Wage Prediction Hackathon

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EDA

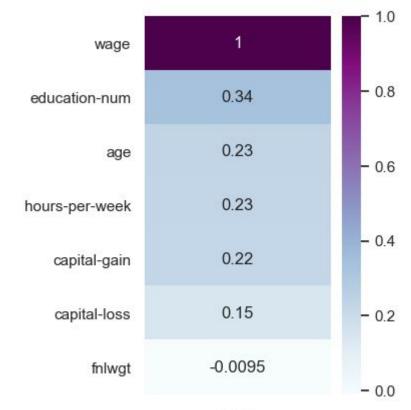
Large Train Sample data - (32561 entries and 14 columns)

7 columns are categorical

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32561 entries, 0 to 32560
Data columns (total 14 columns):
    Column
                    Non-Null Count
                                    Dtype
                    32561 non-null
                                    int64
    age
    workclass
                    32561 non-null
                                    object
    fnlwgt
                    32561 non-null
                                    int.64
                                    object
    education
                   32561 non-null
    education-num 32561 non-null
                                    int64
    marital-status 32561 non-null
                                    object
                                    object
    occupation
                    32561 non-null
    relationship
                                    object
                    32561 non-null
                    32561 non-null
                                    object
    sex
    capital-gain
                    32561 non-null
                                    int64
    capital-loss
                    32561 non-null
                                    int64
    hours-per-week 32561 non-null
                                    int64
    native-country
                                    object
                    32561 non-null
    wage
                    32561 non-null
                                    object
dtypes: int64(6), object(8)
memory usage: 3.5+ MB
```

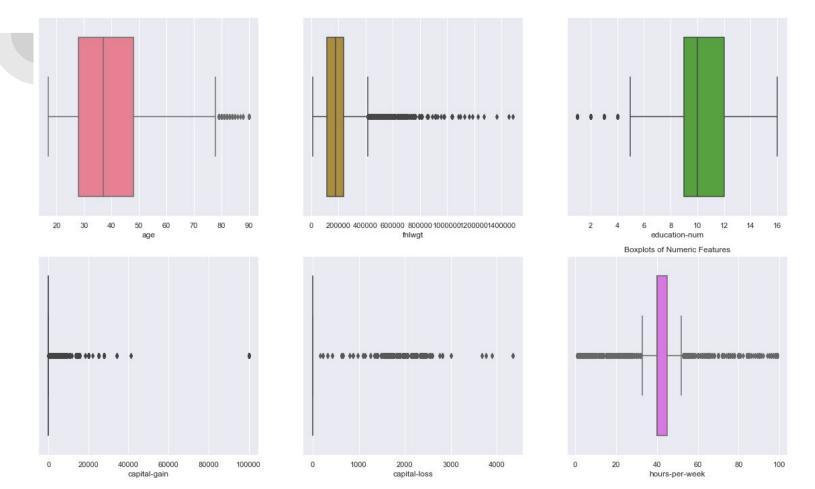
EDA

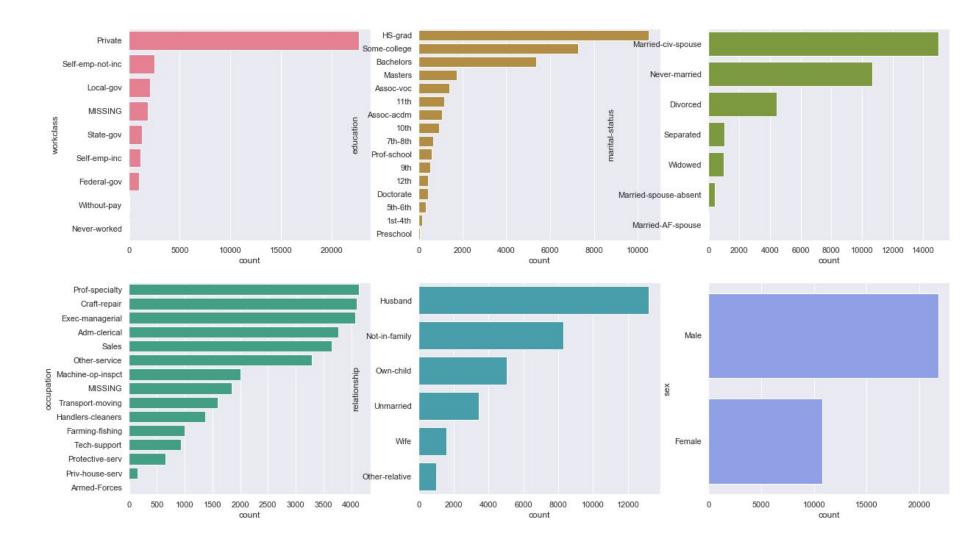
Not a lot of strong correlation



wage

Numeric Features





		wage	1	1.0
	Features	ms_married_civ_spouse	0.44	
		education_num	0.34	- 0.8
		age	0.23	0.0
1.	age	hours_per_week	0.23	
2.	education_num	capital_gain	0.22	- 0.6
3.	capital_gain	sex_Male	0.22	
4.	hours per week	capital_loss	0.15	
5.	wc_gov	wc_gov	0.062	- 0.4
6.	wc_no_work	ms_married_af_spouse	0.012	
7.	ms_married_af_spouse	fnlwgt	-0.0095	
8.	ms_married_civ_spouse	wc_no_work	-0.014	- 0.2
9.	ms_married_spouse_absent	ms_married_spouse_absent	-0.043	
10.	ms_never_married	wc_other	-0.061	
11.	ms_separated	ms_widowed	-0.064	- 0.0
12.	ms_widowed	ms_separated	-0.074	
13.	sex_Male	ms_divorced	-0.13	
	_	sex_Female	-0.22	0.2
		ms_never_married	-0.32	

wage



Models	train score	test score	Mean CV_score	f1score_train	f1score_test
Random Forest	0.8453	0.8462	0.8450	0.6076	0.5979
Logistic Regression	0.8393	0.8393	0.8392	0.6256	0.6177
KNN	0.8491	0.837	0.8359	0.6553	0.6182
Adaboost	0.9322	0.8259	0.8258	0.8576	0.6155
SVC	0.8453	0.8448	0.8448	0.6256	0.6114

Model

```
'ccp_alpha': 0.001,
'max_features': 'sqrt',
'max_leaf_nodes': 30,
'min_impurity_decrease': 0.0,
'min_samples_leaf': 10,
'min_samples_split': 4,
'min_weight_fraction_leaf': 0.0,
'n_estimators': 100
```

- 1. age
- 2. education-num
- 3. marital-status
- 4. sex

[166]:		train	test	Mean_CV_Score	f1score_train	f1score_test
	RForest_Kemal	0.822569	0.821988	0.82099	0.542534	0.522908
	KNN_Kemal	0.830247	0.817382	0.820858	0.611975	0.569498
	SVC_Reem	0.819454	0.819224	0.819454	0.548942	0.532804
	LOGREG_Jonna	0.818533	0.819122	0.818094	0.560934	0.544235
-	Adaboost_Reem	0.845516	0.811854	0.81182	0.656387	0.568139
	BagginClassifier_Jonna	0.844419	0.80561	0.811337	0.651943	0.559499

- 1. age
- 2. education-num
- 3. marital-status
- 4. sex
- 5. workclass
- 6. hours per week
- 7. capital gains

		train	test	Mean_CV_Score	f1score_train	f1score_test
	SVC_Reem	0.845779	0.844406	0.844858	0.629102	0.612443
	LOGREG_Jonna	0.839681	0.839595	0.839461	0.626686	0.617151
_	KNN_Kemal	0.850298	0.836728	0.837706	0.660362	0.618512
	Adaboost_Reem	0.932169	0.82772	0.826957	0.857669	0.617587

- 1. age
- 2. education-num
- 3. marital-status
- 4. sex
- 5. workclass
- 6. hours per week
- 7. capital gains
- 8. relationship
- 9. ms_married_civ_spouse^2
- 10. ms_married_civ_spouse * education_num
- 11. age * education_num

wage 1	_ 1.0
* education_num 0.52	
ation_num * age 0.52	
cation_num * sex 0.47	- 0.8
rried_civ_spouse 0.44	
d_civ_spouse**2 0.44	
civ spouse * sex 0.4	0.0
* education_num 0.39	- 0.6
education_num 0.34	
age 0.23	
hours_per_week 0.23	- 0.4
capital gain 0.22	
sex 0.22	
capital loss 0.15	
wc self 0.11	- 0.2
arried af spouse 0.012	
fnlwgt	
	- 0.0
spouse absent -0.043	
ms_widowed -0.064	
ms separated -0.074	0.0
wc_private -0.079	- -0.2
s never married -0.32	

wage

- 1. age
- 2. education-num
- 3. marital-status
- 4. sex
- 5. workclass
- 6. hours per week
- 7. capital gains
- 8. relationship
- 9. ms_married_civ_spouse^2
- 10. ms_married_civ_spouse * education_num
- 11. age * education_num

	train	test	Mean_CV_Score	f1score_train	f1score_test
SVC_Reem	0.845384	0.844815	0.844814	0.625664	0.611481
LOGREG_Jonna	0.840383	0.837854	0.840471	0.631632	0.61516
KNN_Kemal	0.849158	0.837752	0.835951	0.655373	0.618348
Adaboost_Reem	0.932257	0.82598	0.825816	0.857696	0.615559

Round 2 - Detour

- 1. age
- 2. education_num
- 3. capital_gain
- 4. hours_per_week
- 5. wc_gov
- 6. wc_no_work
- 7. ms_married_af_spouse
- 8. ms_married_civ_spouse
- 9. ms_married_spouse_abse
- 10. ms_never_married
- 11. ms_separated
- 12. ms_widowed
- 13. sex_Male

	train	test	Mean_CV_Score	f1score_train	f1score_test
RForest_Kemal	0.845384	0.846248	0.845077	0.60766	0.597966
LOGREG_Jonna	0.83933	0.83939	0.839286	0.625639	0.617783