

# How well are the wells?

Predicting Tanzanian Water Wells Functionality

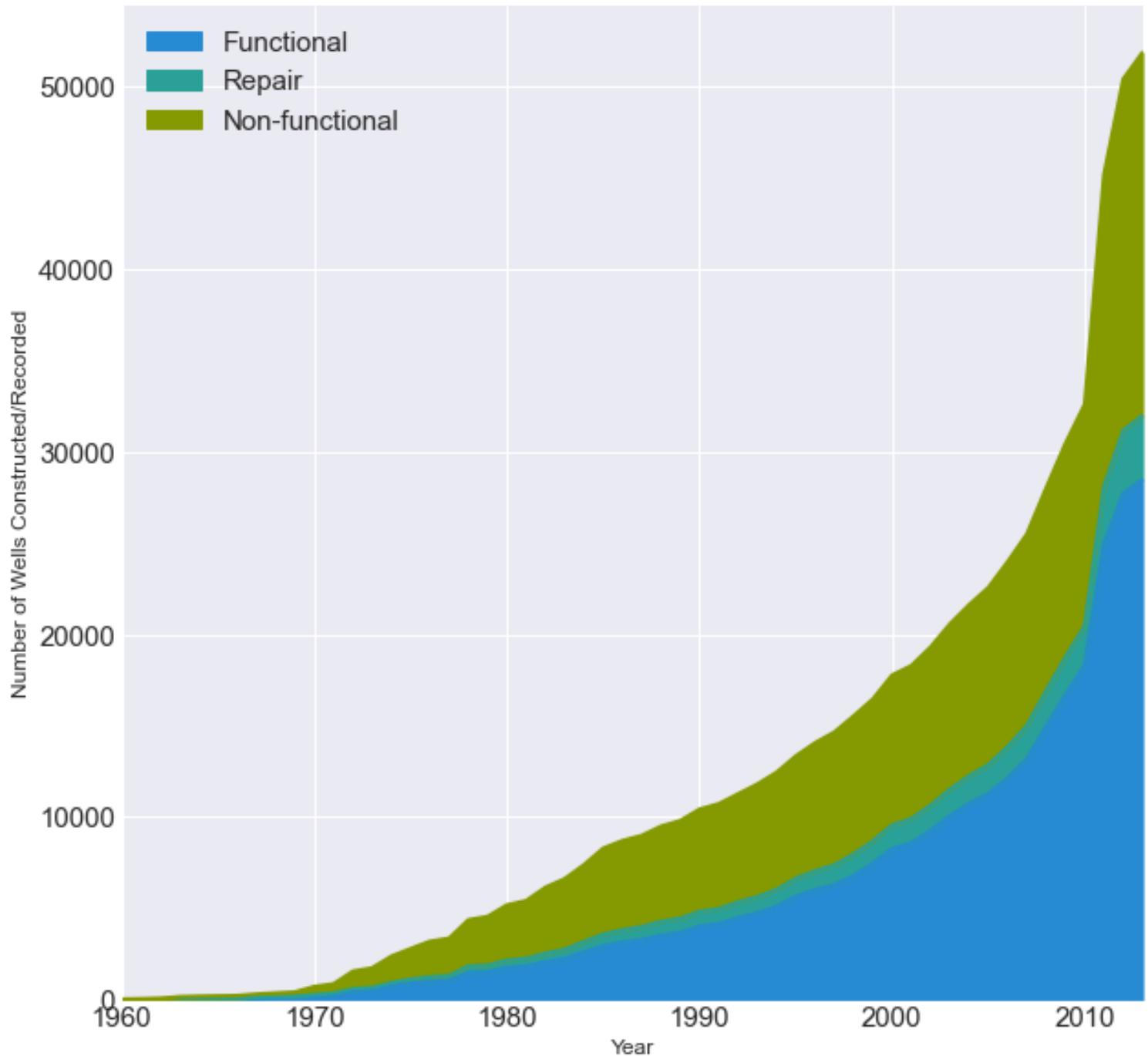
Sung Bae

# Tanzanian Water Crisis Facts

- Importance of water
  - Source of life
  - Improve life quality
  - Increase school attendance
  - Empowers families
- 24 million people without basic access to safe water
- Numerous organizations have been working to provide safe and accessible water



Cumulative Number of Wells Over Time



# Tanzanian Water Crisis Facts

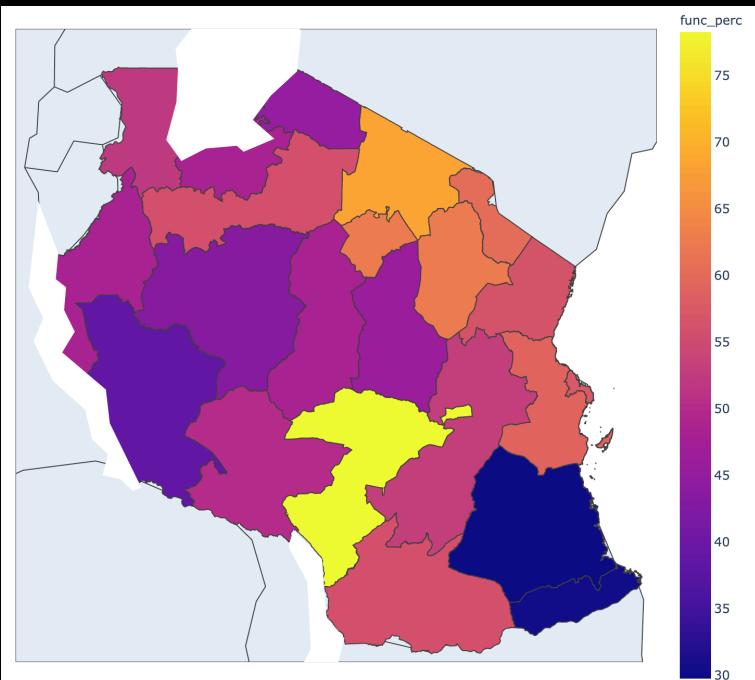
- More than 50,000 water wells are installed by 2013
  - 54.9 % Functional
  - 38.3 % Non-functional
  - 6.8 % Needs repair
- Imperative to determine which wells are not functioning or need repairing accurately

# Goals and Objectives

- Construct a model that can classify
  - [1] functioning wells,
  - [2] functioning but need repairing wells, and
  - [3] non-functioning wells.
- Top Priorities
  - Recalls for [2] and [3]
  - Overall accuracy
- Provide features that affect functionalities

# Geographical Factors

Percent Functioning Wells

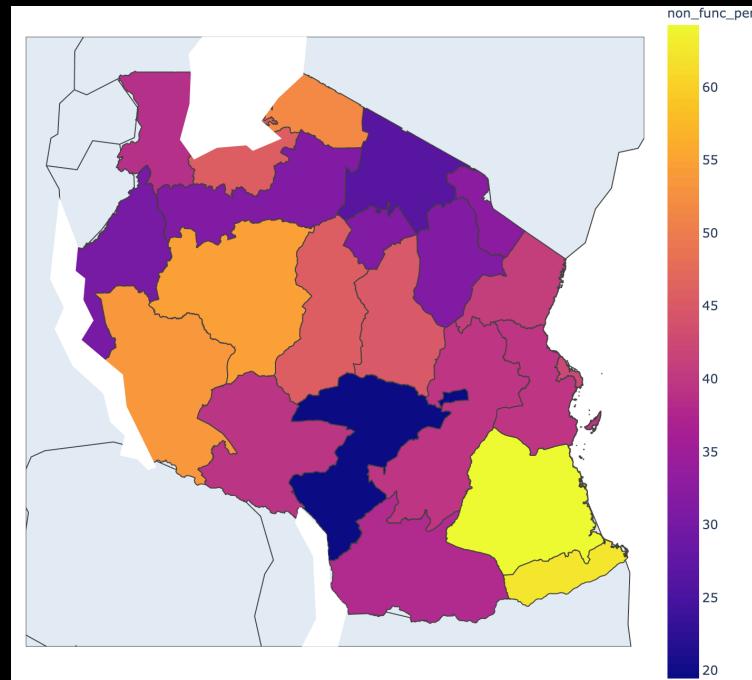


Region: Iringa

N = 5294

Percentage: 78.22%

Percent Non-Functioning Wells

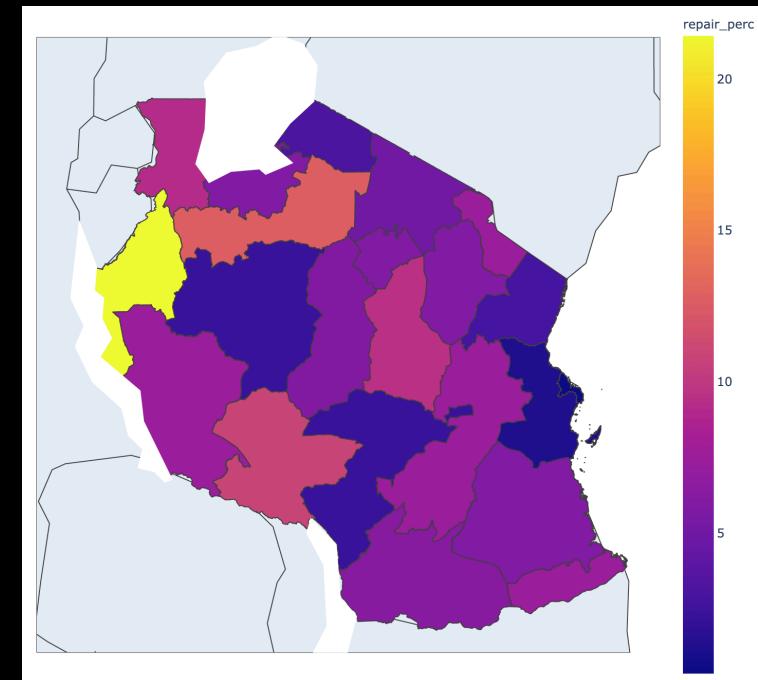


Region: Lindi

N = 1546

Percentage: 64.23%

Percent Need-Repairing Wells

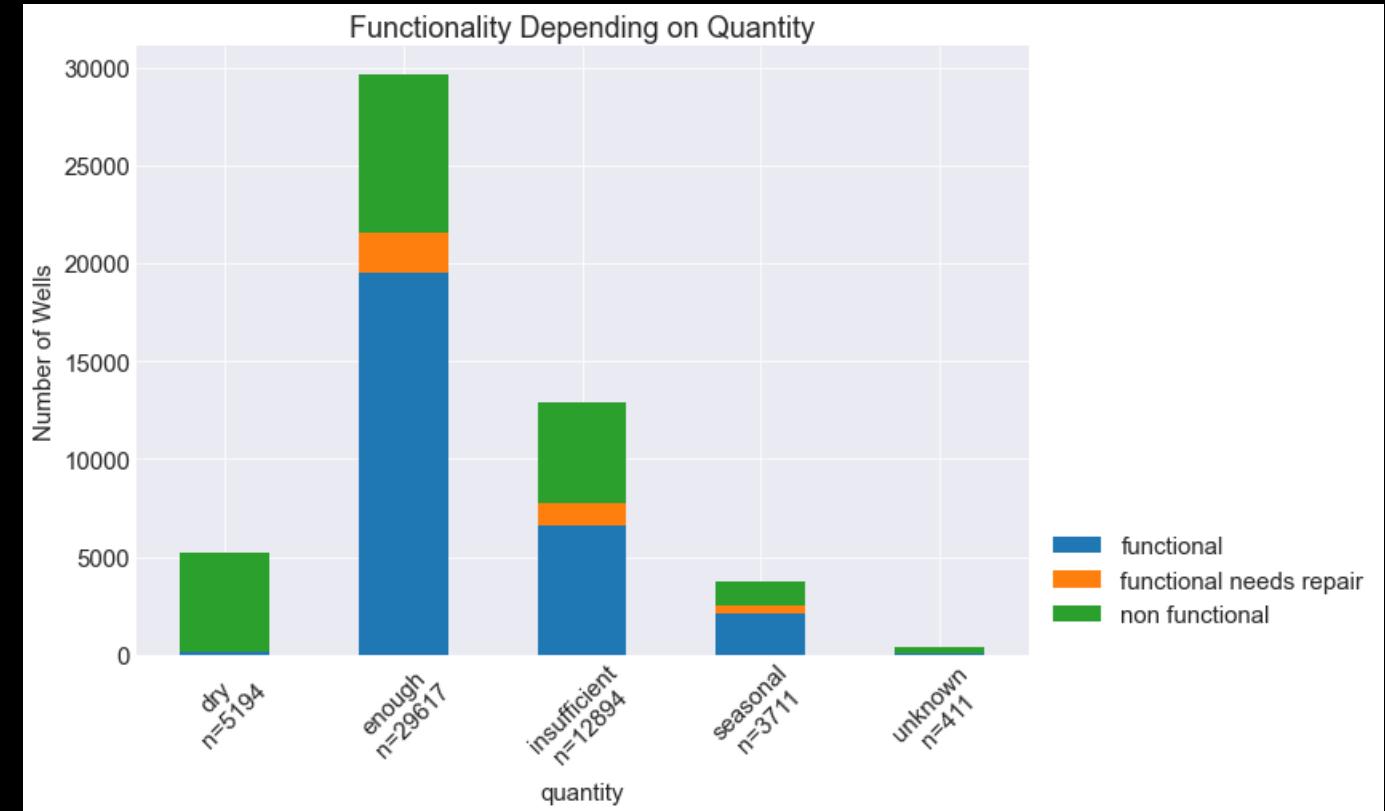
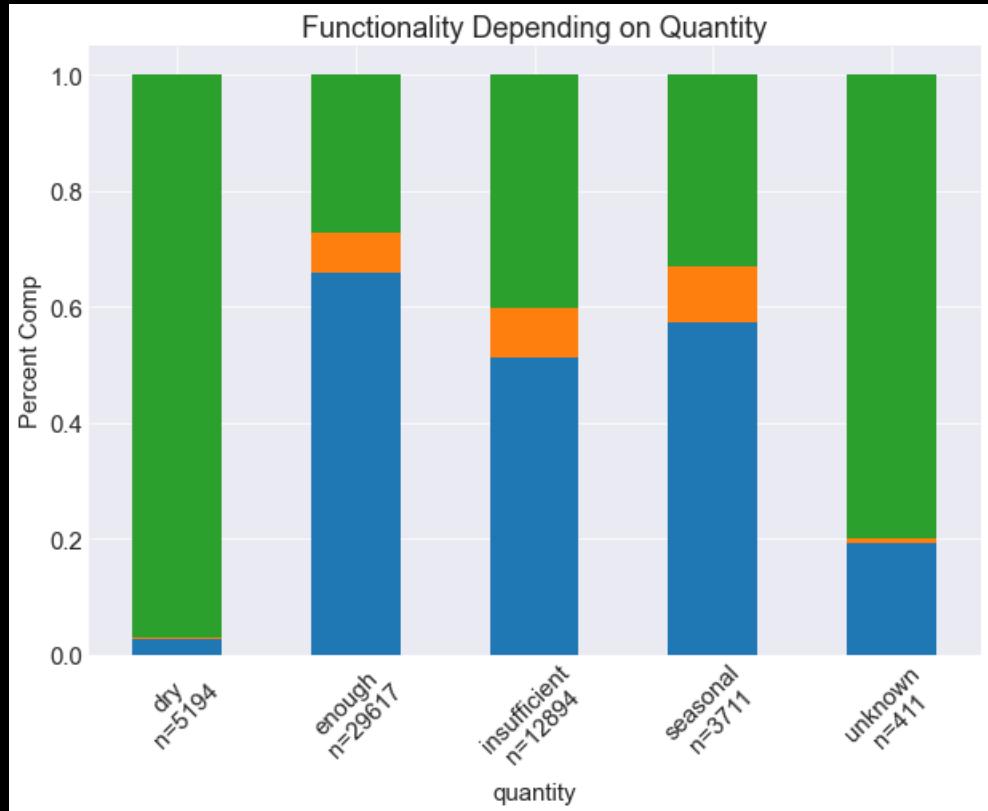


Region: Kigoma

N = 2816

Percentage: 21.41 %

# Quantity Factors



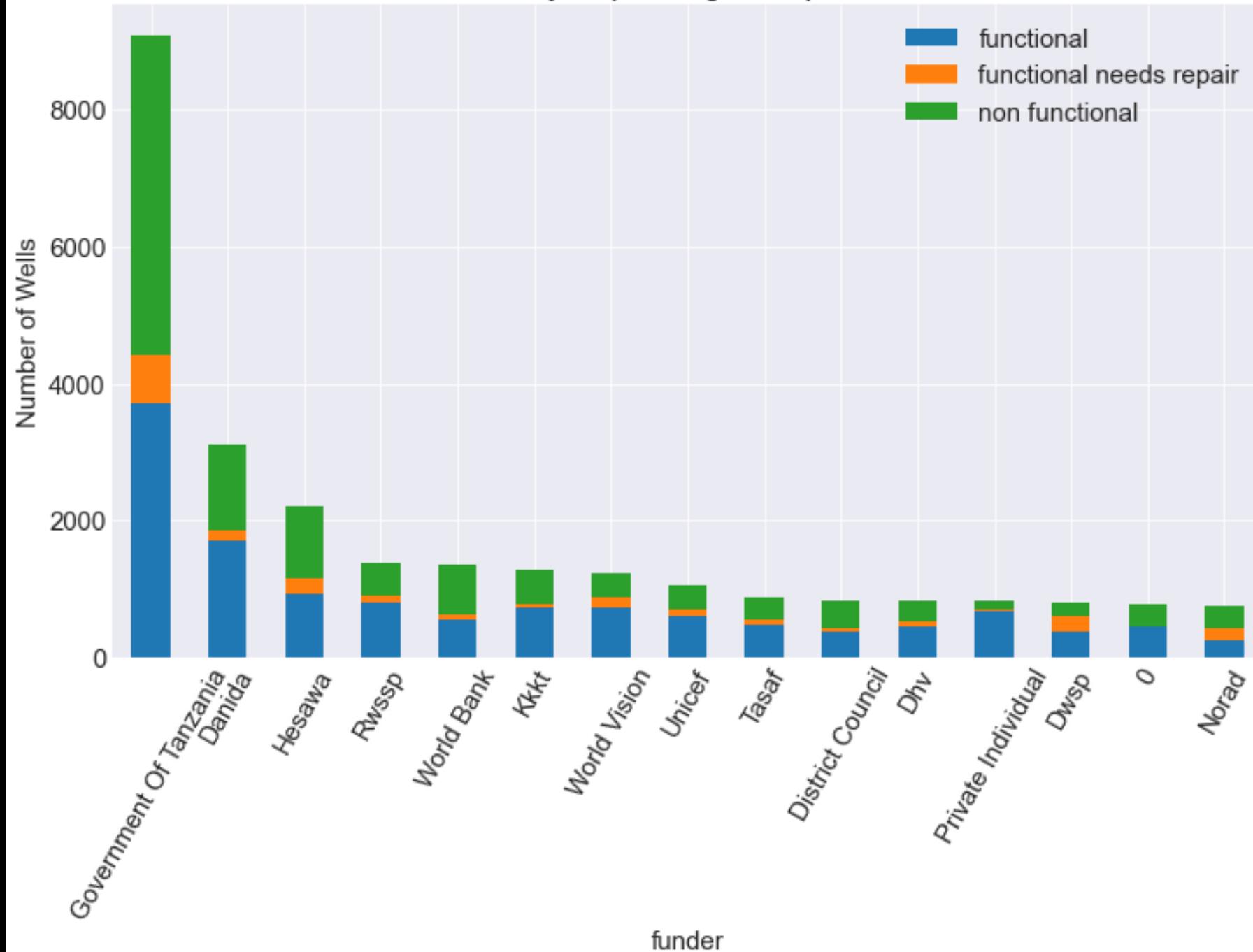
More than 90% non-functional wells for **"dry quantity"** wells.

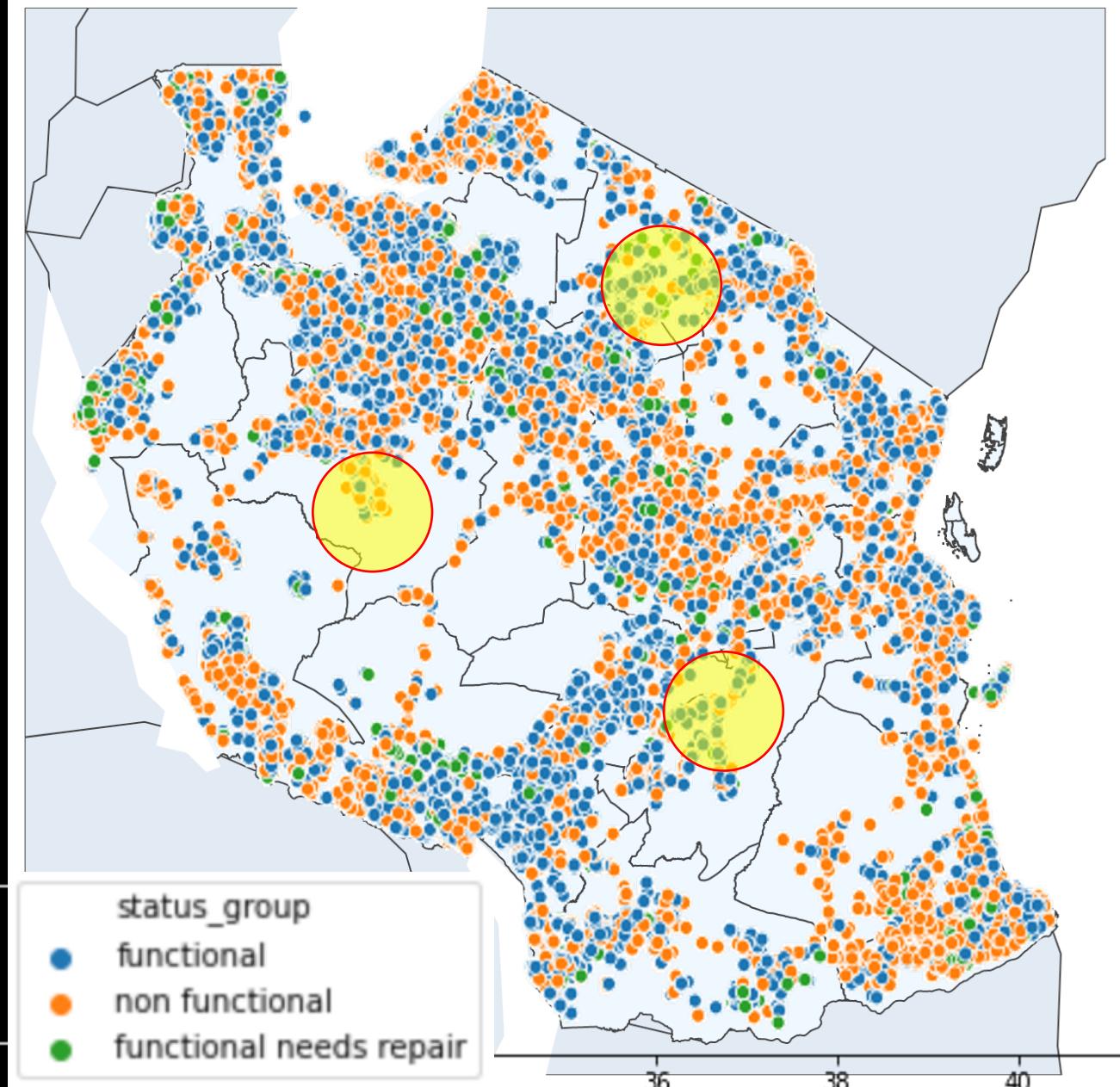
More than 80% non-functional wells for **"unknown quantity"** wells.

# Funders Factor

- More than 50% of wells funded by the government are either not functioning or need repair

Functionality Depending on Top 15 Funders





# Neighboring

Probability of finding

[1] functioning

[2] need repairing

[3] non-functioning

are calculated within 30 km of  
each water well

# Our Plan

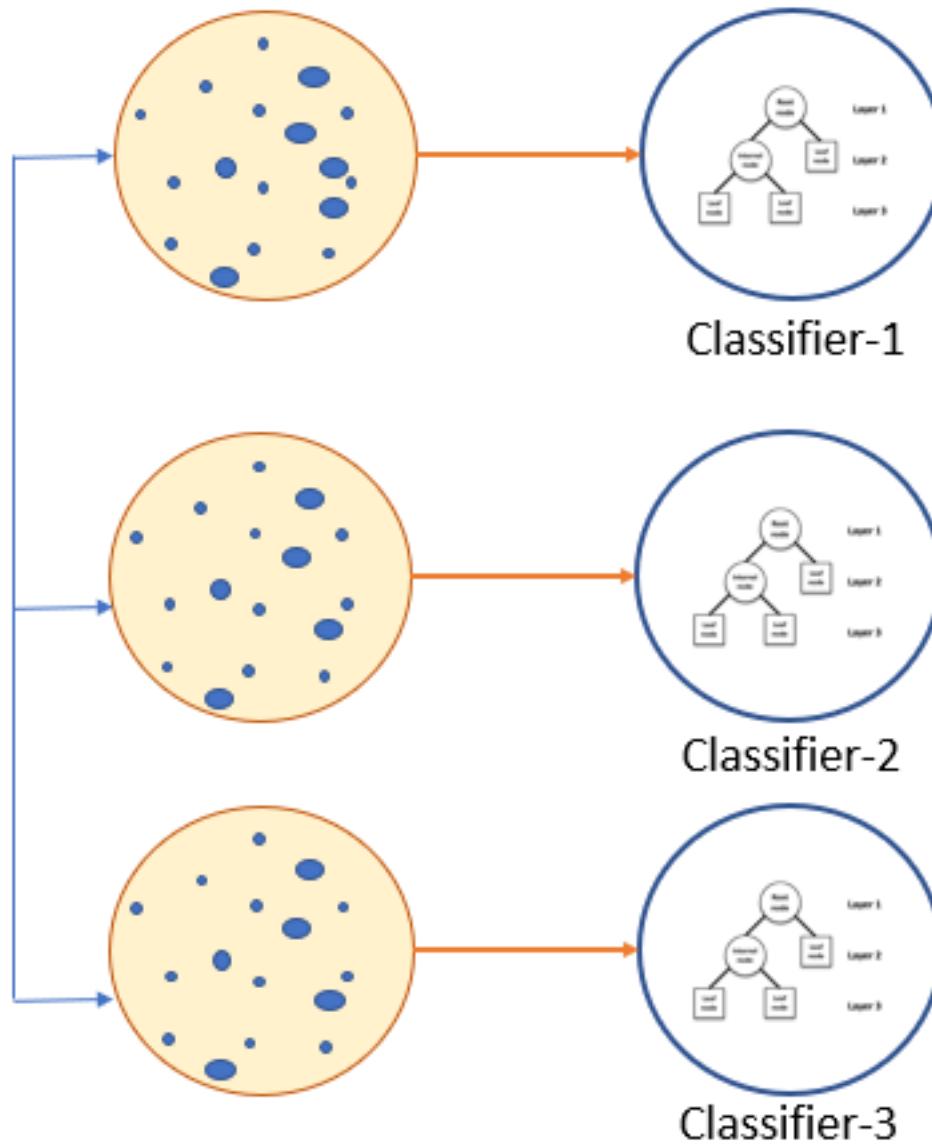
## *Bagging*

- Decreases model's variance
- Examples
  - Random Forest
  - Extra Trees

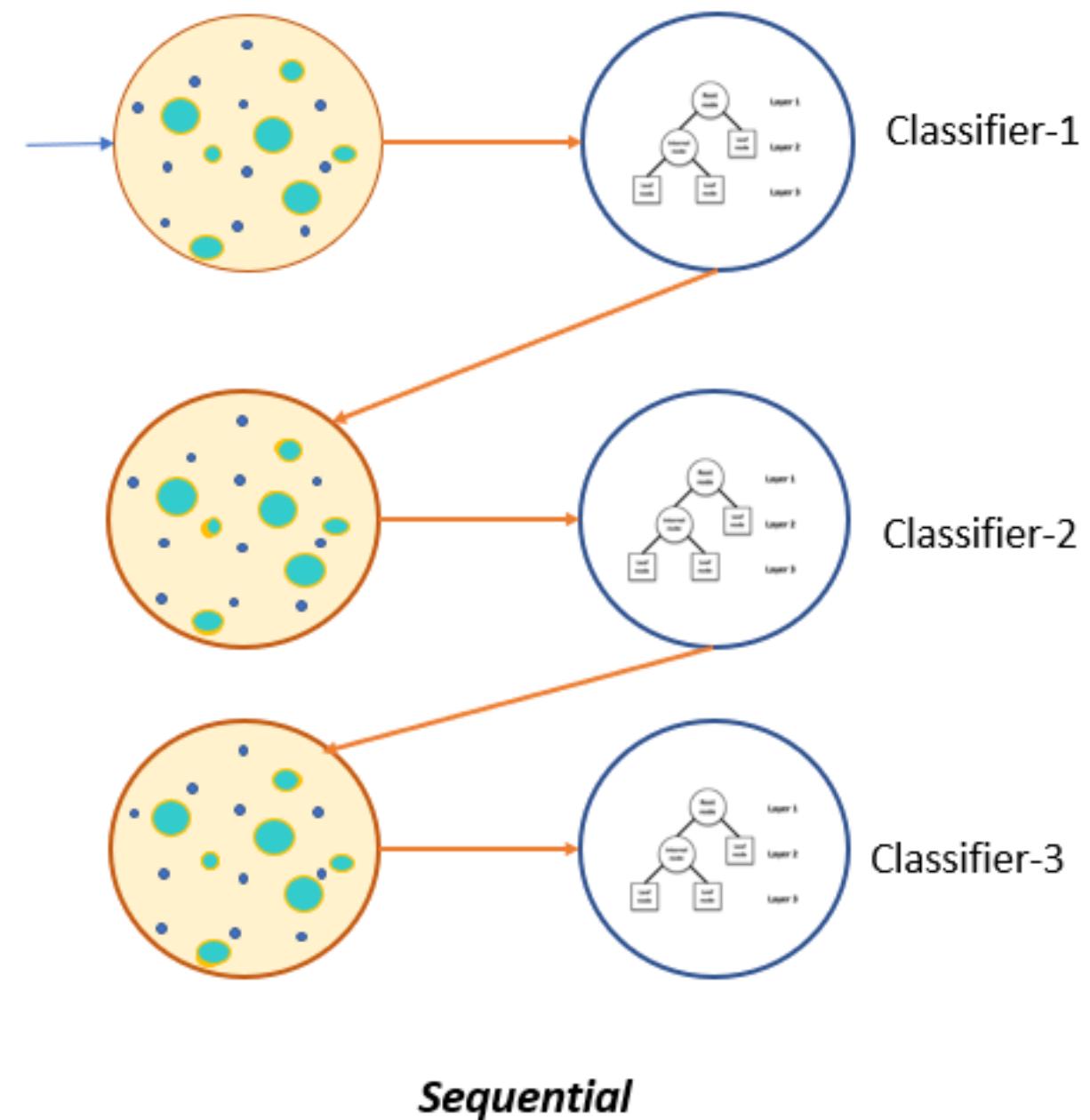
## *Boosting*

- Decreases model's bias
- Examples
  - XGBoost
  - Adaboost
  - Gradient Boost

## Bagging



## Boosting



*Parallel*

*Sequential*

# Our Plan

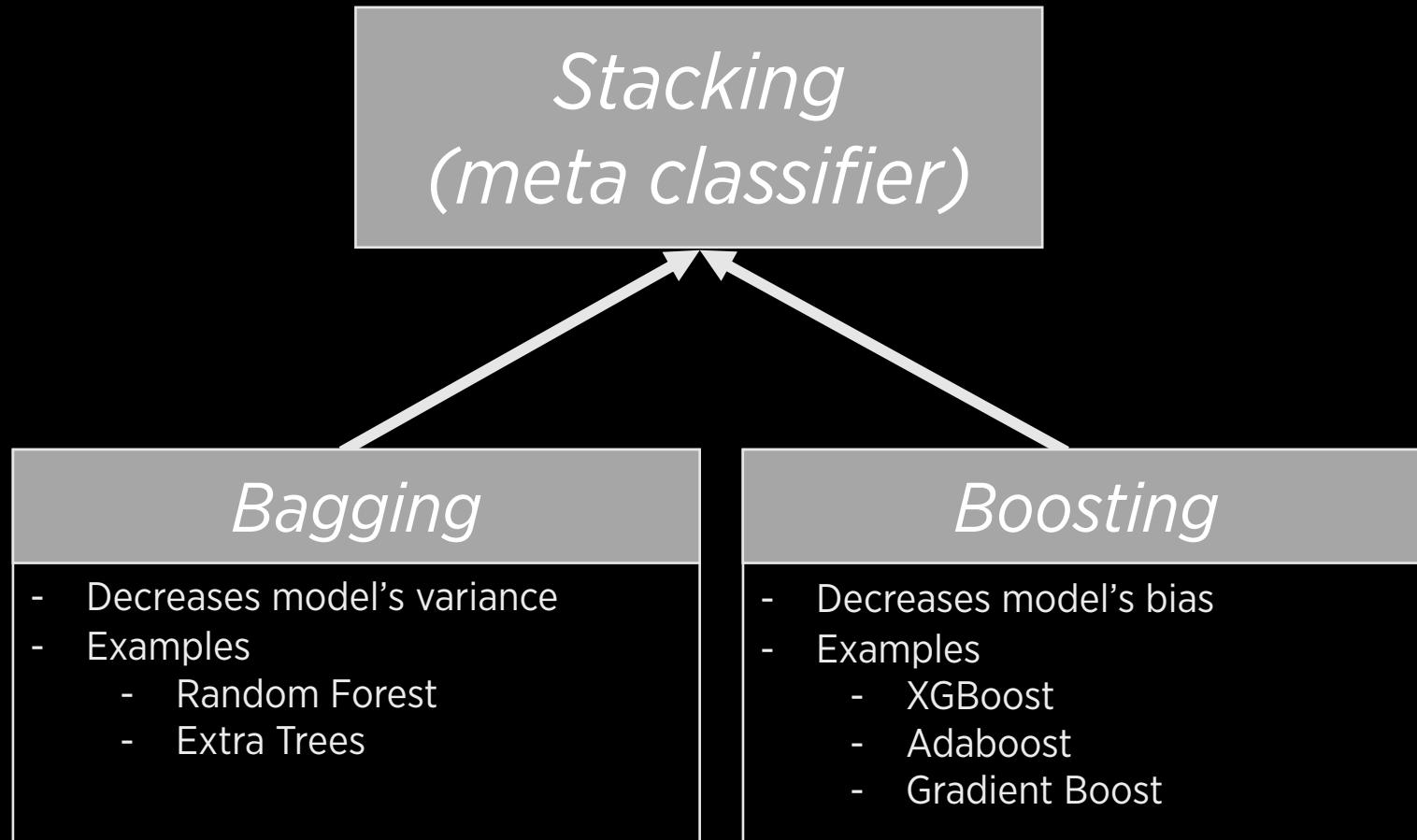
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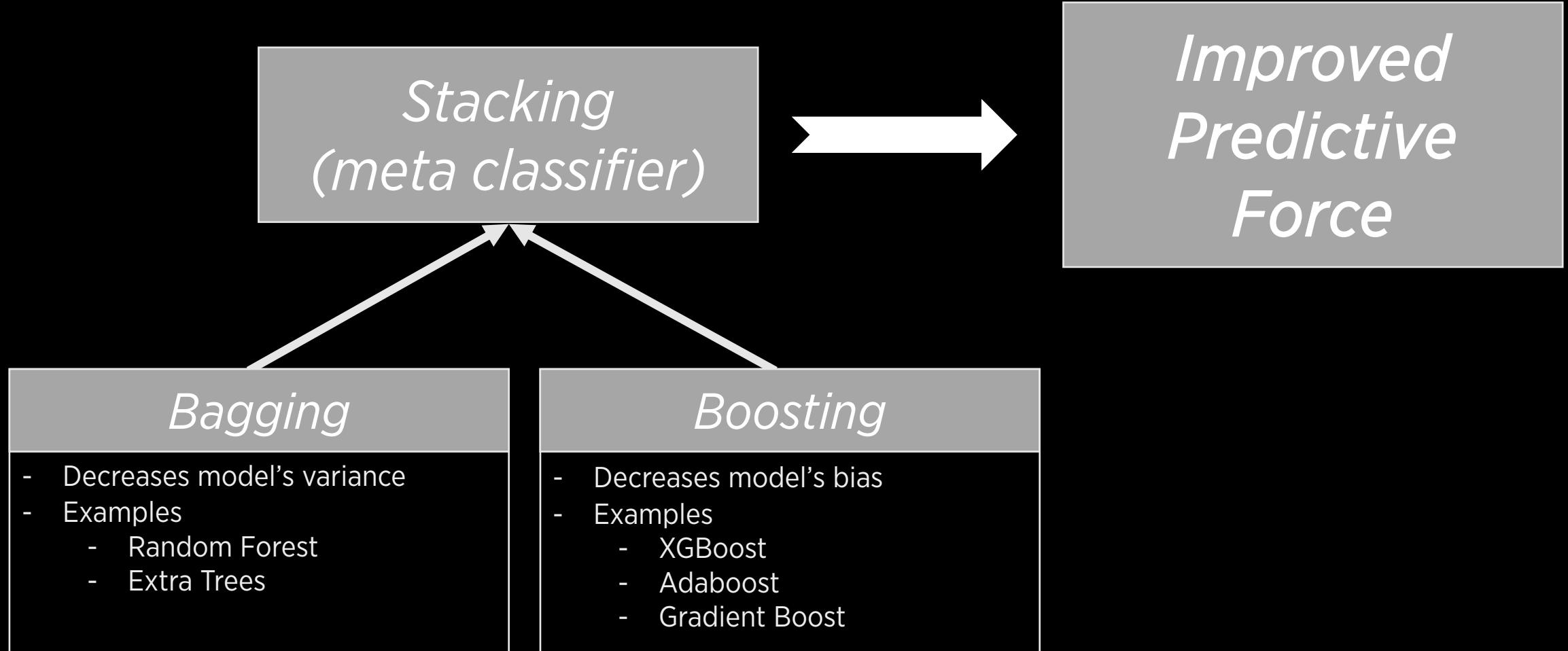
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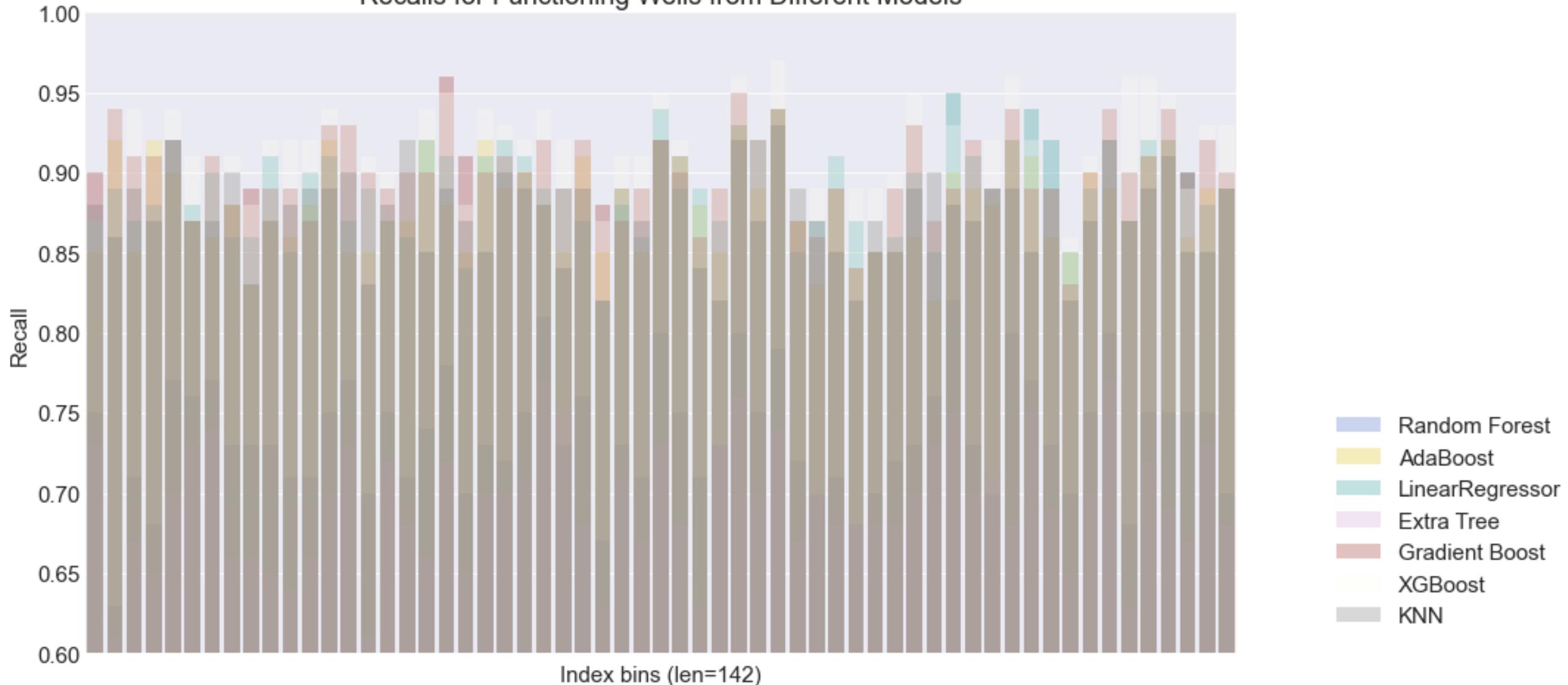
# Out Plan



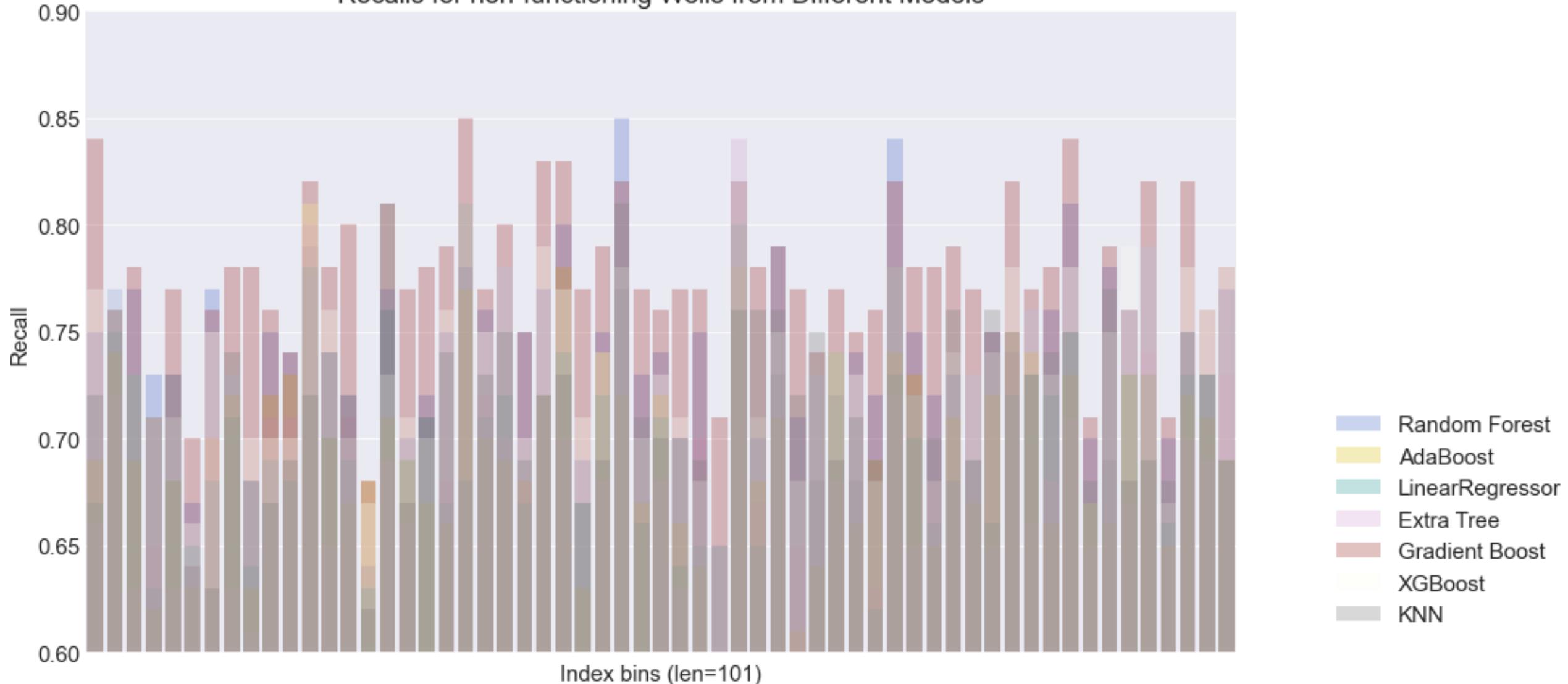
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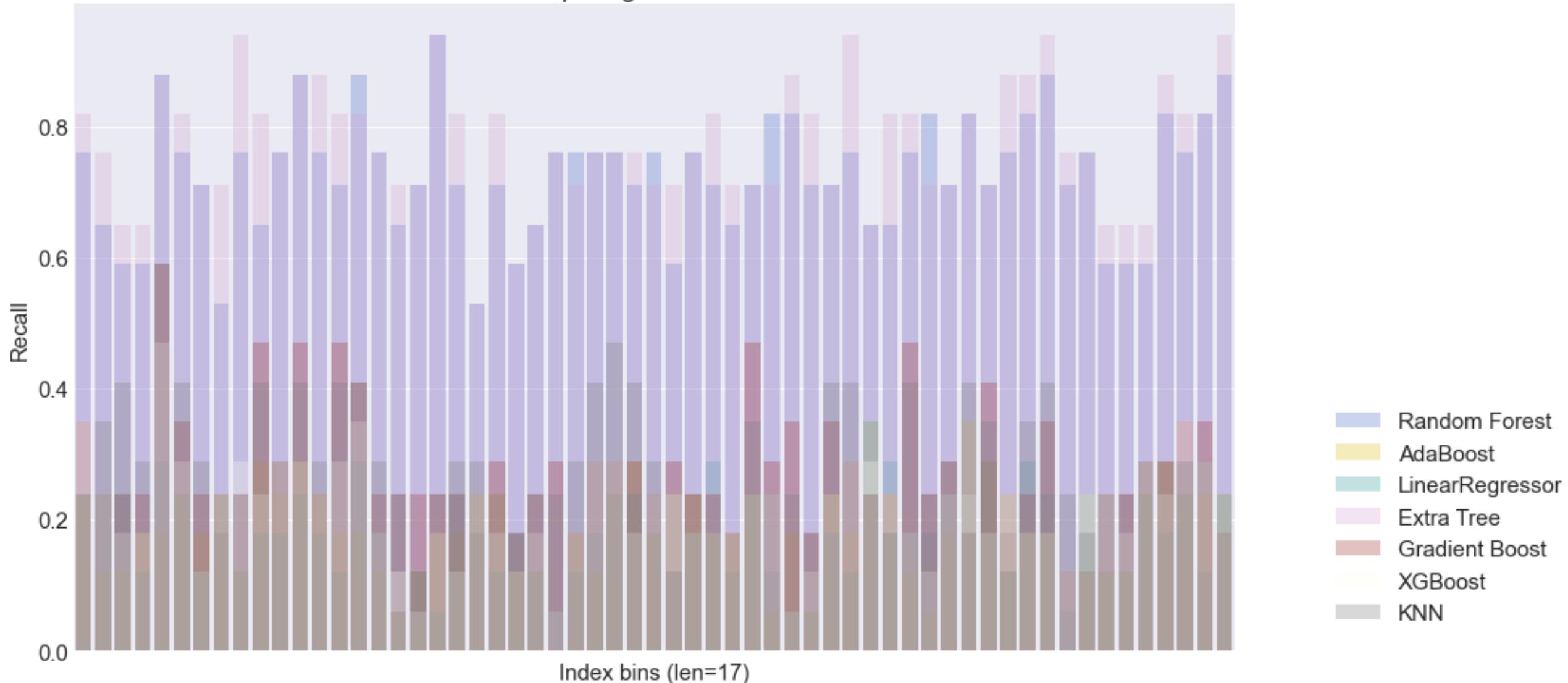
## Recalls for Functioning Wells from Different Models



## Recalls for non-functioning Wells from Different Models

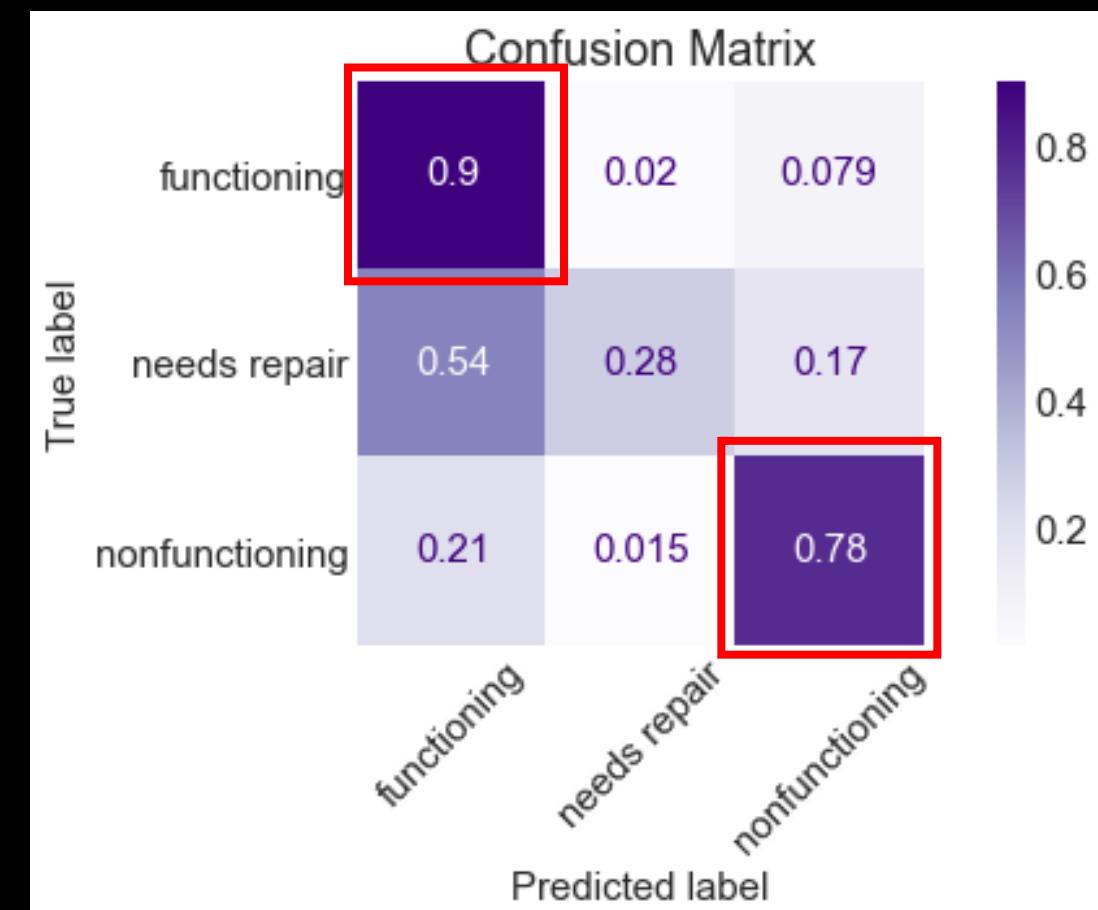


### Recalls for need repairing Wells from Different Models



# Best Accuracy Model: Adaboost

[i] CLASSIFICATION REPORT				
Train Accuracy : 0.934				
Test Accuracy : 0.8138				
Train AUC : 0.9501				
Test AUC : 0.8487				
CV score (n=3) 0.8971				
	precision	recall	f1-score	support
functioning	0.81	0.90	0.85	8490
needs repair	0.53	0.30	0.38	1019
nonfunctioning	0.85	0.78	0.81	6040
accuracy			0.81	15549
macro avg	0.73	0.66	0.68	15549
weighted avg	0.81	0.81	0.81	15549



[1] Possibly overfit [2] Accuracy = 81% [3] Test Accuracy = 79% [4] Low Recall for repair

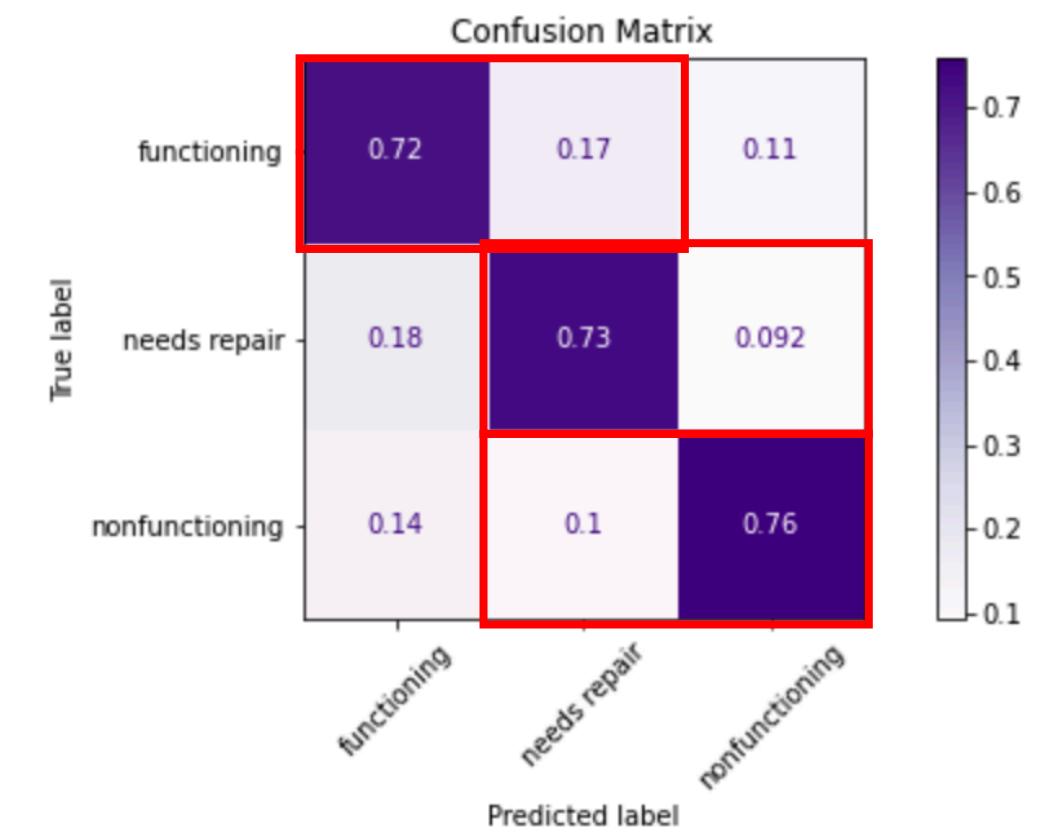
[5] 1<sup>st</sup> Layer Models: All the first layer models were used

# Best Recall Model: Random Forest

## [i] CLASSIFICATION REPORT

```
Train Accuracy : 0.7817  
Test Accuracy : 0.7343  
Train AUC : 0.9036  
Test AUC : 0.8624  
CV score (n=3) 0.7664
```

	precision	recall	f1-score	support
functioning	0.86	0.72	0.78	8490
needs repair	0.26	0.73	0.39	1019
nonfunctioning	0.81	0.76	0.78	6040
accuracy			0.73	15549
macro avg	0.64	0.73	0.65	15549
weighted avg	0.80	0.73	0.76	15549



[1] Recall = 73%

[2] Accuracy = 73%

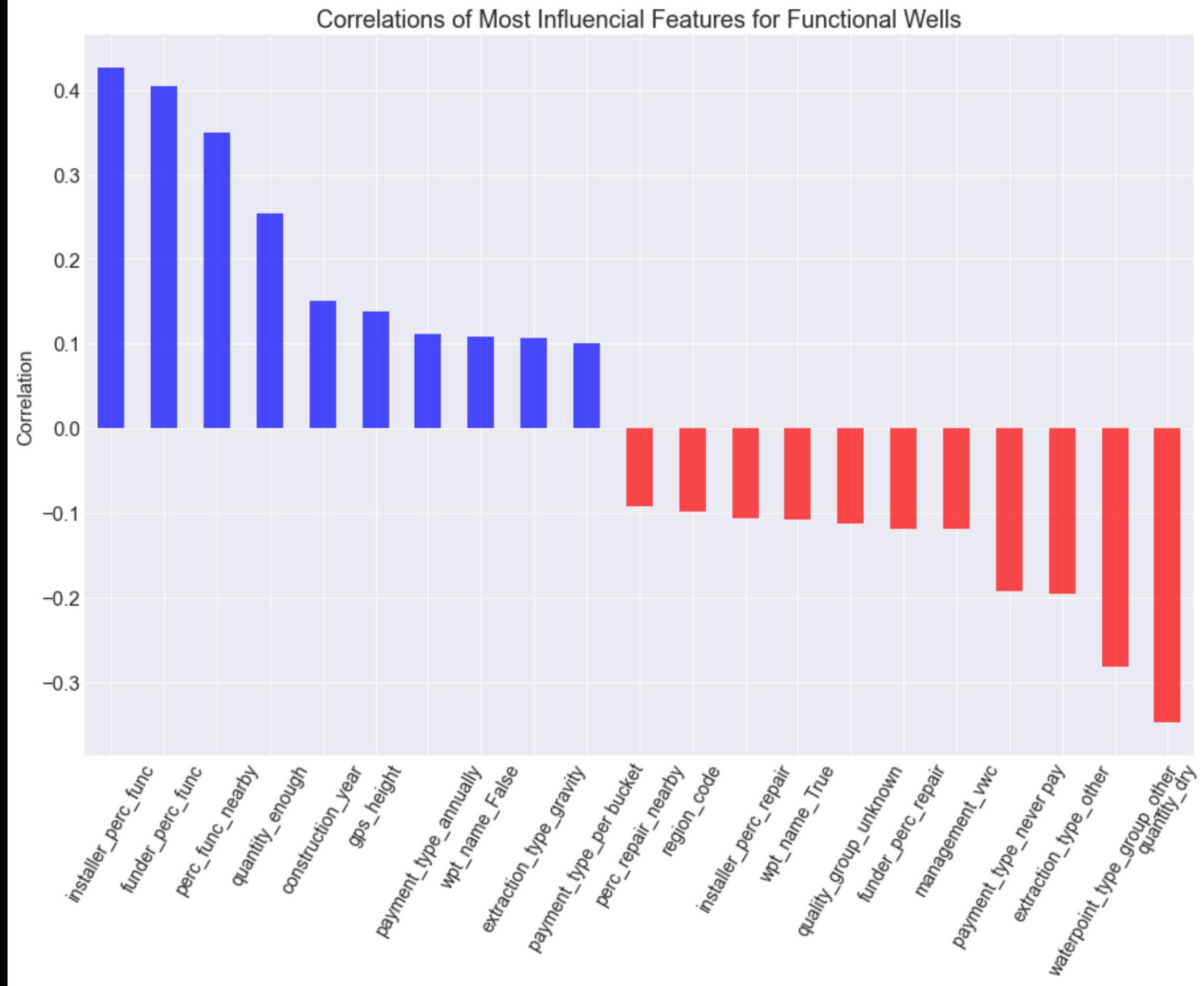
[3] Test Accuracy = ? %

[4] Effective Recalls = 89%, 82%, 86%

[5] 1<sup>st</sup> Layer Models: XGBoost, Random Forest, Extra Trees, KNN

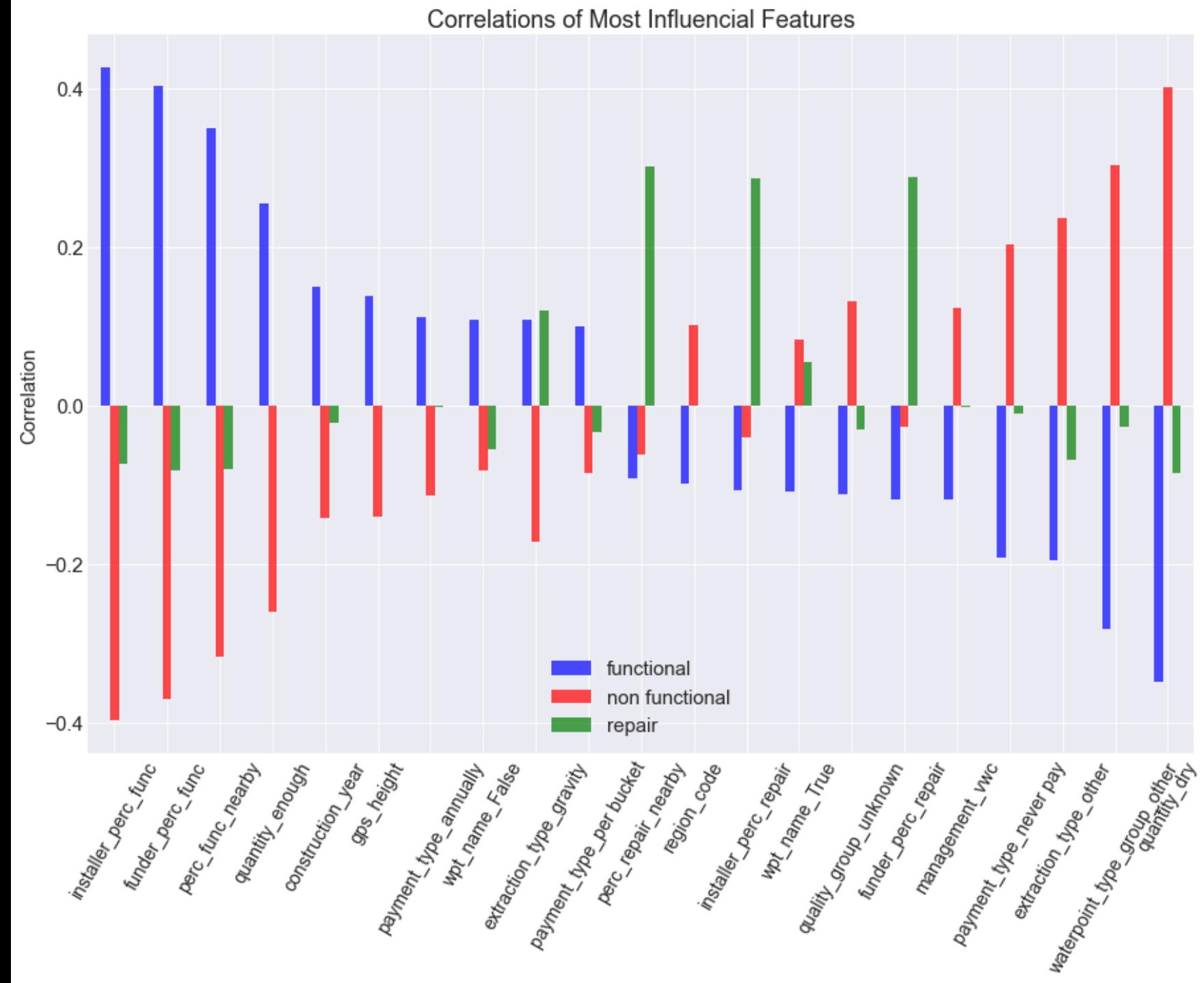
# Interpreting the Model

- Most positive:
  - Installer
  - Funder
  - Neighbor
  - Payment
  - Extractor type
- Most Negative:
  - Quantity
  - Extractor type
  - Management
  - Neighbor



# Interpreting the Model

- Expected  
Functioning and non-functioning have opposite correlation
- New Finding  
Repair is all over the places which makes the prediction extra tough



# Conclusion

- Our final models can
  - Predict with 79% accuracy (Adaboost - 7 1<sup>st</sup> layers)
  - Predict with 85% recall (Random Forest - 4 1<sup>st</sup> layers)
- Important features
  - Positive
    - Installer, funder, neighbor- high functioning percentage
    - Payment - existence
    - Extractor type - gravity
  - Negative
    - Quantity - dry
    - Extractor type – other than gravity
    - Management – VWC (village water committee)
    - Payment – Lack of payment

# Future Studies

- Further hyperparameter tuning can be done for each model used
- Different combinations of ensemble models can be tested
- Different methods of dealing with class imbalance can be used
  - under sampling
  - different class weights

Thank you for listening

# Appendix