# Project discussion:

#### **Dataset on Blog Feedback**

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#### Dataset & Data Cleaning

- Data originates from blog posts
- The prediction task associated with the data is the prediction of the **number of comments** in the upcoming 24 hours
- Original dataset contains one **train** set and multiple **test** sets. Combining all test files into one is **needed**
- **Dimension**:
  - **281** attributes(**280** features and **1** target variable);
  - 52397 individuals in train data;
  - **7264** individuals in test data.

A large set of features.

- Dependent variable is highly skewed.
  - **64.05**% of it are zero;
  - among 75% are less than 10;
  - can be high as **1424**;
- Cleaning of the data is not needed

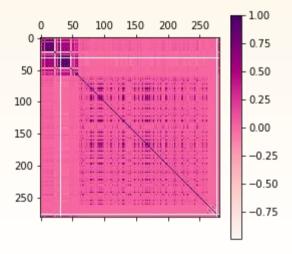
#### **Description**

#### **Attribute Information:**

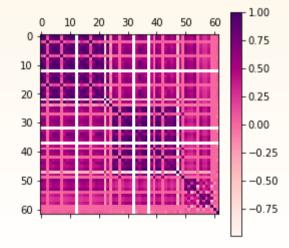
- 1...61: Information about comments to a blog post:
  - number of comments and links in different periods;
  - average, standart deviation, min, max and median of number of comments.
- 62: The length of the blog post.
- 63...262: The 200 bag of words features for 200 frequent words of the text of the blog post.
- 263...276: binary indicator features (0 or 1) for the weekday (Monday...Sunday) of the basetime and day of publication of the post.
- 277...280: Information about parent blog post:
  - number of pages;
  - minimum, maximum, average number of comments that the parents received.
- 281: The target: the number of comments in the next 24 hours

#### Exploratory data analysis

Representation of correlation matrix



Correlation matrix of highly correlated values

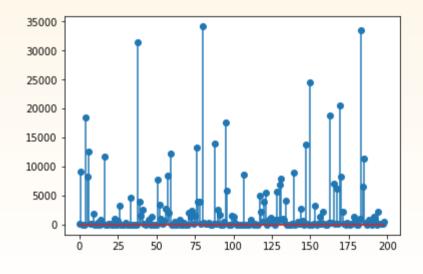


#### Exploratory data analysis

Most correlated attributes with dependent variable

Nº º	Description of the feature	Correlation value
9	median of number of comments in the last 24h before the basetime	0.506540
20	average of the difference between number of comments during 24h	0.503375
5	average of number of comments in the last 24h before the basetime	0.497631
4	median of the total number of coments before basetime	0.491707

#### Exploratory data analysis

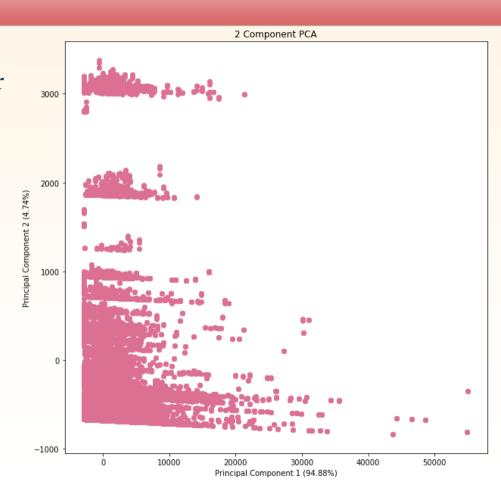


- 200 independent variables for the words contained in blog post;
- 3 words appear in more than half of the train data (probably stop words)
- 117 words appear in less than 523 observations ≈ 1% of observations

#### **Principal Component Analysis**

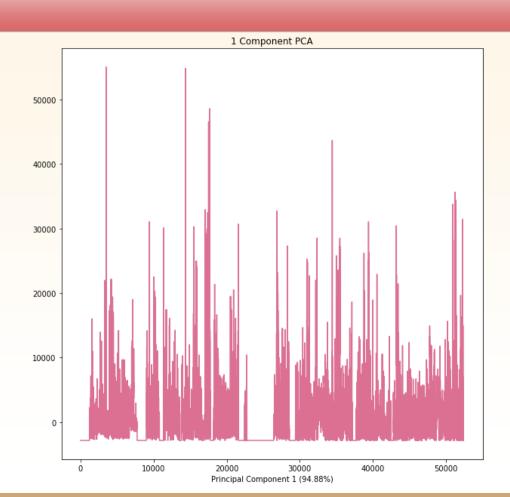
Optimal number of components for representing 95% of data is 2

- Explained variance ratio of the first component is 0.9487
- Explained variance ratio of the second component is 0.0474



#### **Principal Component Analysis**

Even with first variable we can explain almost 95% of the variance:



### Linear Models Analysis(training dataset)

Features selected by algorithm: 276

## Ridge model results:

R<sup>2</sup> value is 0.3591

- - Features selected by algorithm: 42

Lasso model results:

- $R^2$  value is 0.3595
- MSE of the best model is 911.06 MSE of the best model is 910.62

#### Non-Linear Model Analysis(training dataset)

#### Regression trees model results:

Features selected by algorithm: 280

 $R^2$  value is 0.9859

MSE is 19.946

#### Models Results (test dataset)

method	Feature selected	$R^2$	MSE
Lasso	42	0.3145	637.66
Ridge	276	0.3135	638.88
Regression trees	280	-0.19877	1115.15

In regression trees model we get an overfitting

#### Models Results (test dataset)

From results we can see that regression trees model performs very bad and we even get negative  $R^2$  value, which means that our regression line is worse than using the mean value.

$$R^{2} = \frac{ESS}{TSS} = 1 - \frac{RSS}{TSS}$$

$$ESS = \sum (\hat{y}_{i} - \bar{y})^{2}$$

$$TSS = \sum (y_{i} - \bar{y})^{2}$$

$$RSS = \sum (y_{i} - \hat{y}_{i})^{2}$$

#### Conclusions

- Regression tree model is overfitted
- Ridge and Lasso techniques are a great alternative when we are dealing with a large set of features
- For our dataset Lasso works well, because it shrinks the less important feature's coefficient to zero thus, removing some feature altogether

# Thanks for attention!