

PREDICTING THE AVERAGE YEARLY EARNING FOR THE TOP 1000 CHANNELS ON YOUTUBE

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As Project 2 of SDAIA Data Science Bootcamp (T5)



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IMPLEMENTATION

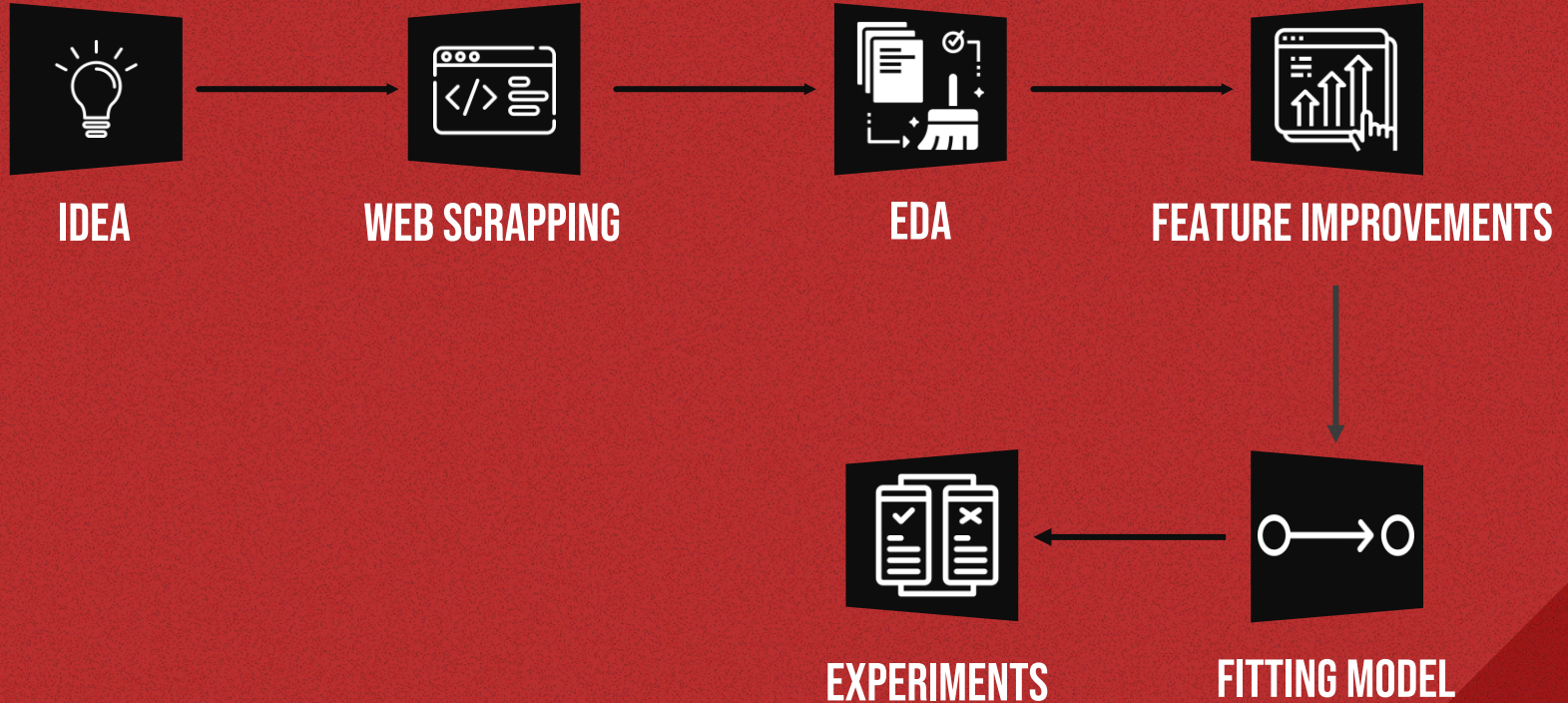
05

CONCLUSION

INTRODUCTION

- Nowadays Social media is considered a wealth source, where everyone can make profit out of it .
- And the YouTube is considered half the internet, where 1.9 billion users logging in it .

WORKFLOW



TOOLS

PYTHON



Jupyter notebook

NumPy, Pandas

Matplotlib, Seaborn

BeautifulSoup

Selenium

Sklearn

HTML



HTML

CSS

WEB SCRAPING



SCRAPING

- Popsonner
- Social Blade



+ 1K ROWS



15 FEATURES

DATASET

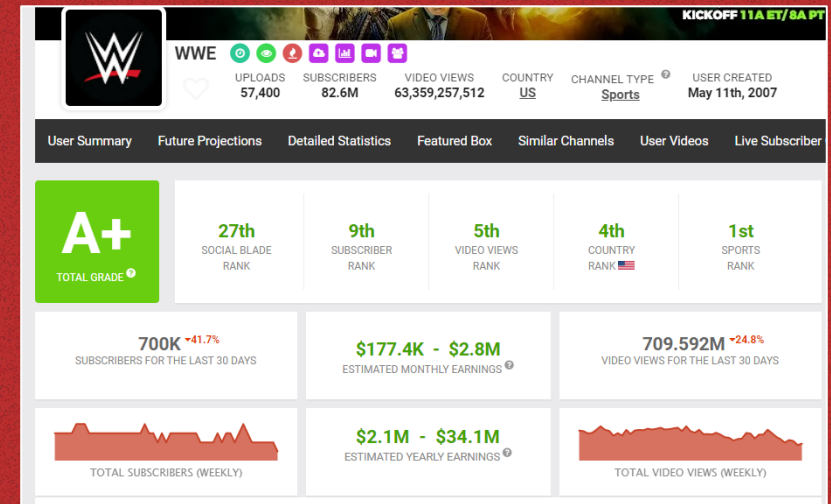
Popsonner

Home Top 500 Videos - All Times Top 1000 YouTube Channels Privacy Policy

Top 1000 YouTube Channels

Show 100 entries

Pos	Channel	Views	Subscriber	Videos	Published
1	T-Series	157,452,055,214	185,000,000	15,528	2006-03-13
2	Cocomelon - Nursery Rhymes	103,803,532,922	113,000,000	654	2006-09-01
3	SET India	90,768,285,232	107,000,000	59,421	2006-09-20
4	WWE	59,710,652,499	78,500,000	55,466	2007-05-11
5	Lila Nastya	58,866,363,302	74,700,000	589	2016-12-06
6	Kids Diana Show	58,484,744,322	80,100,000	891	2015-05-12
7	Sony SAB	56,242,961,978	52,600,000	37,259	2007-08-04
8	Movieclips	52,243,427,733	52,900,000	37,366	2006-04-28
9	Vlad and Niki	50,178,997,905	69,000,000	366	2018-04-23
10	Ryan's World	47,553,197,237	29,900,000	2,002	2015-03-17



- Merged 2 datasets on Channel ID
- Create DataFrame out of them

EDA



NULLS VALUES



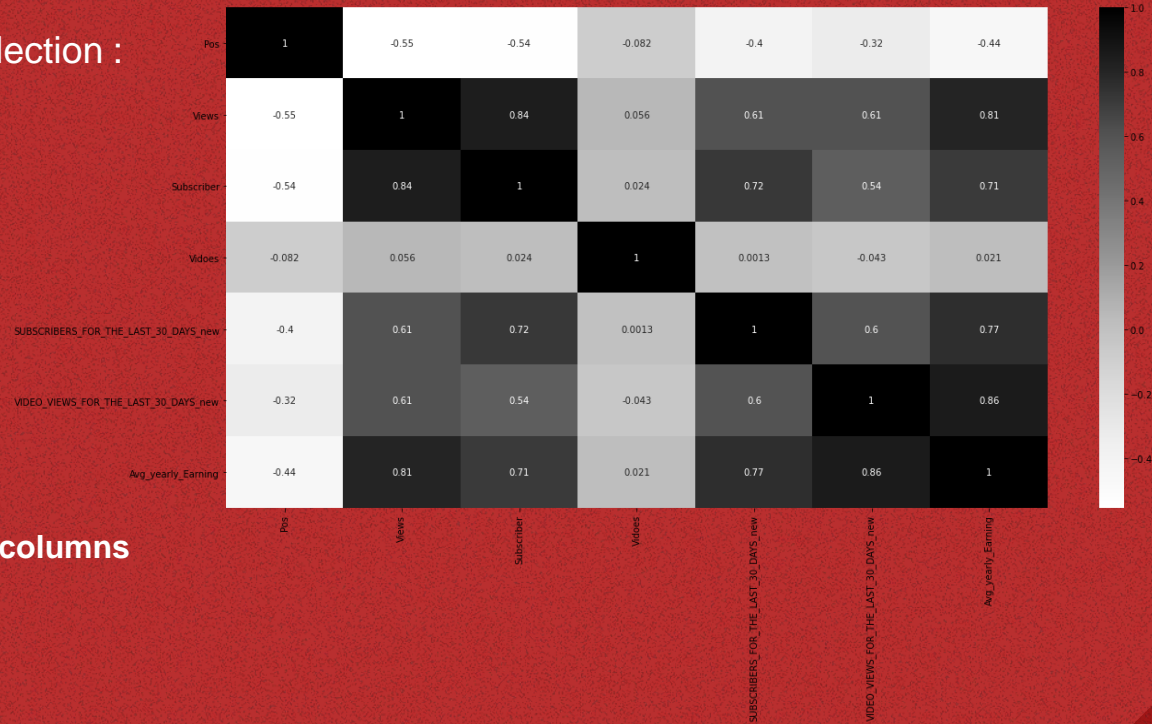
CHANGE COLUMN TYPES



OUTLIERS

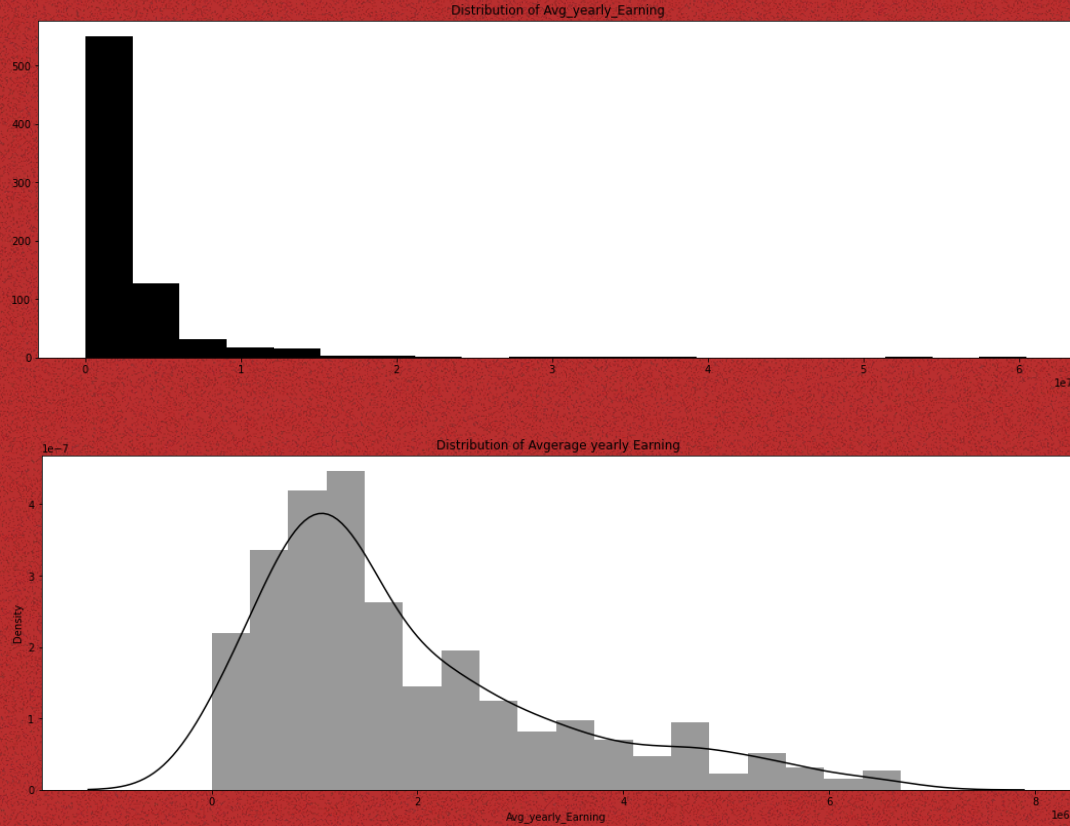
- Features Engineering :
Getting the Average monthly/ yearly earning out of min and max .

- Features Selection :

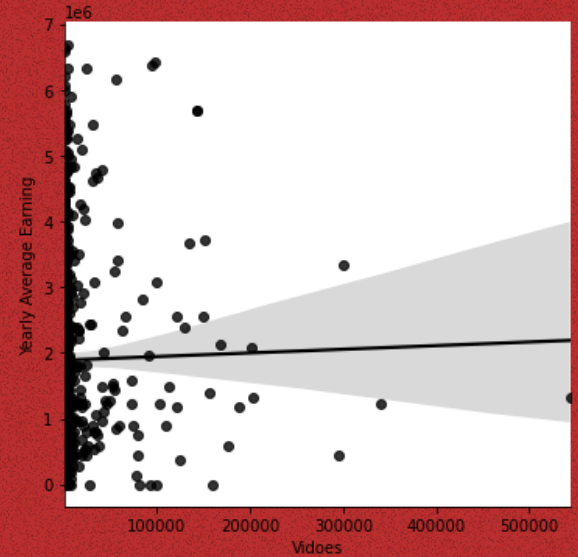
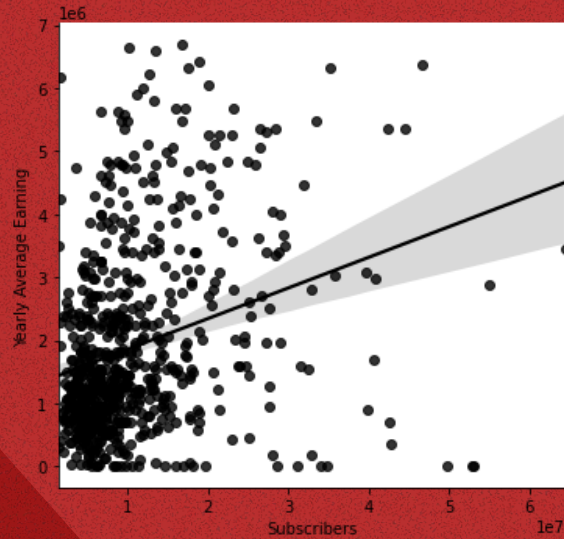
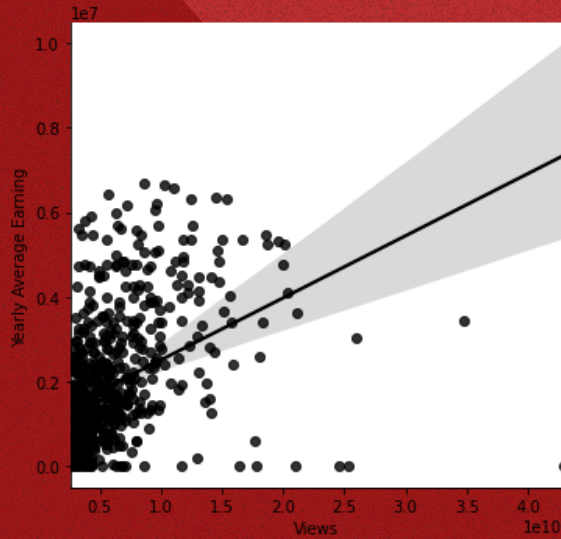


687 rows × 13 columns

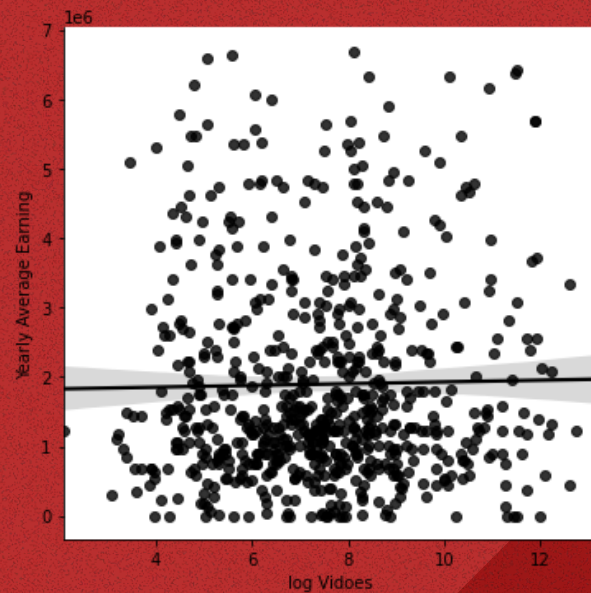
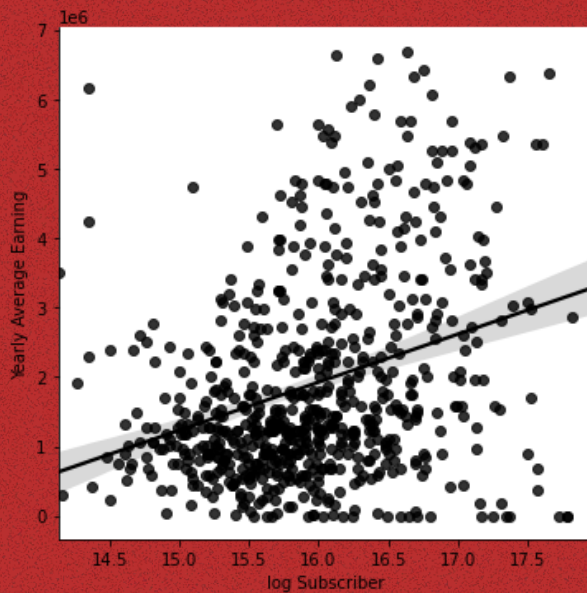
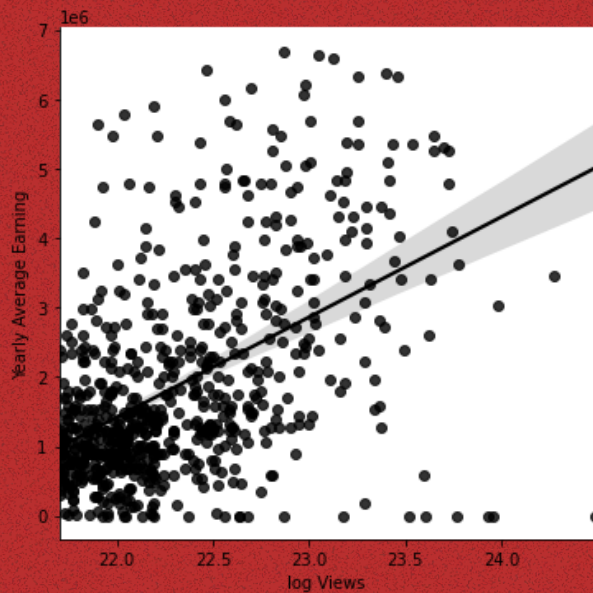
- Outliers :



- Testing Linearity between dependent and independents variables :



- Log Transfromation to establish linear correlation between Y and features :



- Encoding categorical variables :
encode with value between 0 and $n_classes - 1$.



MODELING

- Linear regression result :

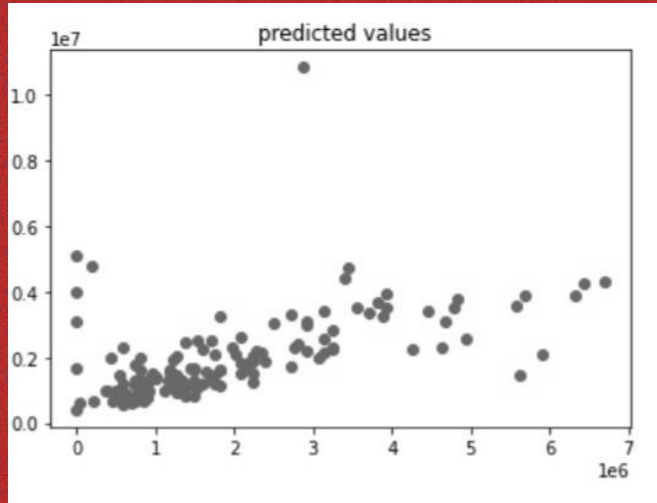
	r_squared	MAE	MSE	RMSE
Linear Regression	0.634396	653861.543143	8.949487e+11	9.460173e+05

```
Index(['Pos', 'Channel', 'SOCIAL_BLADE_RANK', 'VIDEO_VIEWS_RANK',
      'COUNTRY_RANK', 'MUSIC_RANK', 'CHANNEL_TYPE',
      'SUBSCRIBERS_FOR_THE_LAST_30_DAYS_new',
      'VIDEO_VIEWS_FOR_THE_LAST_30_DAYS_new', 'Avg_yearly_Earning', 'Views',
      'Subscriber', 'Videos'],
      dtype='object')
```

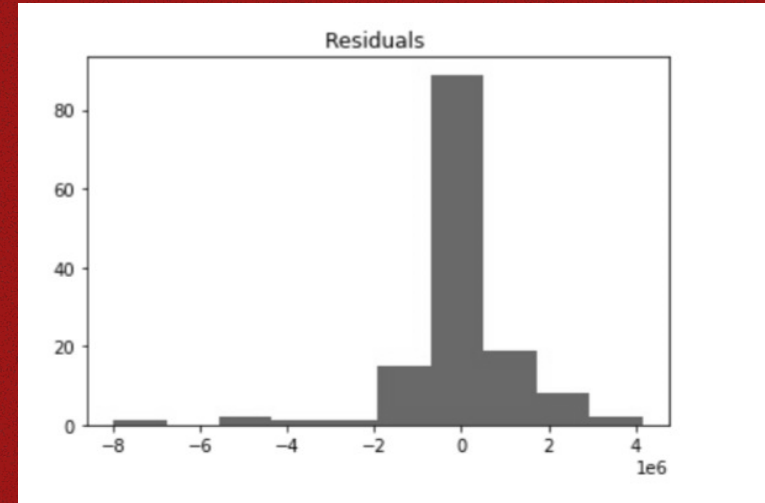
```
1 r = pd.DataFrame(lr.coef_, columns = ['Coefficients'])
2 r
```

	Coefficients
0	1.574779e+03
1	-1.184288e+02
2	-6.511618e+01
3	-1.164976e+02
4	-4.005173e+02
5	-6.594658e+02
6	2.075652e+04
7	6.866476e+00
8	3.876942e-03
9	2.492482e+06
10	-5.830345e+05
11	-2.199701e+03

- Making prediction from LR



- Assess the performance of our model :



- Improving Linear Regression

	r_squared	MAE	MSE	RMSE
Linear Regression	0.634396	653861.543143	8.949487e+11	9.460173e+05
Polynomial degree 4	0.951278	221565.225829	1.192647e+11	3.453473e+05
Polynomial degree 5	0.299057	787351.038821	1.715812e+12	1.309890e+06

- Regularization :

	R Squared	MAE	MSE	RMSE	Best Alpha
Lasso	0.471861	571276.702456	9.130710e+11	955547.479501	0.0
Ridge	0.471861	571276.702456	9.130710e+11	955547.479501	0.0
Elastic Net	0.471861	571276.702456	9.130710e+11	955547.479501	0.0

CONCLUSION

Even though polynomial showed low MSE, R squared is high to level that we reach overfitting . Thus, linear regression isn't the appropriate model to meet our goal !

THANK YOU !

FOR YOUR KIND ATTENTION

