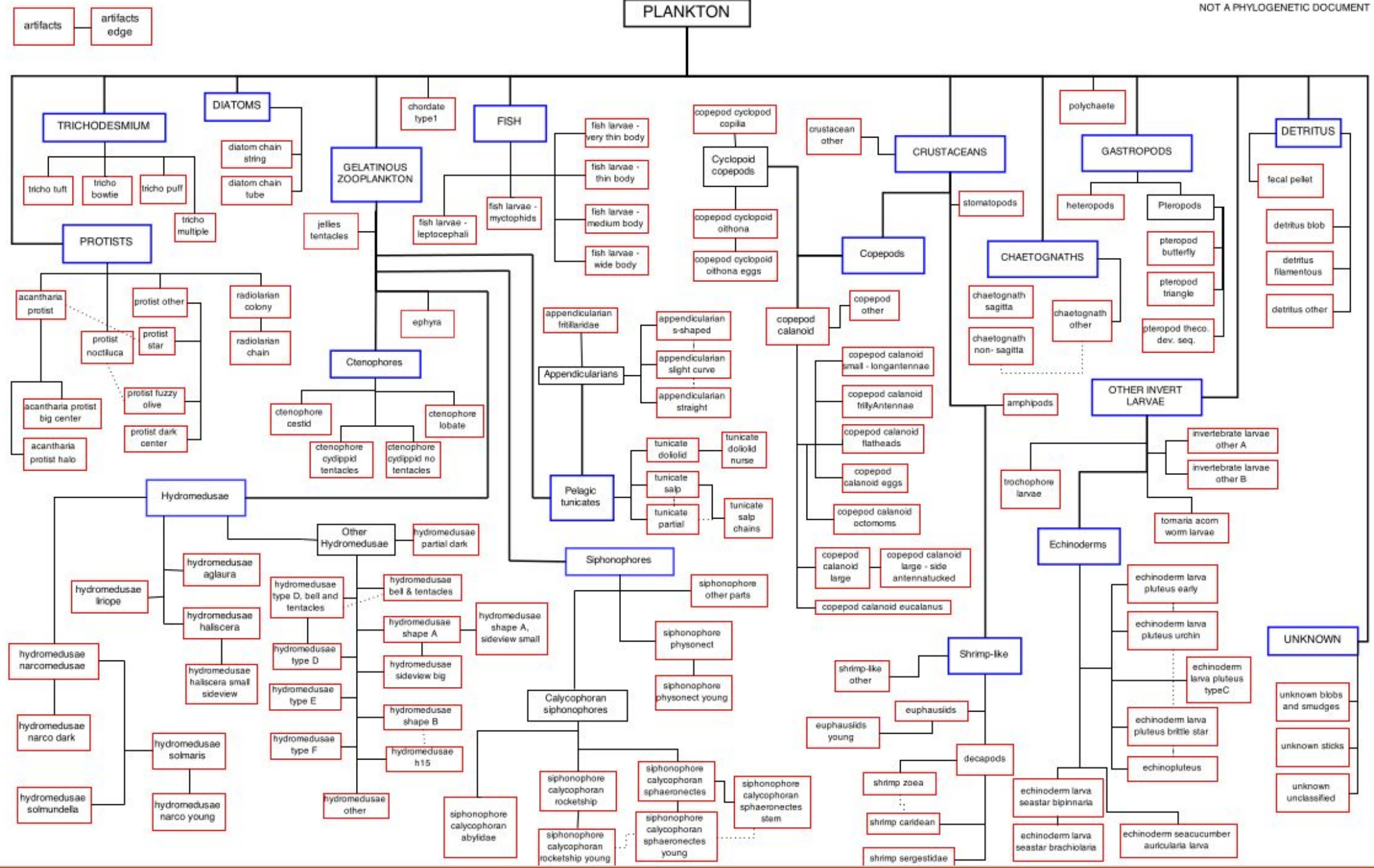
Test data :

120K images



PLANKTON

NOT A PHYLOGENETIC DOCUMENT



acantharia_protist_big_center	diatom_chain_tube	protist_noctiluca	crustacean_other	trichodesmium_tuft
acantharia_protist_halo	echinoderm_larva_pluteus_brittlestar	protist_other	ctenophore_cestid	trochophore_larvae
acantharia_protist	echinoderm_larva_pluteus_early	protist_star	ctenophore_cydippid_no_tentacles	tunicate_doliolid_nurse
amphipods	echinoderm_larva_pluteus_typeC	pteropod_butterfly	ctenophore_cydippid_tentacles	tunicate_doliolid
appendicularian_fritillaridae	echinoderm_larva_pluteus_urchin	pteropod_theco_dev_seq	ctenophore_lobate	tunicate_partial
appendicularian_s_shape	echinoderm_larva_seastar_bipinnaria	pteropod_triangle	decapods	tunicate_salp_chains
appendicularian_slight_curve	echinoderm_larva_seastar_brachiolaria	radiolarian_chain	detritus_blob	tunicate_salp
appendicularian_straight	echinoderm_seacucumber_auricularia_larva	radiolarian_colony	detritus_filamentous	unknown_blobs_and_smudges
artifacts_edge	echinopluteus	shrimp_caridean	detritus_other	unknown_sticks
artifacts	ephyra	shrimp_sergestidae	diatom_chain_string	unknown_unclassified'
chaetognath_non_sagitta	euphausiids_young	shrimp_zoea	jellies_tentacles	hydromedusae_typeF
chaetognath_other	euphausiids	shrimp-like_other	polychaete	invertebrate_larvae_other_A
chaetognath_sagitta	fecal_pellet	siphonophore_calycophoran_abyllidae	protist_dark_center	invertebrate_larvae_other_B
chordate_type1	fish_larvae_deep_body	siphonophore_calycophoran_rocketship_adult	protist_fuzzy_olive	
copepod_calanoid_eggs	fish_larvae_leptocephali	siphonophore_calycophoran_rocketship_young	hydromedusae_narco_young	
copepod_calanoid_eucalanus	fish_larvae_medium_body	siphonophore_calycophoran_sphaeronectes_stem	hydromedusae_narcomedusae	
copepod_calanoid_flatheads	fish_larvae_myctophids	siphonophore_calycophoran_sphaeronectes_young	hydromedusae_other	
copepod_calanoid_frillyAntennae	fish_larvae_thin_body	siphonophore_calycophoran_sphaeronectes	hydromedusae_partial_dark	
copepod_calanoid_large_side_antennatucked	fish_larvae_very_thin_body	siphonophore_other_parts	hydromedusae_shapeA_sideview_small	
copepod_calanoid_large	heteropod	siphonophore_partial	hydromedusae_shapeA	
copepod_calanoid_octomoms	hydromedusae_aglaura	siphonophore_physonect_young	hydromedusae_shapeB	
copepod_calanoid_small_longantennae	hydromedusae_bell_and_tentacles	siphonophore_physonect	hydromedusae_sideview_big	
copepod_calanoid	hydromedusae_h15	stomatopod	hydromedusae_solmaris	
copepod_cyclopid_copilia	hydromedusae_haliscera_small_sideview	tornaria_acorn_worm_larvae	hydromedusae_solmundella	
copepod_cyclopid_oithona_eggs	hydromedusae_haliscera	trichodesmium_bowtie	hydromedusae_typeD_bell_and_tentacles	

Approaches

Preprocessing

- Resizing
- Augmentation
- Edge detection - Canny filter and BW

Feature Extraction

- PCA
- GLCM - Haralick Features
- DCT

Models

- SVM
- Neural Network
- Decision Tree
- KNeighborsClassifier
-

Ensembling

- RandomForestClassifier
- xgboost, ExtraTree,
- Adaboost

- % GLCM Features (Soh, 1999; Haralick, 1973; Clausi 2002)
- % f1. Uniformity / Energy / Angular Second Moment (done)
- % f2. Entropy (done)
- % f3. Dissimilarity (done)
- % f4. Contrast / Inertia (done)
- % f5. Inverse difference
- % f6. correlation
- % f7. Homogeneity / Inverse difference moment
- % f8. Autocorrelation
- % f9. Cluster Shade
- % f10. Cluster Prominence
- % f11. Maximum probability
- % f12. Sum of Squares
- % f13. Sum Average
- % f14. Sum Variance
- % f15. Sum Entropy
- % f16. Difference variance
- % f17. Difference entropy
- % f18. Information measures of correlation (1)
- % f19. Information measures of correlation (2)
- % f20. Maximal correlation coefficient
- % f21. Inverse difference normalized (INN)
- % f22. Inverse difference moment normalized (IDN)

Results

Primilary Results (Error - Logloss)

C = 10

SVC(degree=5, kernel='linear')

('Cross Val Error: ', 0.4770399735711926)

('Training Error: ', 0.31020812685827553)

('Score', 0.52296002642880735)

SVC(degree=3, kernel='rbf')

('Cross Val Error: ', 0.47092831185992734)

('Training Error: ', 0.08462724369562824)

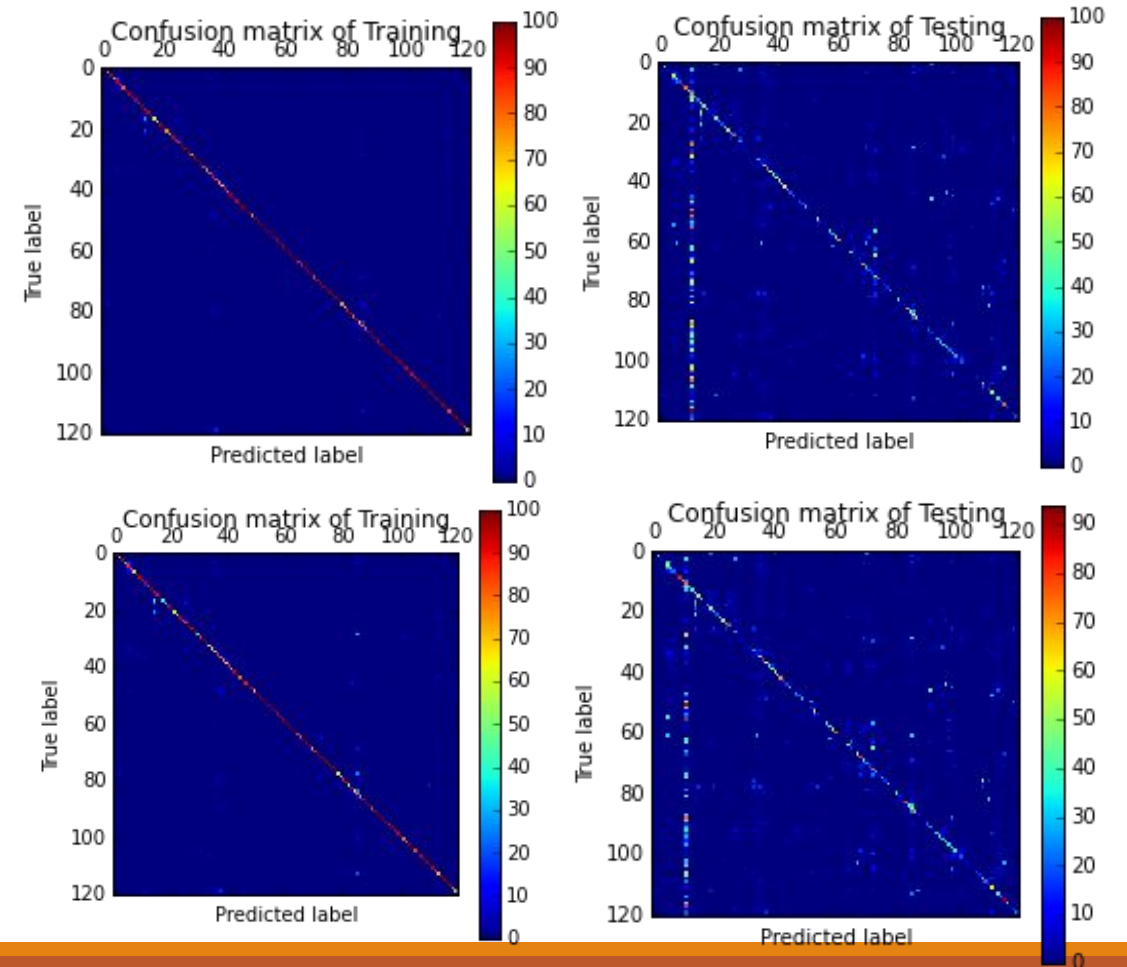
('Score', 0.52907168814007266)

SVC(degree=5, kernel='rbf')

('Cross Val Error: ', 0.45201519656425504)

('Training Error: ', 0.12884043607532211)

('Score', 0.54798480343574496)



Results

Log loss

-- 7.977

-- 6.57

-- 6.2

-- 6.19

-- 4.7

-- 4.4

-- 2.18

-- 1.82

Log loss

-- 1.77

-- 1.73

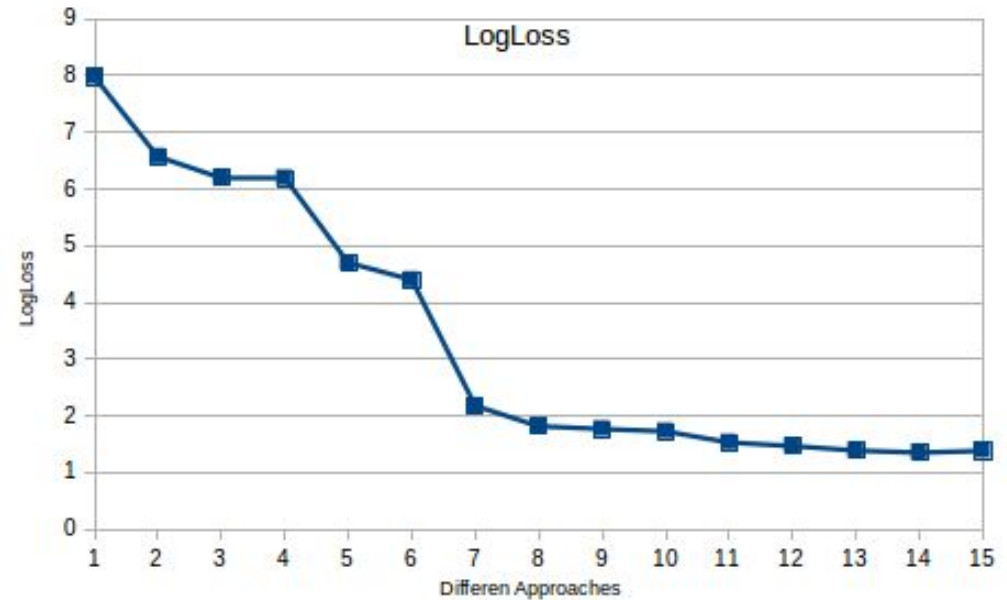
-- 1.533

-- 1.47

-- 1.39

-- 1.355

-- **1.3856** --Last Achieved



2. Mutual Liberty – Regression

Lesson Learned

- Not to combine very accurate models
- Try different features for different models
- Boost models with different training sets
- Combine with cascading

Any Question ? ? ? ?

Thank You..