Task AES: Automated Essay Scoring

Federico Rausa – mat . 919795



Dataset

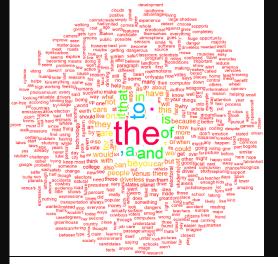
Variables:

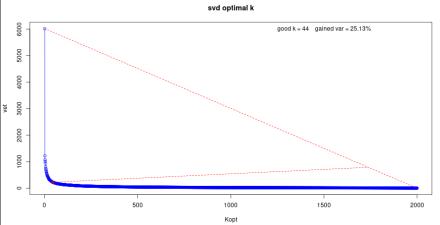
- Full text: essay written by the student as unique string
- Score: evaluation of the essay given by the teacher (int from 1 to 6), who should follow general criteria

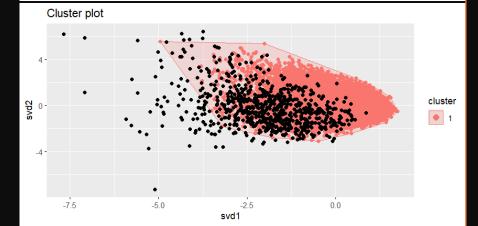
∆ full_text	=	# score	=
17307 unique values		1	6
Many people have where they live. thing they don't know is that when you use a car alo of t	The	3	
I am a scientist NASA that is discussing the "face" on mars. I will be explaining how the "face"	g	3	
People always wish they had the same technology that the have seen in moving or the best new piece	hey	4	
We all heard abou	t	4	

Full Text preprocessing:

- 1. DTM + trimming
- SVD and choice of #components (25 for 20% explained var)
- 3. Noise Removal with DBSCAN (#noisePts=~760, #clusters=1, eps=5, minPts=5)







Data splitting for supervised learning

- Splitting with Stratified Sampling (follow score distribution)
- Validation set: ~ 4000 obs (for hyperparams optimization)
- Train-Test set: ~ 12000 obs (for bootstrap 50% comparisons)

	1	2	3	4	5	6	N
scoreMainDist	7.23	27.29	36.29	22.68	5.6	0.9	17307
scoreValidationDist	6.97	28.04	37.01	22.61	4.82	0.55	4002
scoreTrainTestDist	7.15	27.86	37.02	22.61	4.84	0.53	12551
scoreNoiseDist	10.08	13.79	20.29	24.27	22.55	9.02	754

Evaluation metrics used:

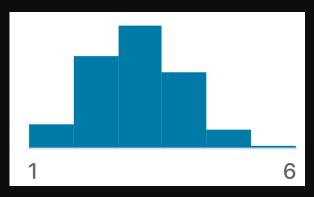
Quadratic Weigthed Cohen's Kappa (QWK):

higther penalties for errors far from the diagonal of the Confusion Matrix

[-1, 1]

$$QWK = 1 - rac{\sum W_{ij}O_{ij}}{\sum W_{ij}E_{ij}}$$
 with weigths $W_{ij} = rac{(i-j)^2}{(K-1)^2}$

- Accuracy [0,1]
- MAE [0, +Inf)
- F1 score on extreme classes (1 and 6) [0,1]



Different supervised models for different task

- Regression Models (minimize MAE):
 Lasso, KNN, SVD, GBM, XGB
- Classification Methods (maximize Accuracy):
 Decision Tree, SVD, GBM, XGB
- Ranking Methods
 (maximaze QWK):
 Cumulative Logit, XGB with Pairwise Loss, ranking with binary groups

Hyper – parameters optimization on Validation Set

With Grid-Search:

- Lasso (L1 regularization)
- KNN (K)

With Bayesian Optimization:

- SVD (kernel, C, gamma)
- GBM (learning rate, #trees for boosting, bag fraction for each tree)
- XGB (learning rate, #trees for boosting, regularization,
- gamma/minimal error reduction for a new split)

Ranking models

Ordinal logistic regression:

• XGB for the minimization of the Pairwise Logistic Loss:

$$P(y_i \le j) = \frac{exp(\alpha_j + \beta x_i)}{1 + exp(\alpha_j + \beta x_i)}$$

$$P(y_i = j) = P(y_i \le j) - P(y_i \le j - 1)$$

$$pairwiseLoss = L(\overline{x}, \overline{y}, f) = \sum_{(i,j) \in Pairs} loss_{ij}$$

$$loss_{ij} = -\left(z_{ij} * ln(p_{ij}) + (1 - z_{ij}) * ln(1 - p_{ij})\right)$$

$$\Delta_{ij} = f(x_i) - f(x_j)$$

$$p_{ij} = \frac{1}{\left(1 + exp(-\Delta_{ij})\right)}$$

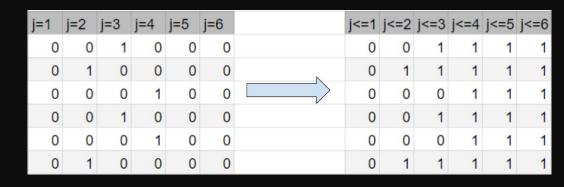
$$z_{ij} = \begin{cases} 1 & y_i > y_j \\ 0 & y_i < y_j \end{cases}$$

Ensemble strategy for ranking

Group of binary models for CDF prediction:

- K-1 binary models to predict K-1 cdf dummies
- Same hyper-parameters to follow

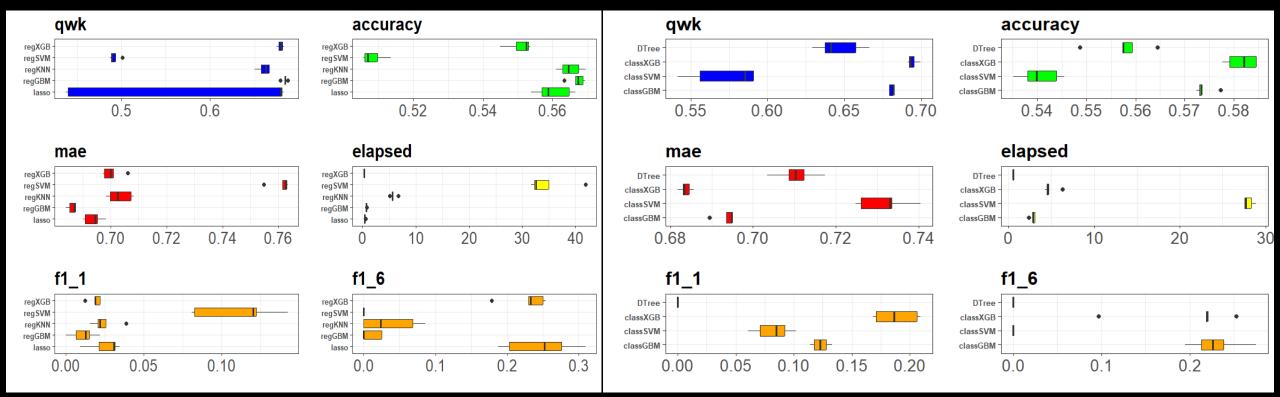
$$P(y_i \le j) > P(y_i \le j - 1)$$



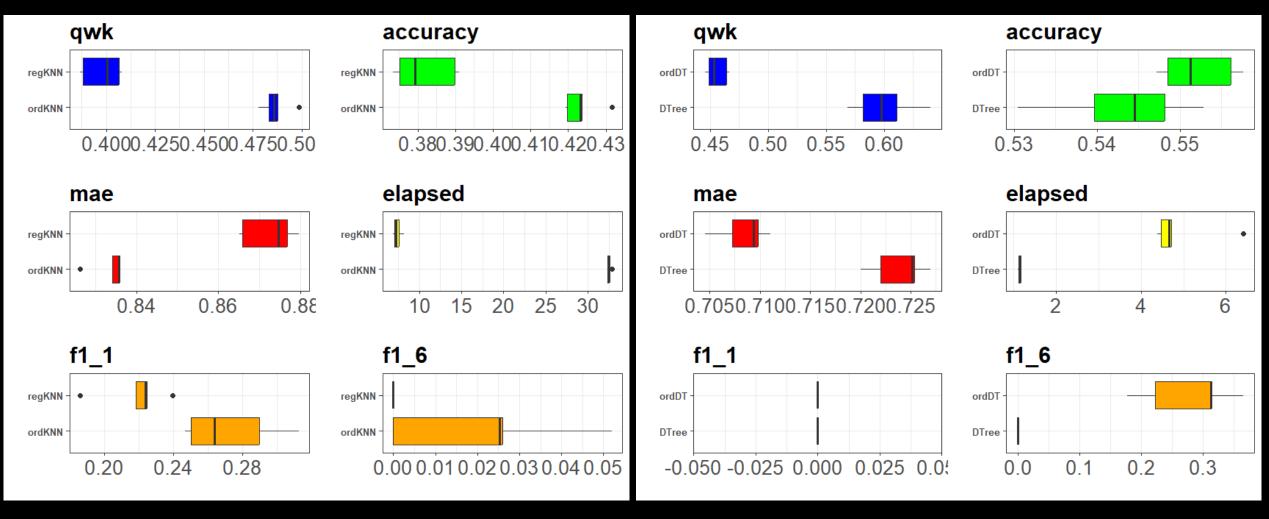
$$y_{ij} = \begin{cases} 1 & y_i \ge j \\ 0 & y_i < j \end{cases}$$

$$P(y_i = j) = (1 - P(y_i \ge j)) - (1 - P(y_i \ge j - 1)) = P(y_i \ge j - 1) - P(y_i \ge j)$$

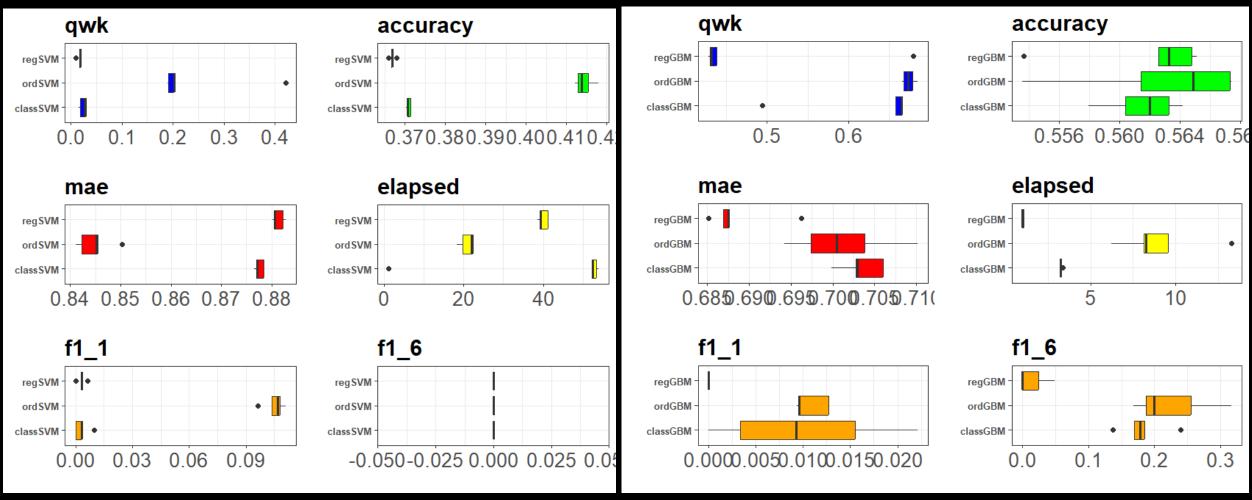
Bootstrap final comparisons: classification and regression



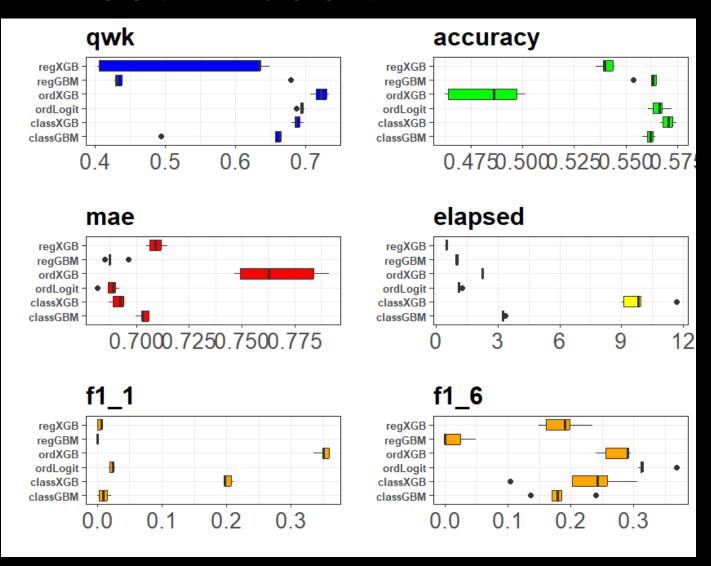
Bootstrap final comparisons: improvements of ranking groups (KNN, DT)



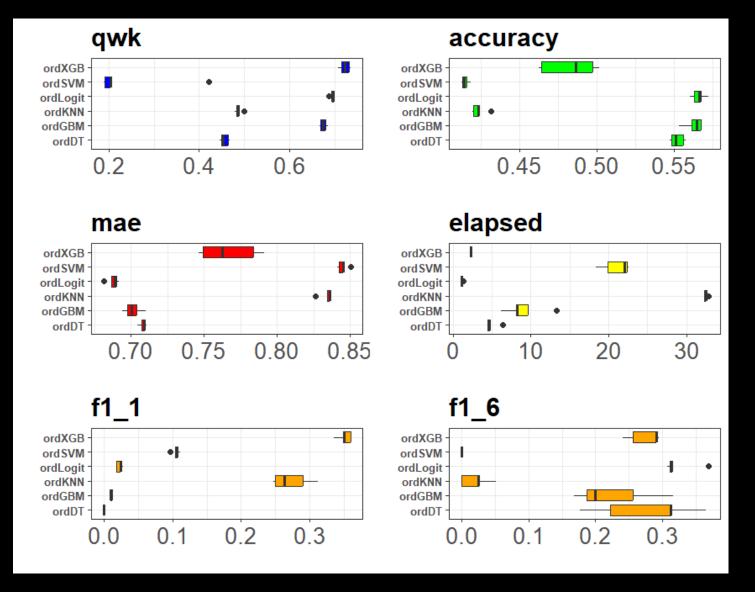
Bootstrap final comparisons: improvements of ranking groups (SVD, GBM)



Bootstrap final comparisons: best models



Bootstrap final comparisons: ranking models



THANK YOU