Distributed Random Forests: Resilient?

Raksha Kumaraswany
and
Katherine Metcalf

Problem Description

- Explore the effect of learning distributed mini-forests on local data sets that varying according to feature value and label distributions
- Important question b/c passing around data to build partitions with globally representative distributions is computationally expensive and puts the data at higher security risks
- The PAMDAP2 is a time series, activity classification data set:
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  - > 3M data points
- Split the PAMDAP2 data set among the HARP Mappers by person to create local data sets with distinct feature value and label distributions

Random Forest

- ensemble classifier
- idea - divide & conquer
- divide - the dataset into bootstrap samples
- conquer - by learning tree for each sample
- gather all trees - a forest, the new model
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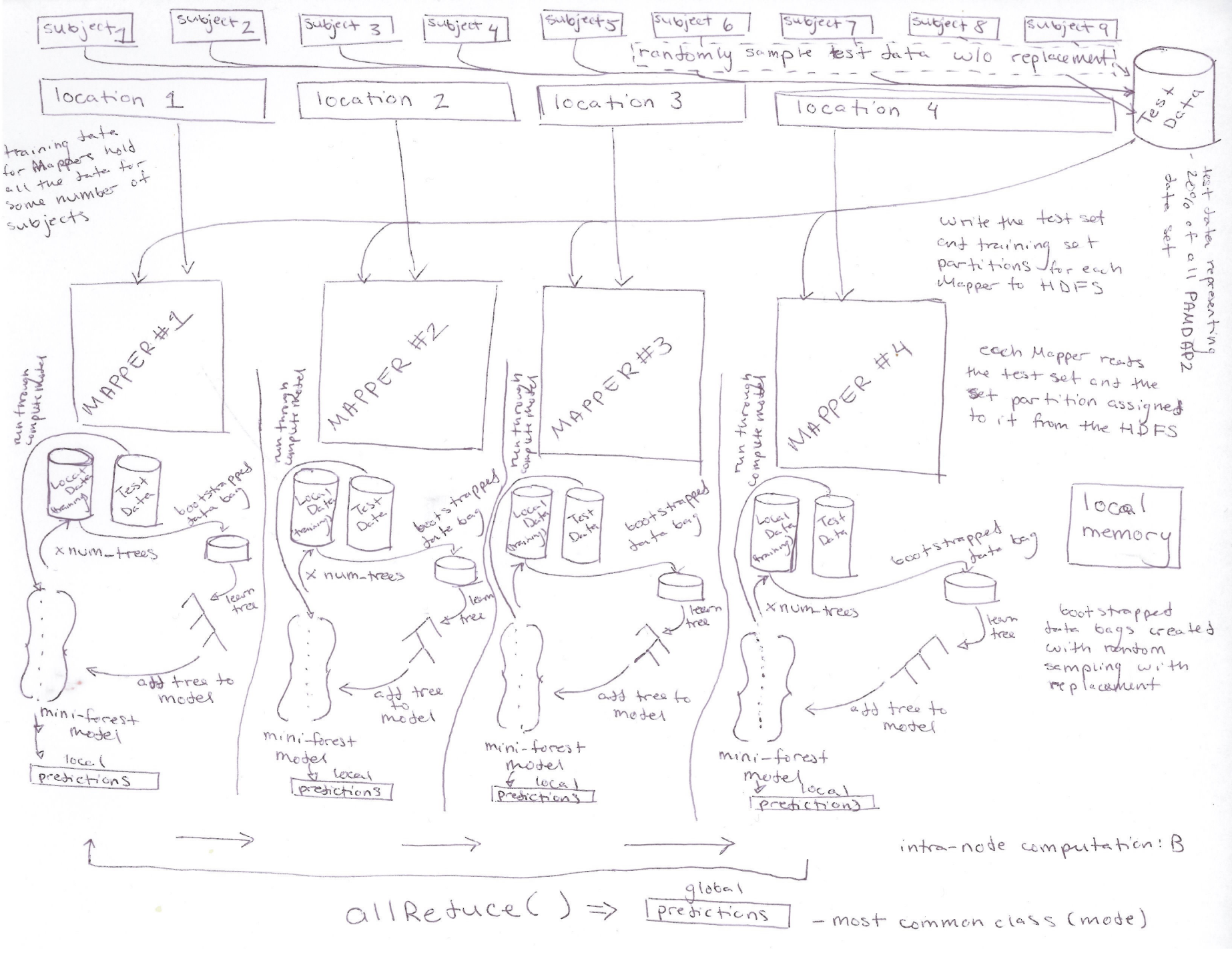
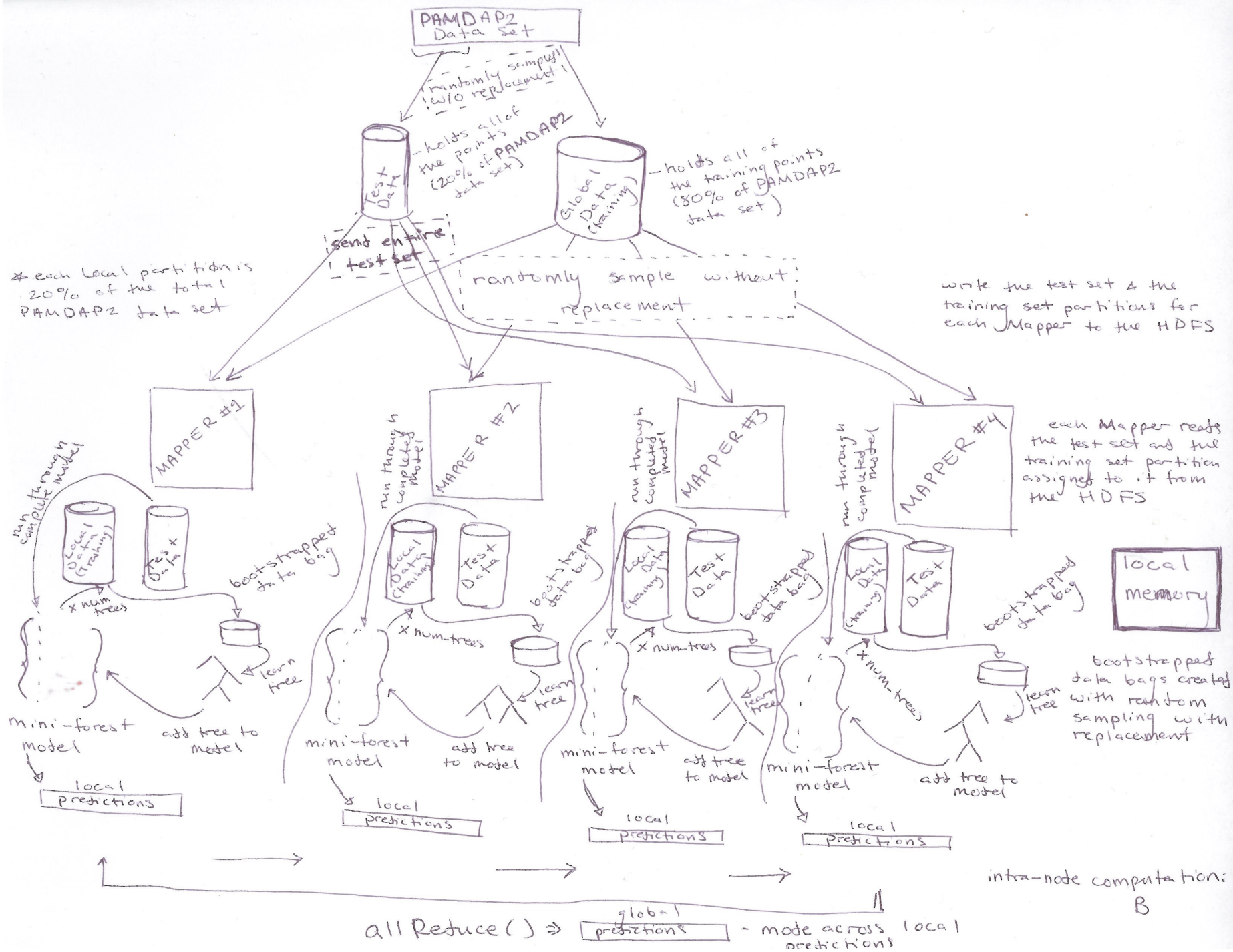
- Advantage:
  - these independently learned models, when aggregated create a resilient model
  - not prone to bias
- Disadvantage:
  - computational complexity scaled with data size: many avenues for parallelism
  - bootstrap sample creation, forest creation, tree creation, prediction.
  - prone to variance, but can be controlled with sampling strategies: strategic bag-of-little bootstraps
- What we do - parallel forest creation, with strategic bag-of-little bootstraps

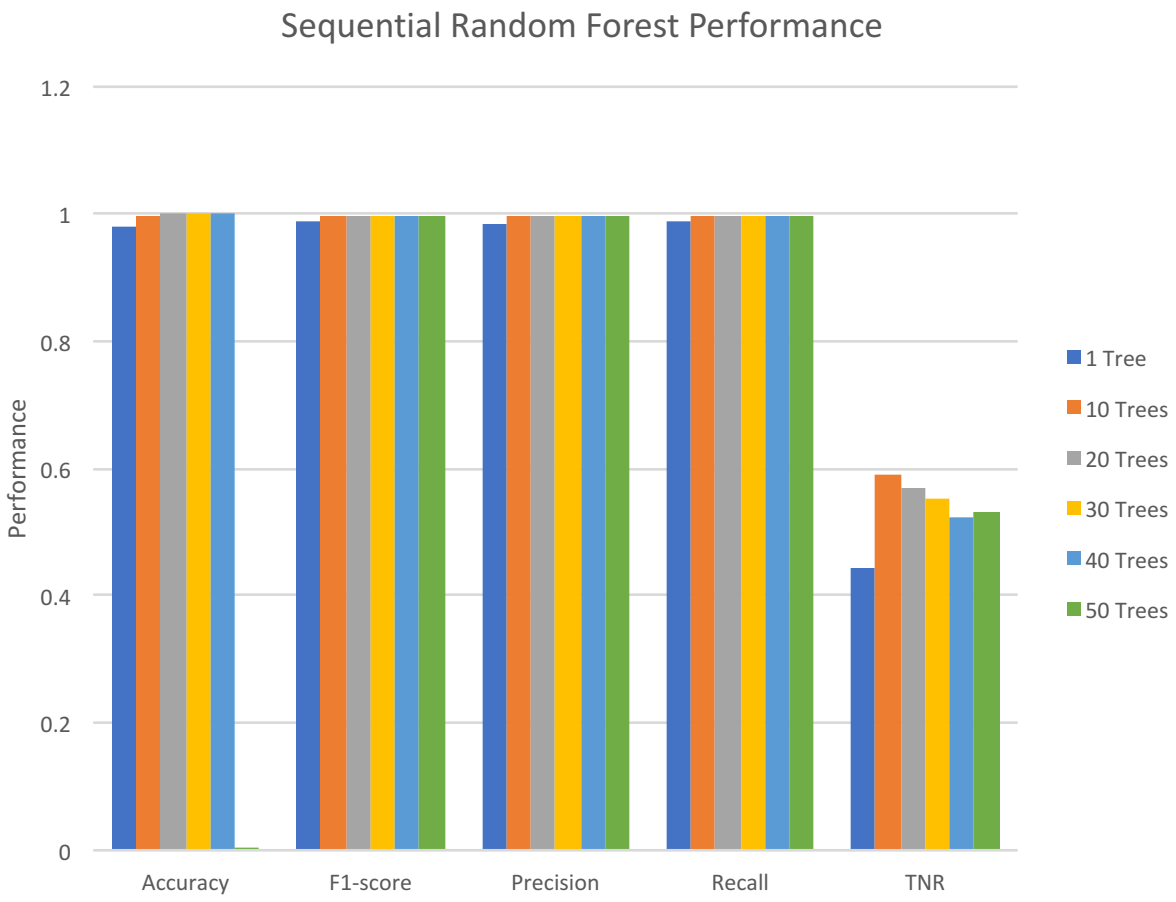
Methods: Local-Label and Local-Label-Feature data

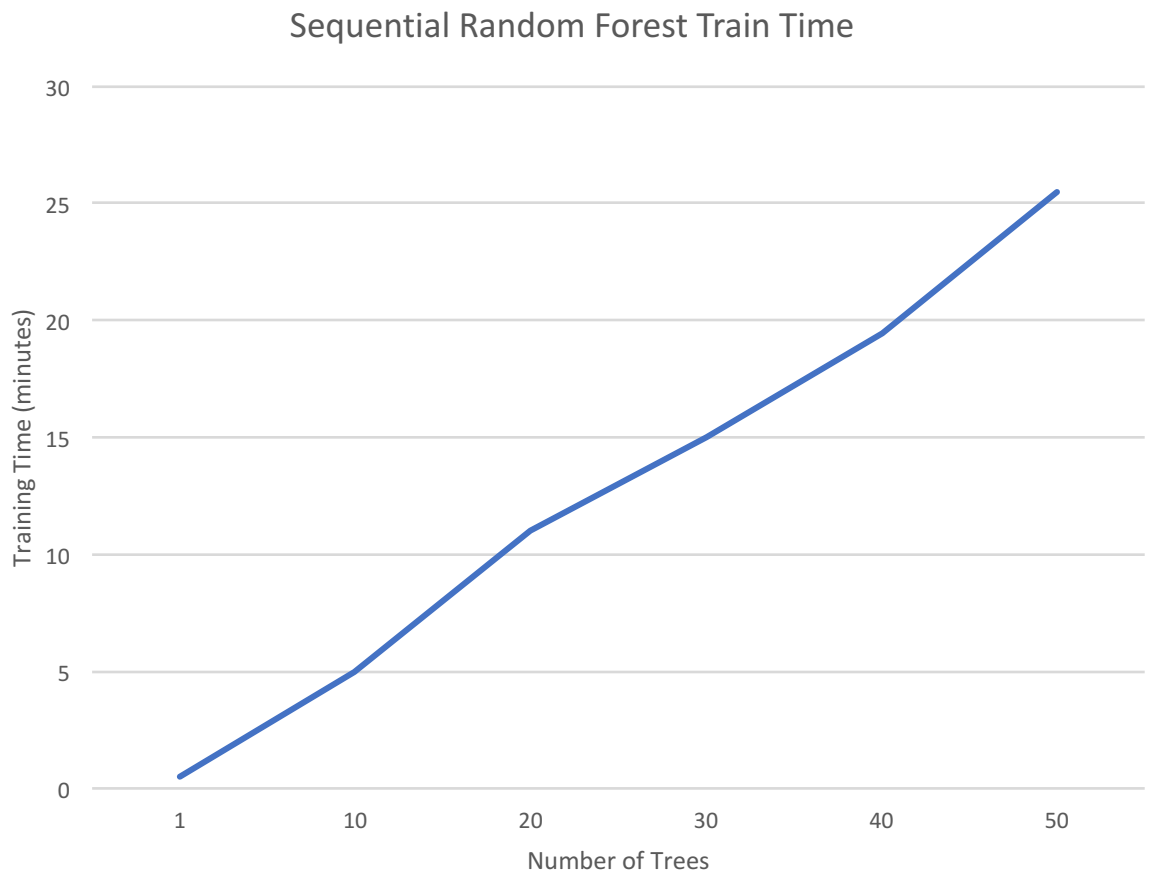


Methods: Global data

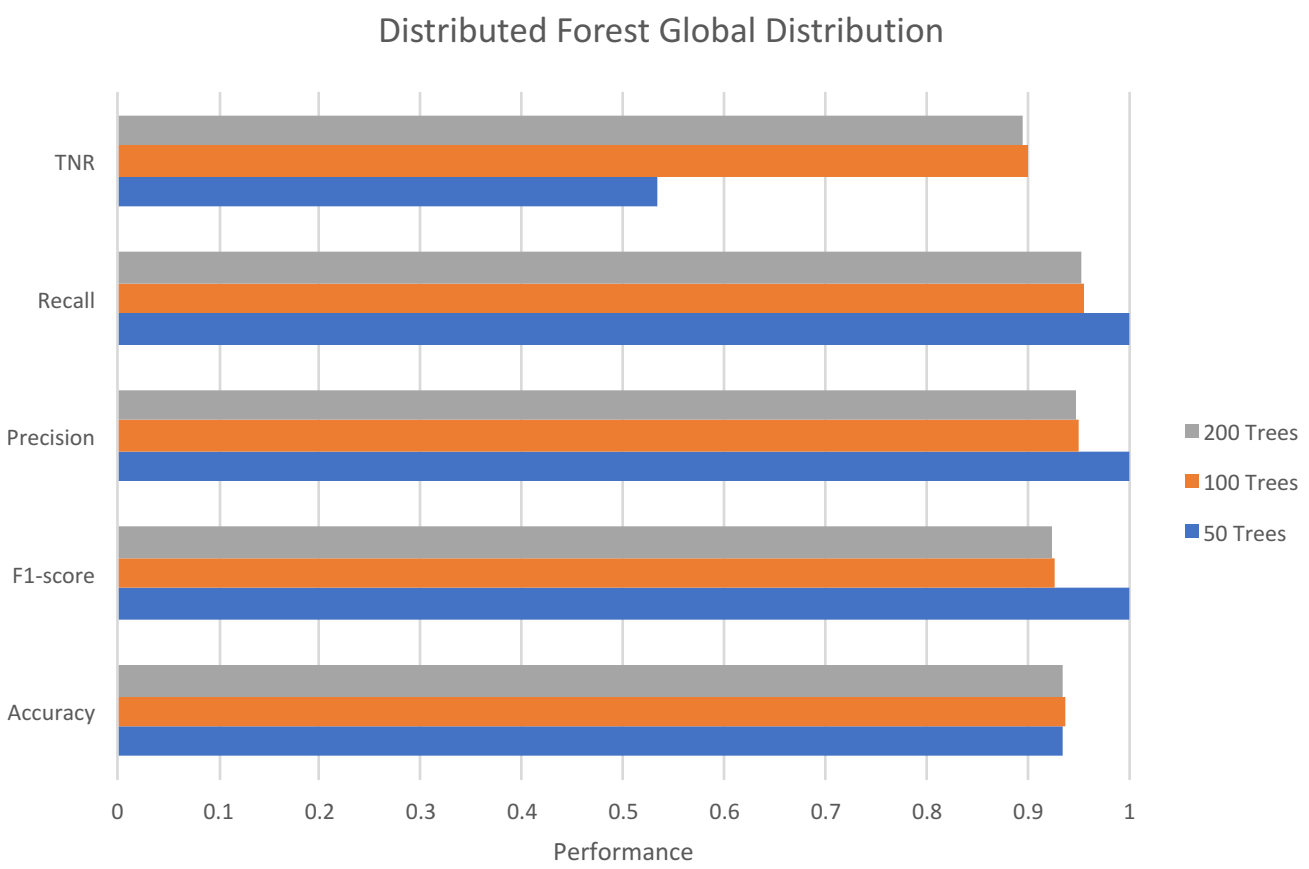


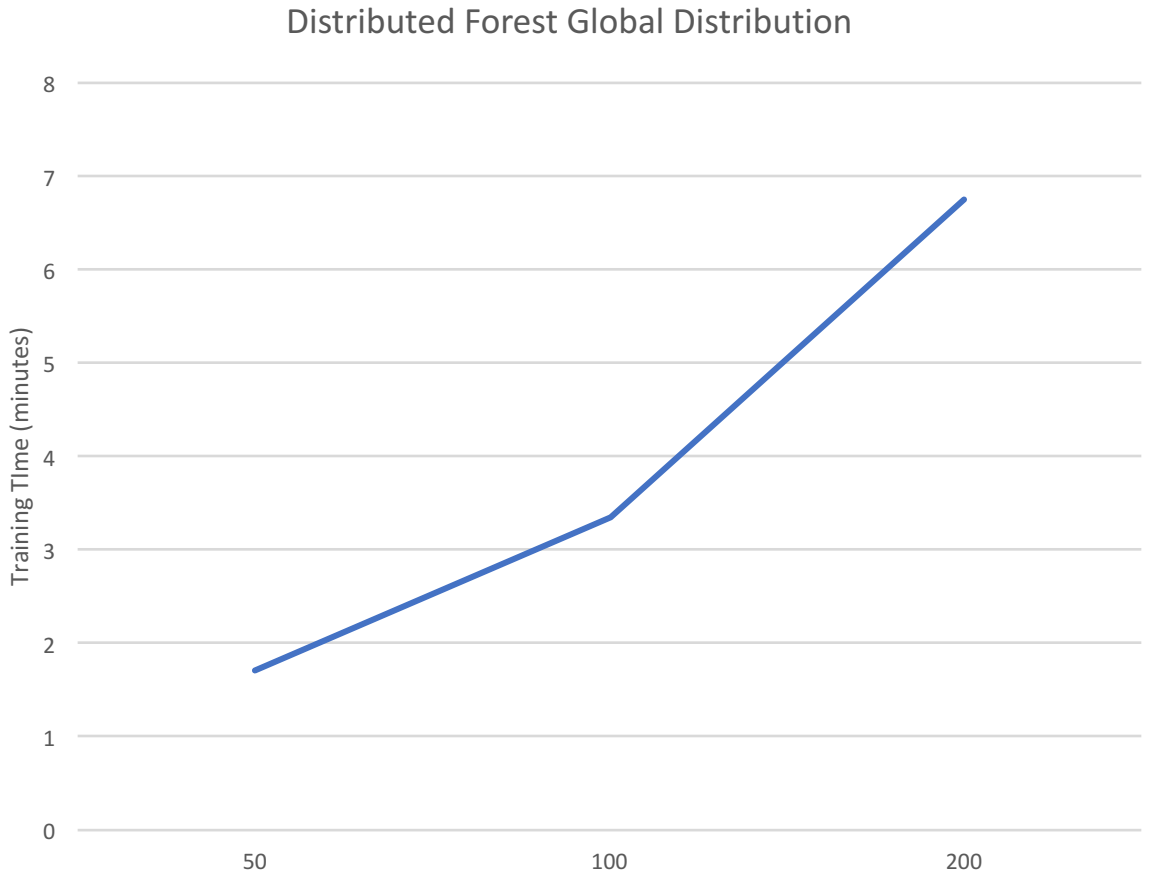
Sequential Results

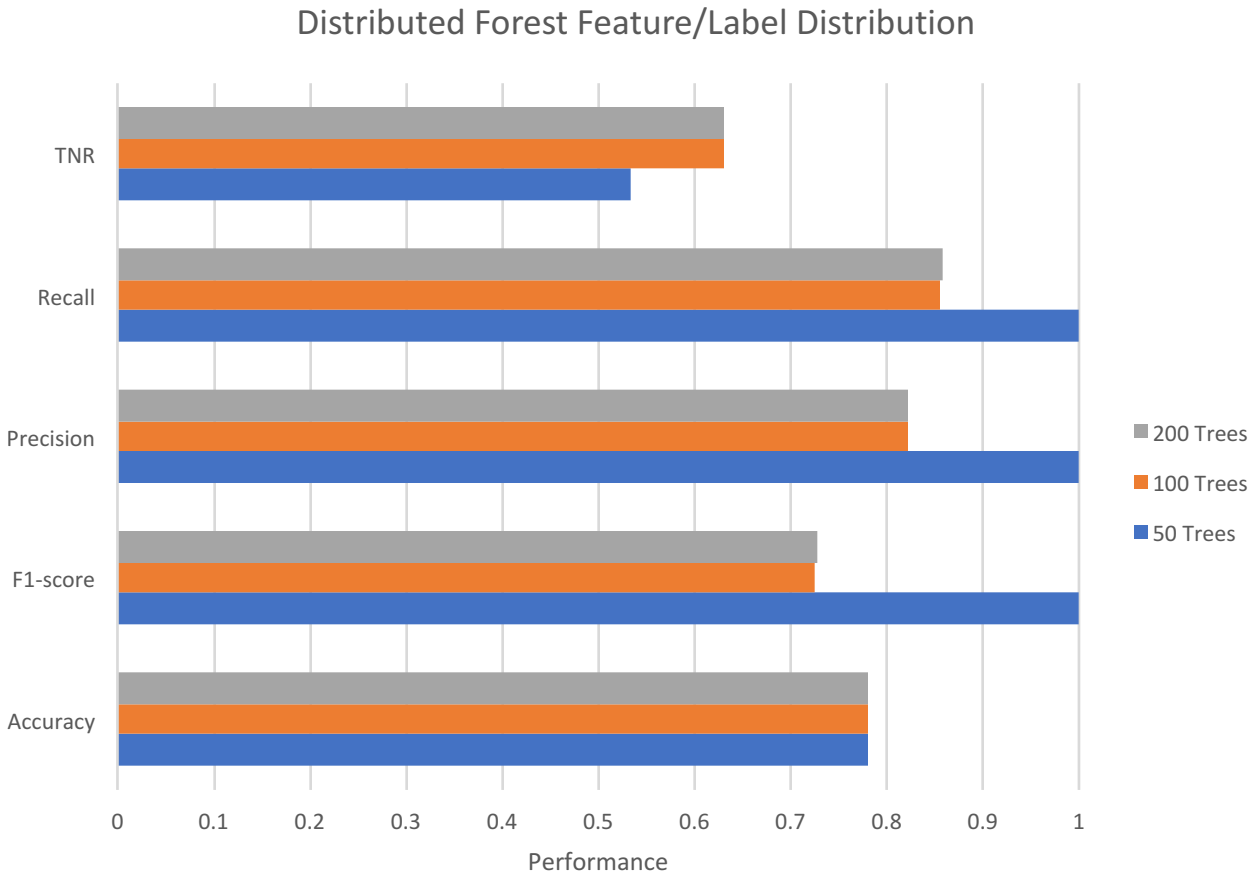


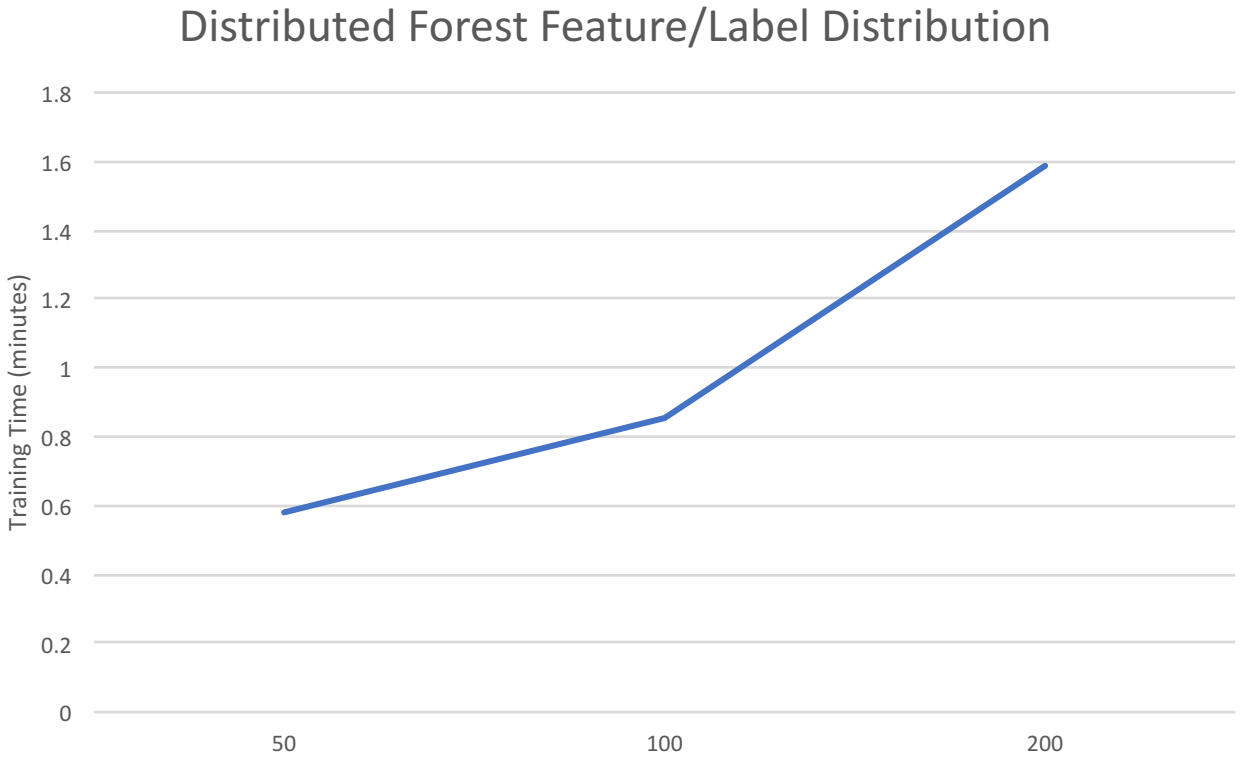


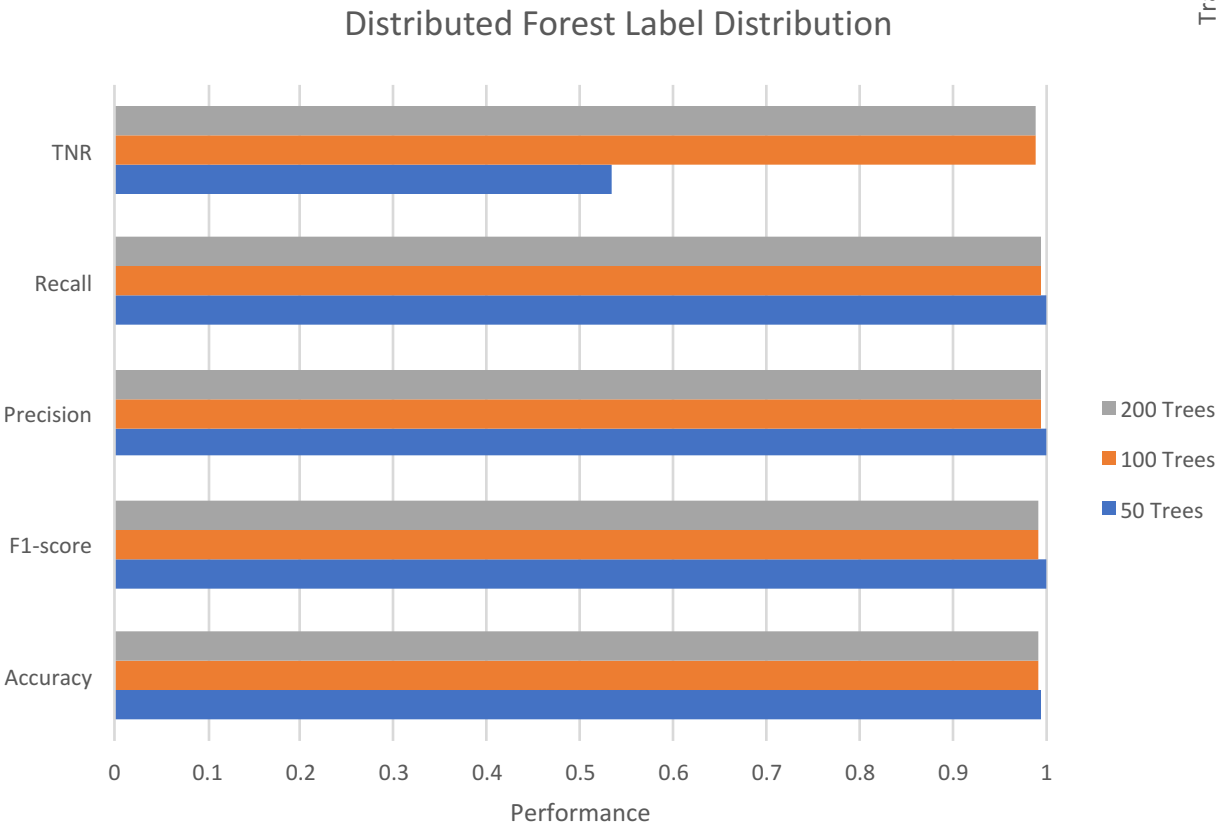
Distributed Results






Distributed Forest Feature/Label Distribution
TNR
Recall
Precision
F1-score
Accuracy
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
Performance
200 Trees
100 Trees
50 Trees


Distributed Forest Feature/Label Distribution
Training Time (minutes)
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
50
100
200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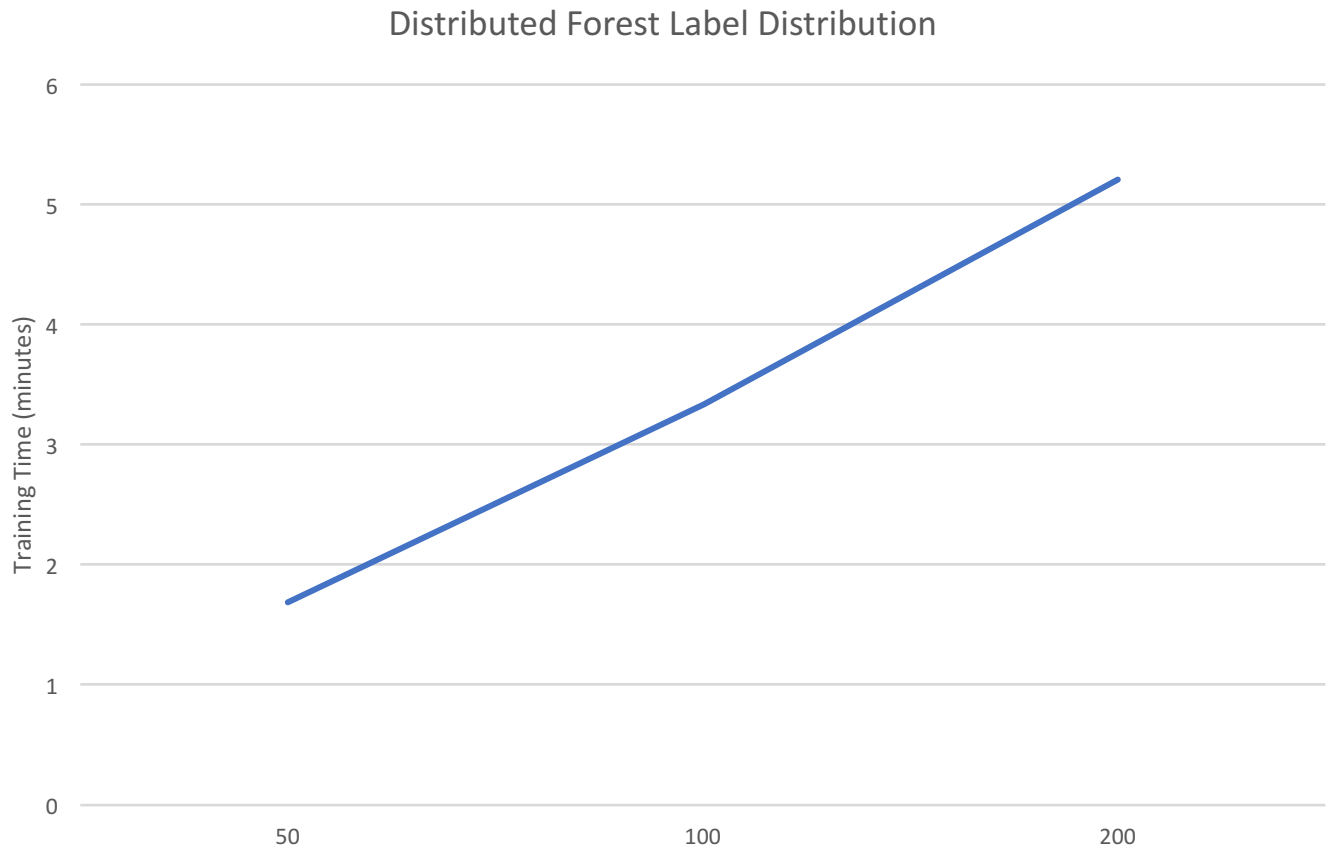
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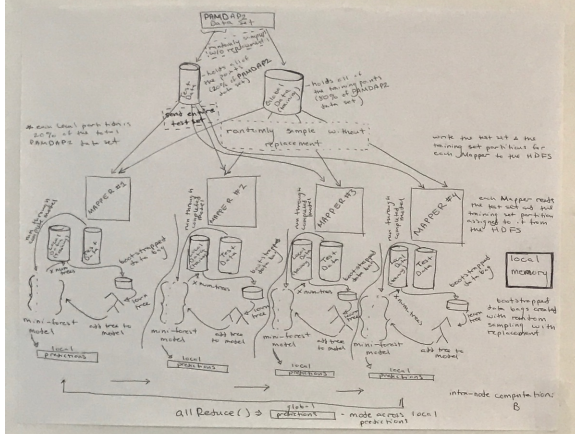

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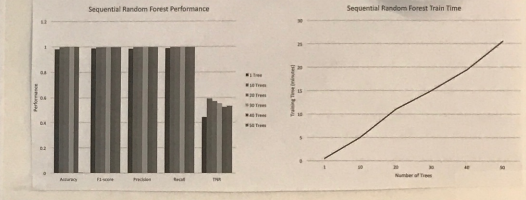

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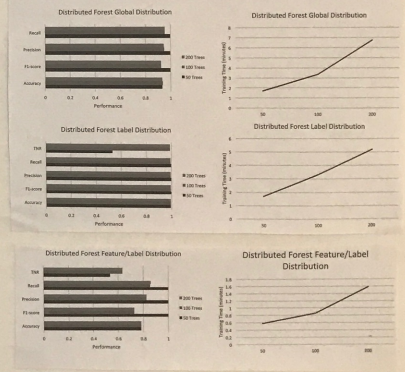

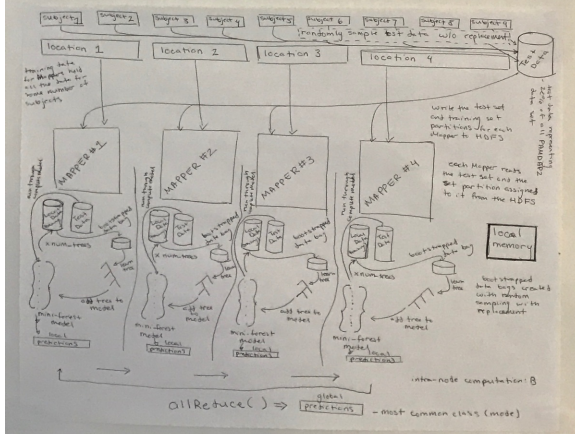

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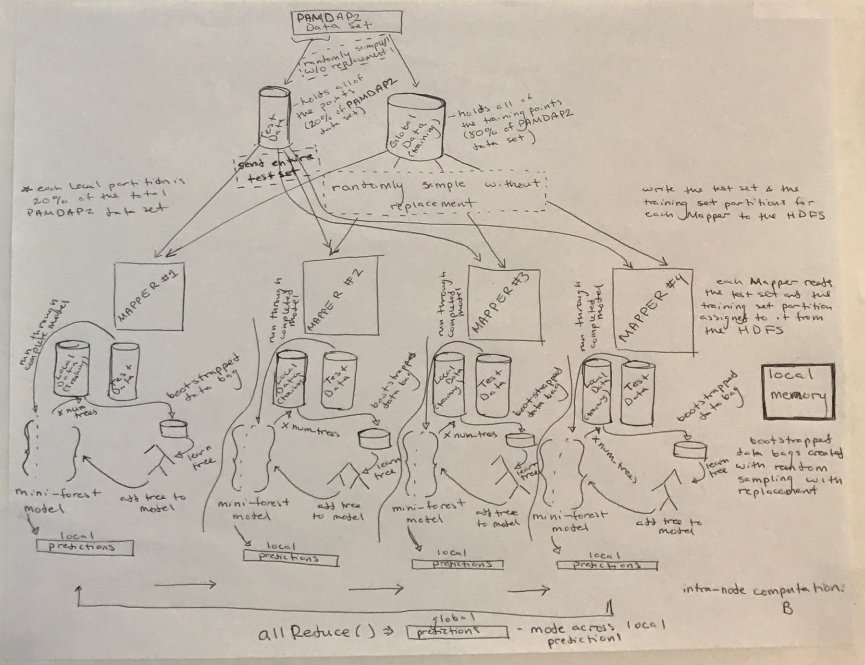

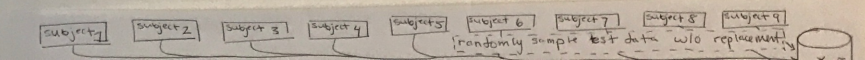

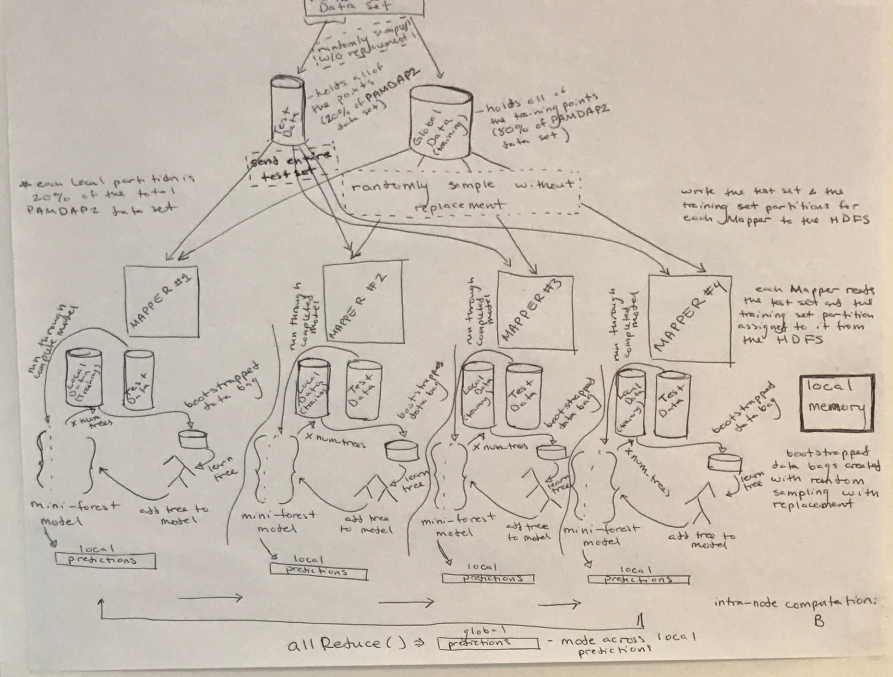

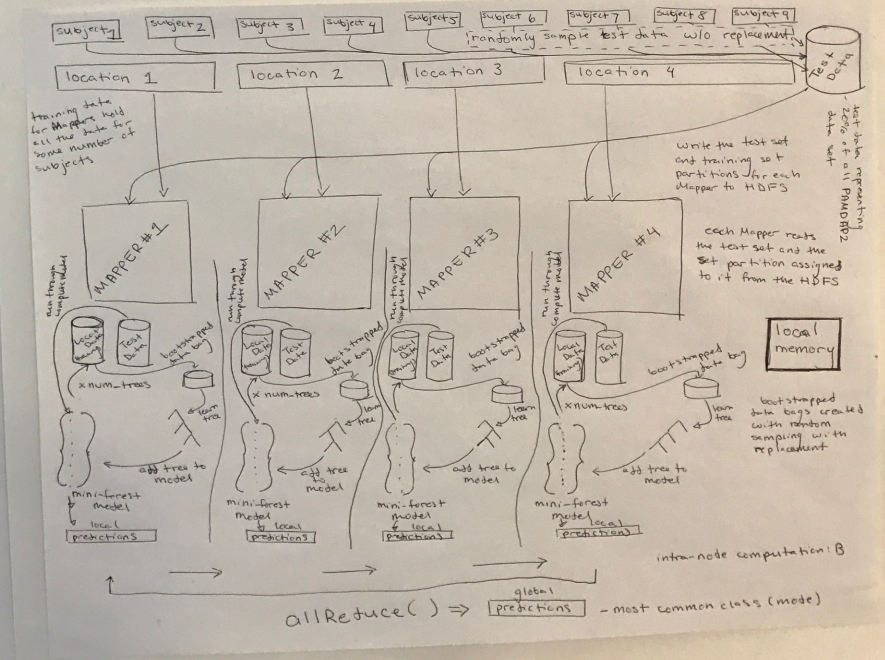

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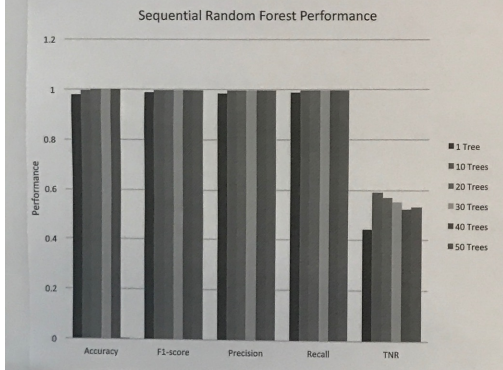

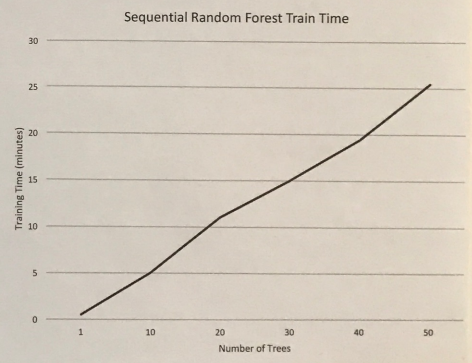

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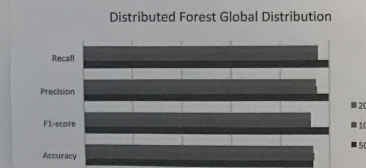

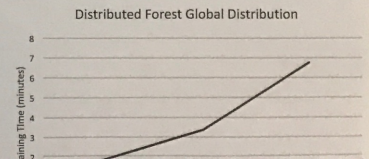

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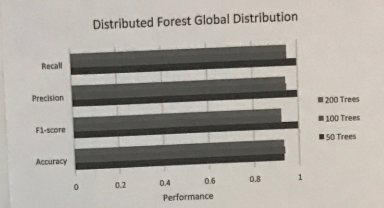

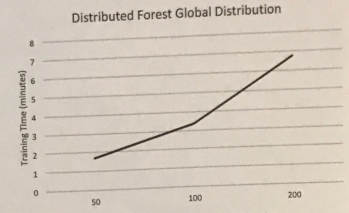

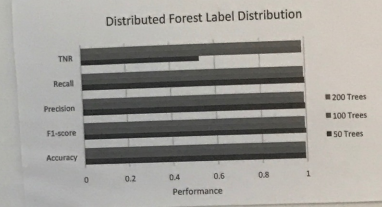

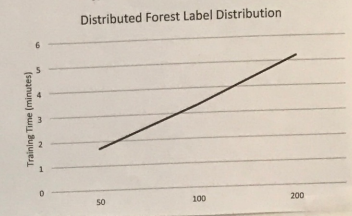

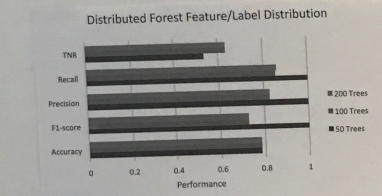

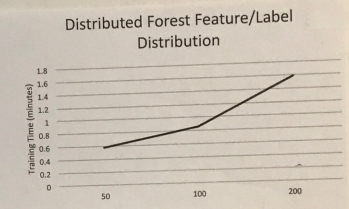

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