CRAFTML, an Efficient Clustering-based Random Forest for Extreme Multi-label Learning

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Outline

Overview

- Extreme Multi-label Learning (XML) is designed for the large data sets with huge number of labels that can exceed one million.

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- Parallel approach with trees, which reduces the problem into small subproblems.
- Inclusion of randomization in tree based approach, Uses Random forest approach.

Prior Work

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  - Optimization Tricks and Parallelization: PDSparse, PPDSparse, DISMEC
  - Dimensionality Reduction:WSABIE, LEML, SLEEC, AnnexML
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  - Dimensionality Reduction:WSABIE, LEML, SLEEC, AnnexML
  - Tree-based Methods: LPSR, FastXML, PFastReXML
- Several Tree Based approach also exists in XML literature.(e.g.,RF-PCT, HOMER, LPSR, FastXML).

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- Exploring two directions: Using very fast partitioning strategies and exploiting tree feature/label randomization.
- Lower complexity computation in each node.
- A projection is able to preserve more information than a selection for a same
- joint random projection of features and labels is more promising to deal with the extreme number of labels ratio of compression

Now Comes the CRAFTML...

Let the number of training examples = n

$$x \in \mathbb{R}^{d_x} \;\; and \;\; y \in \{0,1\}^{d_y}$$

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- train data split is 9:1 ratio for train and validation datasets
- each node in decision tree is implemented as object and each node having train_tree and train_node_classifier methods.

Results

validation data set used for hyperparameter value:

mediamill dataset:

p@value	Actual Accuracy(%)	TEST data achived accuracy(%)
p@1	85.86	81.22
p@2	69.01	64.84
p@3	54.65	50.74

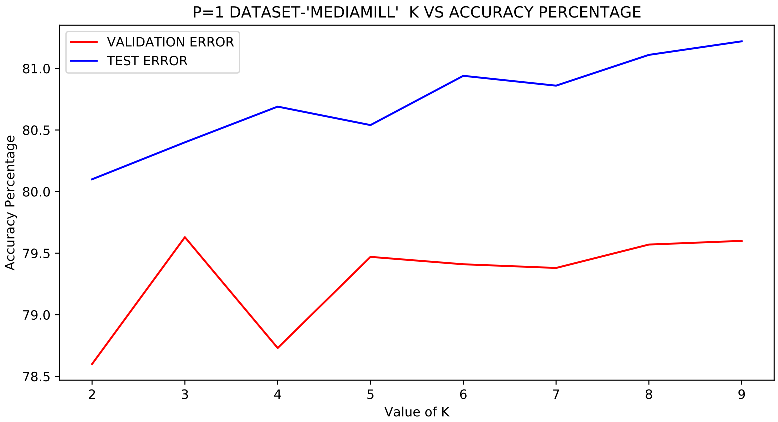
bibtex dataset:

p@value	Actual Accuracy(%)	TEST data achived accuracy(%)
p@1	65.15	61.83
p@3	39.83	27.49
p@3	28.99	20.58

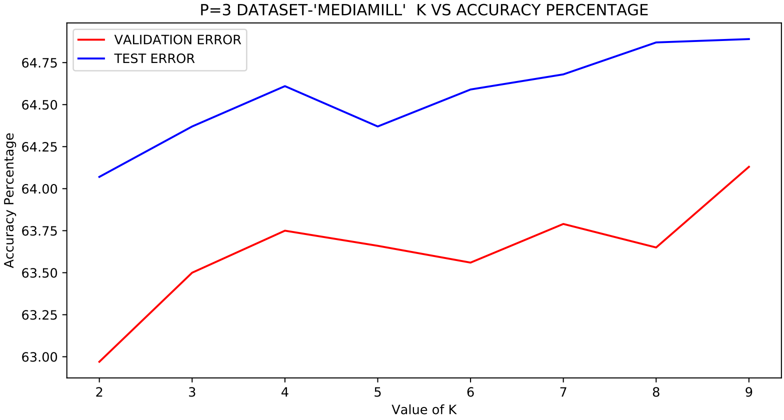
delicious dataset

p@value	Actual Accuracy(%)	TEST data achived accuracy(%)
p@1	70.26	62.85
p@2	63.98	56.43
p@3	59.00	52.17

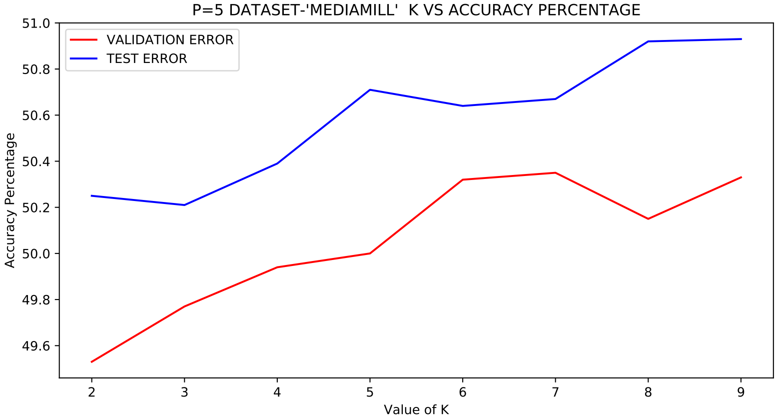
MEDIAMILL Dataset for P = 1



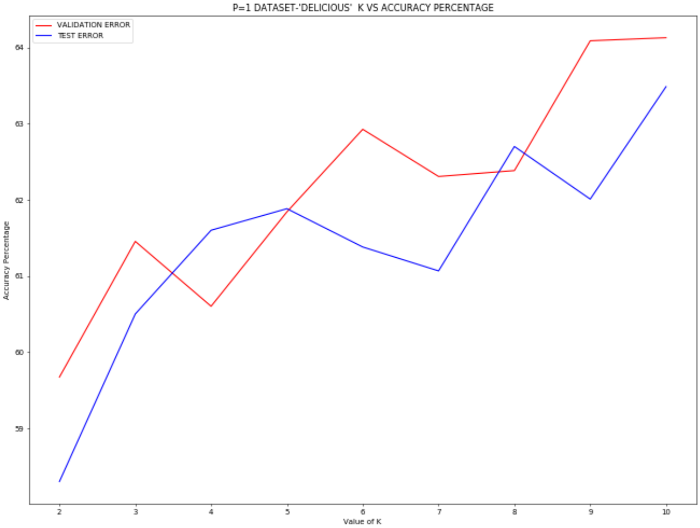
MEDIAMILL Dataset for P = 3



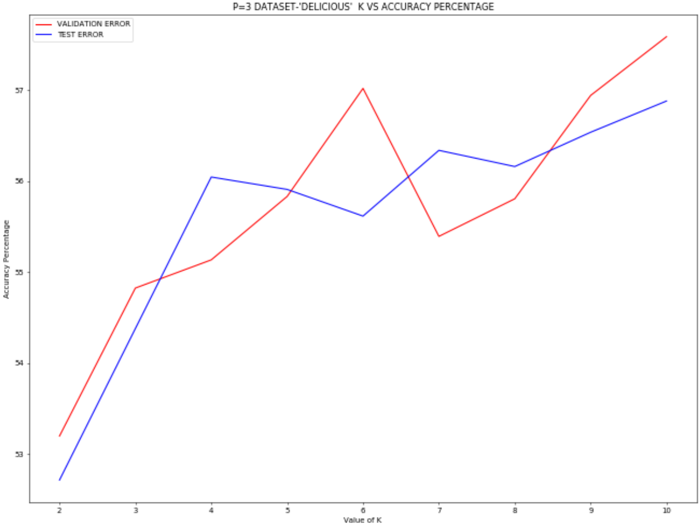
MEDIAMILL Dataset for $P = 5$



DELICIOUS Dataset for P = 1



DELICIOUS Dataset for P = 3



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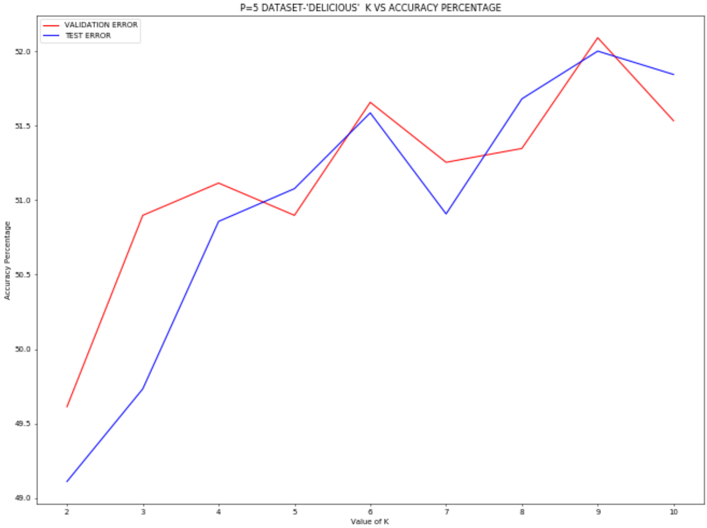
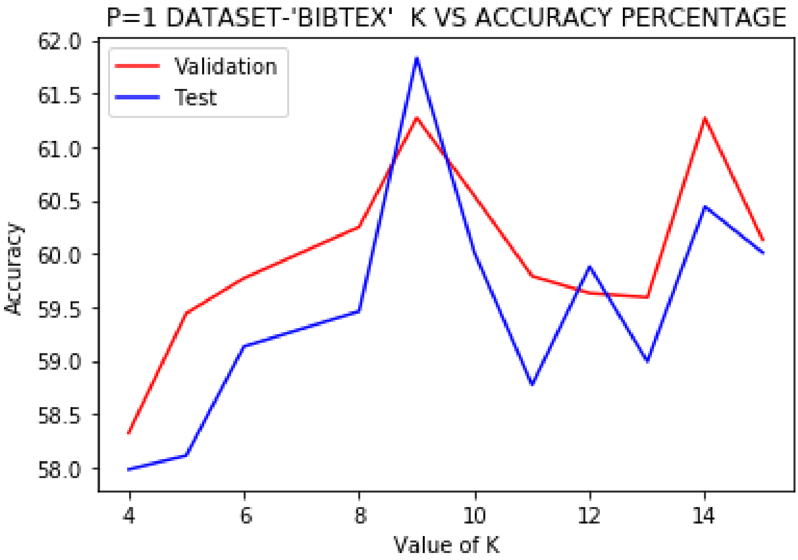
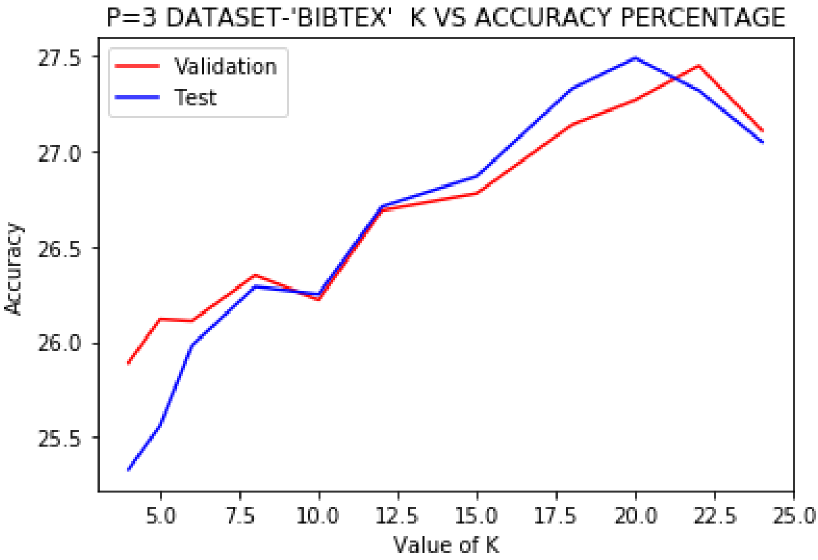


BIBTEX Dataset for P = 1



BIBTEX Dataset for P = 3



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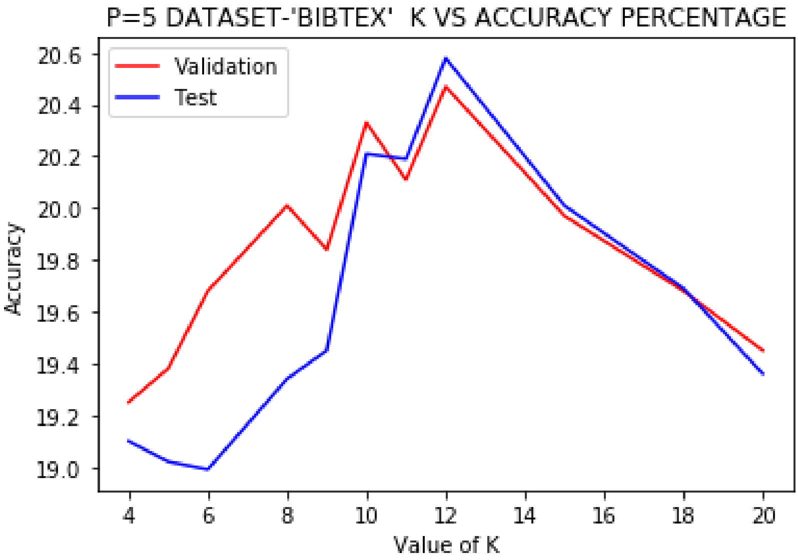

Conclusion

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- Studied the behaviour of model with different values.
- Also perform the testing on test data and get the accuracy of the mode.
- We have seen that, with closer cluster number for all trees in decision forest keeping all parameters constant, increases the accuracy.

Thank You!