Predicting Bug Resolution on Eclipse Browser

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We trained 5 types of models and found that Random Forest gave the best AUC (Area Under the Curve) score.

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Assignments to developers who will work on fixing the bug sometimes choose to not fix bugs due to just how labor intensive they will be.

Bug Prediction

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To do this, we will employ 5 types of models on an altered dataset and compare their results to draw conclusions.

LOGIT Regression

1. This model takes linear combination of the factors and transforms it to return a value $p \in [0, 1]$

- Regression equation:

$$\ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 x + ... + \beta_k x_k$$

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3. Our optimal threshold to label output as 1 was 0.56

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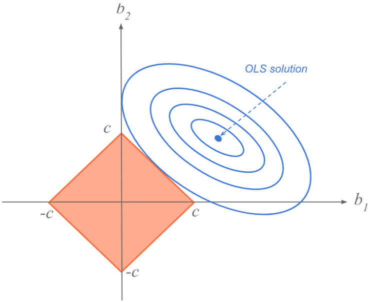
Lasso Regularization

1. This improves the previous LOGIT model by adding to the loss function L

$$L + \lambda \sum_i |\beta_i|$$



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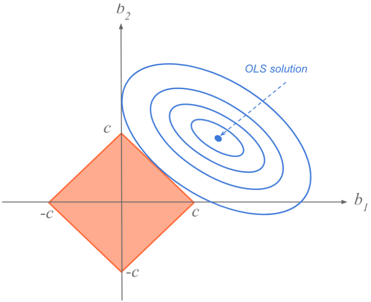
2. Model is encouraged to push (and even set) β_i's to 0.



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Bagging

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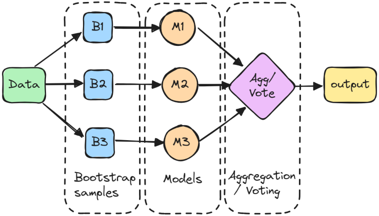
1. Reduces variance in a noisy dataset



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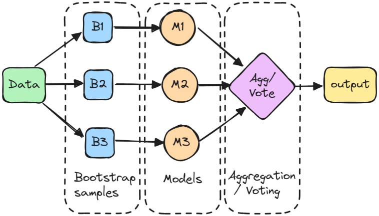

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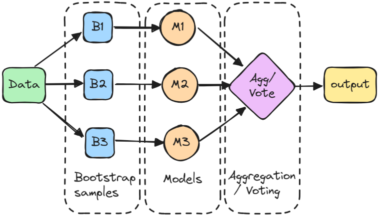
3. Smaller models are averaged/aggregated to make overall model



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Random Forest

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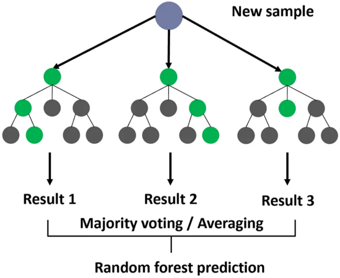

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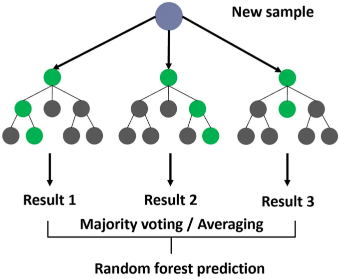

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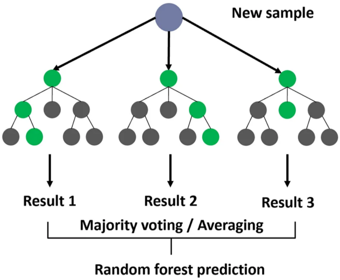

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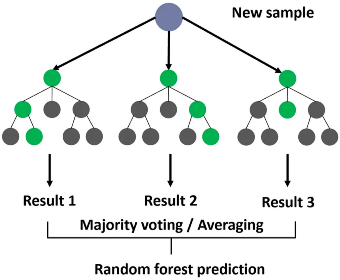
4. The random selection leads to more independent trees which can help prediction



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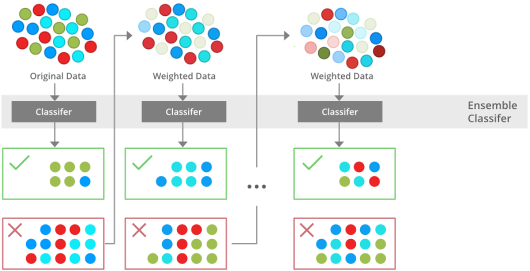

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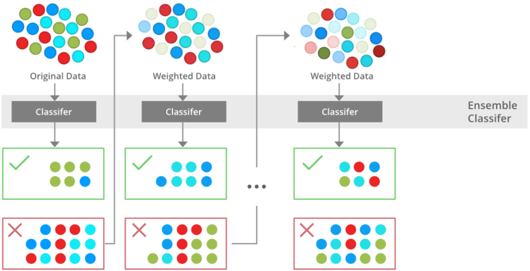

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Boosting

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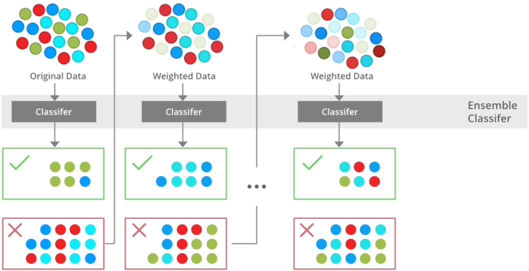
3. We used Gradient Boosting, which tries to build learners that are more efficient than the previous



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- New variables created using information in dataset
- Excel and SQLite3 were used to cleanup the data and create new variables

Data Structure

id	curr_res	reporter	stat_upd	num_intrst	op_sys	component	prod	severity
287149	FIXED	17941	2	6	Linux-GTK	SWT	Platform	normal
89374	FIXED	57	5	1	Windows 2000	UI	Platform	normal
89378	FIXED	8126	3	5	Windows XP	SWT	Platform	normal

Sample of dataset. Some new variables include:

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Sample of dataset. Some new variables include:

- Total time bug report is open
- Max priority/severity
- Number of reassignments/status changes
- Success rate of initial assignee

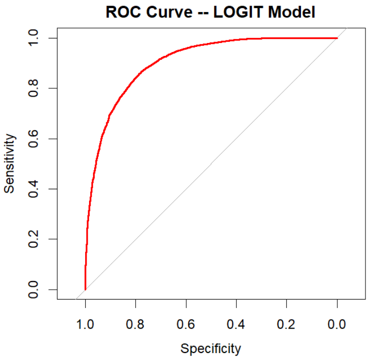
Variable Descriptions (1)

- id: Unique identifier for bug
- curr_res: Whether a bug is fixed or won't be fixed
- reporter: Unique identifier for the bug reporter
- stat_upd: Number of times the bug status was updated
- num_intrst: Number of emails interested in the bug
- op_sys: Operating system that bug affects. Most recent update value used
- prod: Software/product that the bug pertains to
- component: Subsystem of product that the bug affects
- severity: Highest severity given to the bug

Variable Description (2)

- version: The version of the product that the bug affects
- times_assigned: Number of times the bug was reassigned
- succ_rate: The success rate of the initial assignee
- res_upd: Number of times the resolution of a bug was changed
- res_time: Time until the bug was resolved
- reporter_report_cnt: How many bugs the reporter has reported in the dataset
- desc_length: Sum of lengths of the descriptions on the bug
- prio: Highest priority value assigned to the bug

Model: LOGIT Regression (with poly)



Confusion Matrix

class	Wont Fix	Fixed
Wont Fix	2848	777
Fixed	3070	29624

Figure: AUC: 0.9048

Model: LASSO Regularization (with poly)

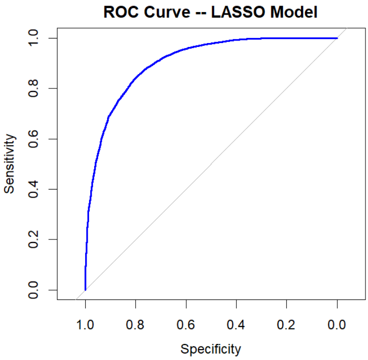
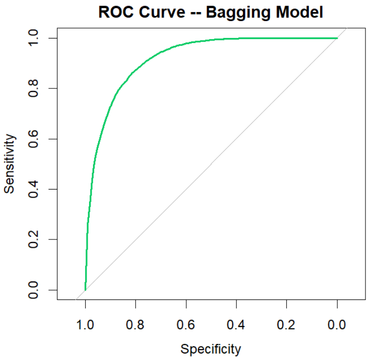


Figure: AUC: 0.9286

Confusion Matrix

class	Wont Fix	Fixed
Wont Fix	3161	826
Fixed	2757	29575

Model: Bagging

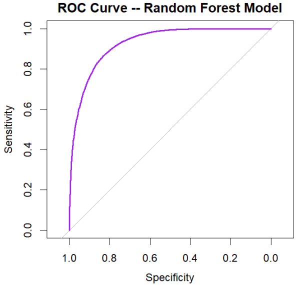


Confusion Matrix

class	Wont Fix	Fixed
Wont Fix	3425	521
Fixed	2493	29880

Figure: AUC: 0.9186

Model: Random Forest

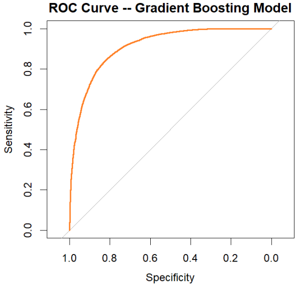


Confusion Matrix

class	Wont Fix	Fixed
Wont Fix	3431	438
Fixed	2487	29963

Figure: AUC: 0.9286

Model: Boosting



Confusion Matrix

class	Wont Fix	Fixed
Wont Fix	3349	916
Fixed	2569	29485

Figure: AUC: 0.9122

Important Variables

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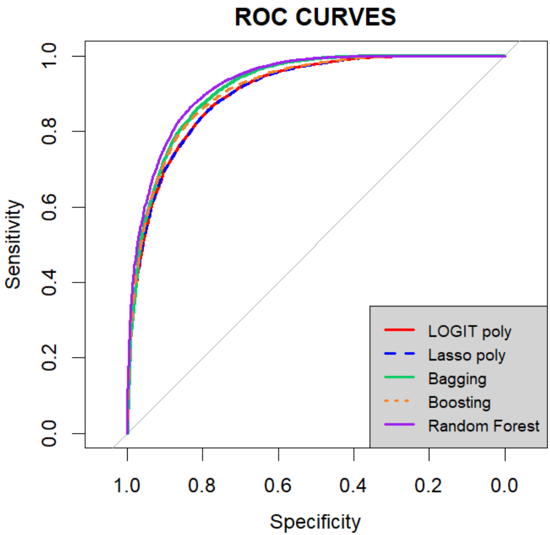
2. Almost every variable we examined was significant
3. The only variable that was found to not be significant was "Component"

Summary of LOGIT variables (no poly)

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-2.4051	0.1819	-13.22	0.0000
reporter	-0.0000	0.0000	-19.40	0.0000
stat_upd	0.5816	0.0208	27.90	0.0000
num_intrst	0.1420	0.0095	14.99	0.0000
op_sys	0.0039	0.0012	3.25	0.0012
component	-0.0007	0.0016	-0.40	0.6888
prod	-0.1186	0.0179	-6.62	0.0000
severity	0.2028	0.0113	17.90	0.0000
version	0.0382	0.0025	15.53	0.0000
times_assigned	0.2017	0.0179	11.28	0.0000
succ_rate	5.1959	0.1233	42.15	0.0000
res_upd	-0.7482	0.0322	-23.26	0.0000
res_time	-0.0000	0.0000	-46.34	0.0000
reporter_report_cnt	-0.0002	0.0000	-15.26	0.0000
desc_length	-0.0022	0.0003	-6.46	0.0000
prio	-0.1457	0.0151	-9.65	0.0000

ROC Curve Comparison



Selection of Best Model

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3. We used the Area Under the Curve to determine our best model. Without poly(), Boosting, Random Forest, and Bagging all returned similarly high AUC scores
4. Using our training/testing set, Random Forest gave the highest AUC, i.e. the best testing performance, regardless of whether we utilized the poly() function or not.

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4. Boosting was expected to outperform every other model but ranked below both Bagging and Random Forest
5. Rankings could change with different val/train splits

Citation

Ahmed Lamkanfi, Javier Perez, and Serge Demeyer, *The eclipse and mozilla defect tracking dataset: a genuine dataset for mining bug information*, MSR '13: Proceedings of the 10th Working Conference on Mining Software Repositories, May 18-–19, 2013. San Francisco, California, USA, 2013.