# Production prediction assessment

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# **S&P Global**Commodity Insights

# 1. Data validation and data understanding

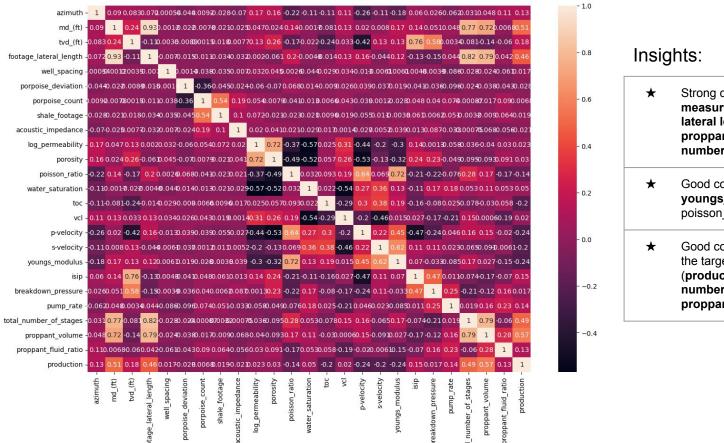
## Overview

28
1000
1920
6.9%
0
0.0%
399.5 KB
409.0 B
Categorical: 3

## First insights:

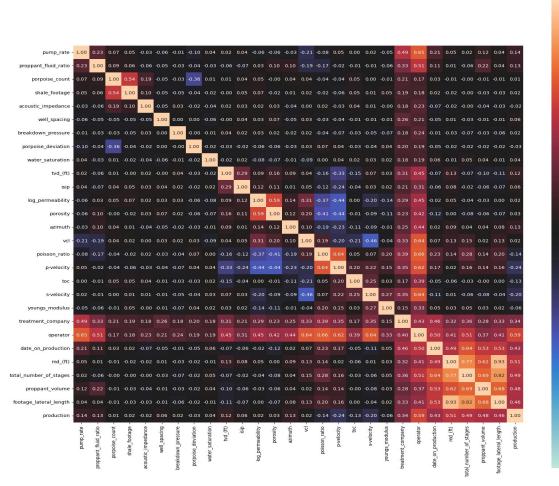
Variable	Description/Notes			
treatment company	31 different companies			
date on production	Data from 01/01/2011 to 03/01/2019			
operator	36 different operators			
water saturation	has 57.7% missing values			
breakdown pressure	has 74.4% missing values			
azimuth	has 91.4% negative values			
shale footage	has 33% zeros			

# 1. Data validation and data understanding - Correlations



- ★ Strong correlation between measure depth, footage lateral length, and proppant volume with "total number of stages"
- ★ Good correlation between youngs\_modulus and poisson\_ratio.
- Good correlation between the target variable (production) with total number of stages and proppant volume.

# 1. Data validation and data understanding - Correlations Cat and Numeric



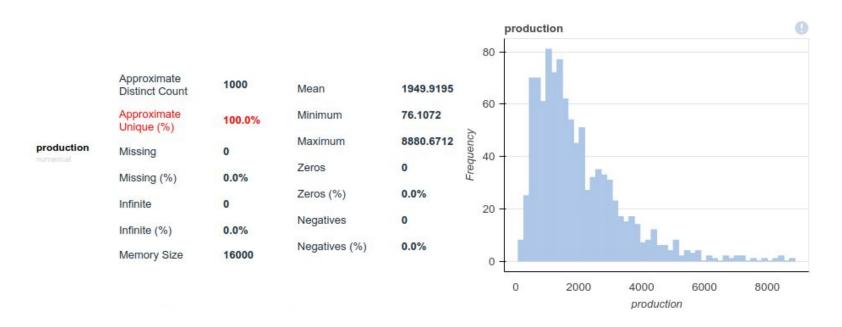
#### Insights:

- -0.25

- -0.75

- ★ Good correlation between operator and production.
- ★ Regular correlation between treatment company and production
- ★ Good correlation between operator and pump rate.

# 1. Data validation and data understanding - prediction variable



## Insights:

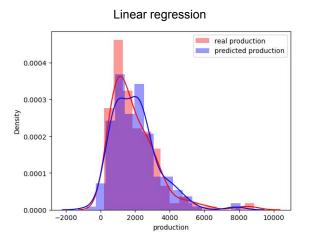
- This variable has a left skewed distribution.
- Target variable to predict with trained models

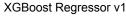
# 2. Modeling process

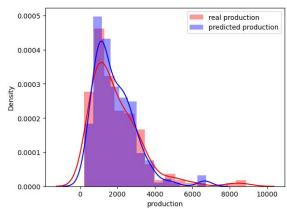
Training Test - split	
Training	800 rows
Test	200 rows

Model	Description/Notes				
Linear regression	Sklearn model				
Neural Network	Sequential model builded with Keras and tensorflow.  Its architecture is composed of 2 Dense layers with 64 neurons each one and finally a Dense layer with 1 neuron to compute the output.  The early stopping applied is useful to avoid overfitting.  There aren't a lot of data for deep complex models, our proposal architecture with a small				
	net with a few hidden layers to avoid overfitting.				
XGBoost Regressor v1	Model optimized with Bayesian Optimization. Logged with Weights and Biases (https://wandb.ai/dbabativa/spq/sweeps/z8dmz 4o5/table?workspace=user-dbabativa)				
XGBoost Regressor v2	Version 2 with optimizer technique.				

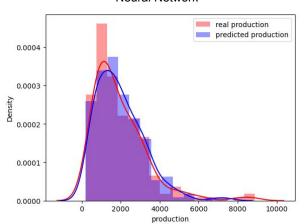
# 3. Modeling selection



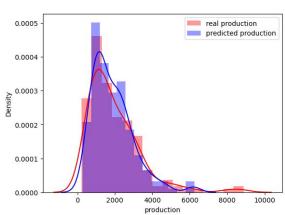




#### Neural Network



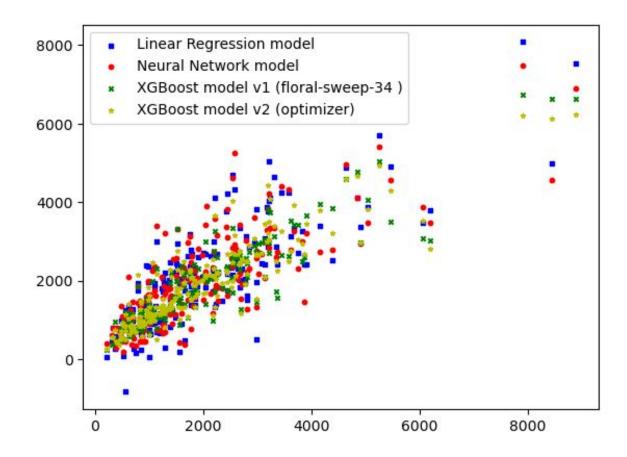
#### XGBoost Regressor v2



## Insights:

- ★ Very similar distributions (real vs predicted) with XGBoost models
- ★ The Linear regression and neural network models missing a high density from 0 to 2000 mmcf.

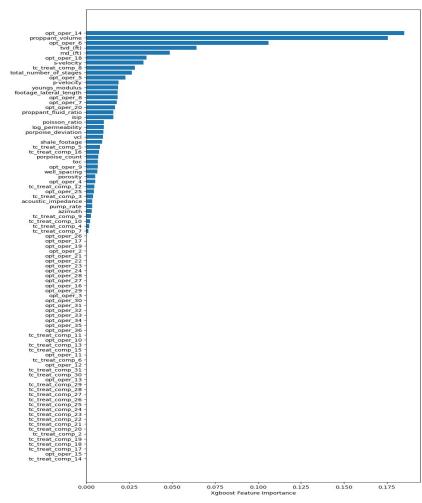
# 3. Modeling selection - Scatter visualization



### Insights:

- This plot concatenates the result of y\_true and y\_pred values for all trained models in a scatter plot.
- Although all models have external points, one more time XGBoost models have a good fitting

## 3. Modeling selection - metrics results



model	MAE	MSE	RMSE	RMSLE	R2
Linear Regression model	598.217705	663173.173157	814.354452	6.702396	0.669309
Neural Network model	611.814959	719874.629228	848.454259	6.743416	0.641034
XGBoost model v1 (floral-sweep-34)	376.539161	399816.404012	632.310370	6.449380	0.800631
XGBoost model v2 (optimizer)	407.586408	427512.000198	653.844018	6.482869	0.786821

#### Insights:

- ★ The best results were achieved by XGBoost model v1 optimized with Bayesian Optimization.
- The another XGBoost model can be a candidate to do a blind test with other data (more updated for example)
- ★ If we inspect over the feature importance of XGboost model v1, variables such as operator, proppant volume and md (ft) are taking into account for the prediction. This make sense with the correlation analysis done in Data Understanding stage.

XGBoost model v1 Feature importance