

# Political Stance Prediction Based on Online Information Diffusion

Pilli Yogesh Kumar

**Laboratory Hubert Curien - University of Sydney**

*Advisors:- Christine Largeron Andrei-Marian Rizoiu*

7th July 2020

# Overview

- 1 State of Art
- 2 Dataset
- 3 Social Network Analysis
  - Illustration of Comment Tree
  - Notion of Edge Homogeneity
  - Notion of Source Node and Target Node on smallest thread
- 4 Political Stance Predictor
  - Long Short Term Memory -Neural Network
- 5 Results
- 6 Conclusion and Future Work
- 7 QA

# State of Art

Myers, Seth A., Chenguang Zhu, and Jure Leskovec. (2012)  
“Information diffusion and external influence in networks.”

**Information Diffusion:** Spreading of information from node to node along the edges of a social network

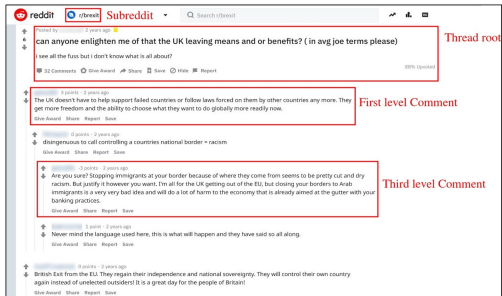
Shuai, X., Ding, Y., Busemeyer, J., Chen, S., Sun, Y., Tang, J.  
(IJSWIS , 2012) - “Modeling indirect influence on twitter

**Social Influence:** Process in which an individual's thoughts, feelings or actions are affected by other people

Benoit, K. and Matsuo, A. (2018) - “Network analysis of Brexit discussion on social media.”

**Political Stance Classifier:** Labels users Stance as AgainsBrexit, ProBrexit or Neutral.

# Data



- **Time Frame:** Nov'2015 - Apr'2019
- **Users:** 14,362 users
- **Threads:** 21,725 threads
- **Comments:** 207,894 comments

# Social Network Analysis

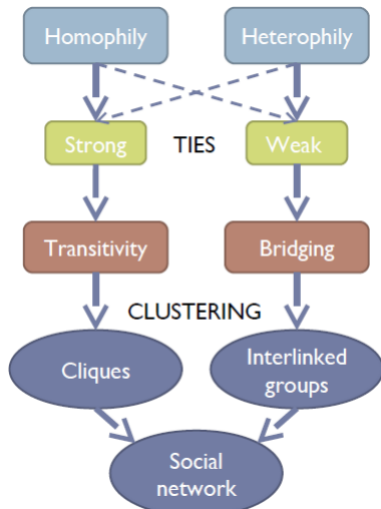
## Homophily

It is tendency of people to form friendships with others with similar characteristics

## Social Influence

It is tendency of people may modify their behaviors to bring them more closely into alignment with the behaviors of their friends.

# Social Network Analysis

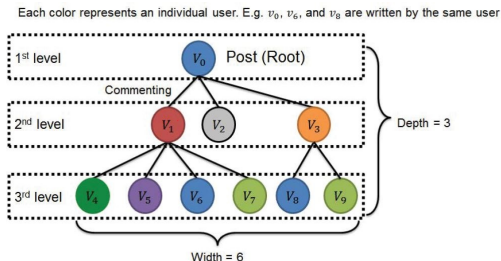


- **Transitivity** in SNA is a property of ties: if there is a tie between A and B and one between B and C, then in a transitive network A and C will also be connected
- **Bridges** are nodes and edges that connect across groups



# Social Network Analysis

## Illustration of Comment Tree



- We define Comment Tree as an undirected Tree,  $T = (V, E)$ , where  $V$  is the set of all messages, which includes the original post(root) and follow-up comments in the thread, and  $E$  is the set of edges, each of which connects two messages that are linked by comment



# Social Network Analysis

## Notion of Edge Homogeneity

We define user polarization  $\sigma = 2p - 1$ , where  $p$  is probability, which lies in  $[0,1]$  and hence  $\sigma$  lies in between  $[-1,1]$

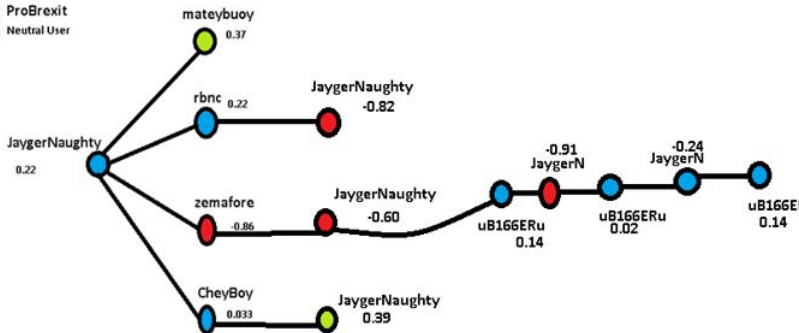
From user polarization we define edge homogeneity, for any edge  $e_{ij}$  between the nodes  $i$  and  $j$

$$\sigma_{ij} = \sigma_i \sigma_j \quad (1)$$

# Social Network Analysis

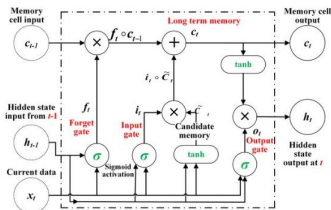
## Notion of Source Node and Target Node on smallest thread

- AntiBrexit
- ProBrexit
- Neutral User



# Political Stance Predictor

- LSTM is Variant of Recurrent Neural Network which introduces number of special and internal gates
- Internal gates help with the problem of learning relationships between long and short sequences in data
- **PRO:** Introduces many more internal parameters which must be learned - **Flexible**
- **CON:** Due to introducing many more internal parameters, It take time to learn - **Time Consuming**



# Political Stance Predictor

- Input gate  $i$  :

- Takes previous output  $h_{t-1}$  and current input  $x_t$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

- Forget gate  $f$ :

- Takes previous output  $h_{t-1}$  and current input  $x_t$

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

- if  $f_t = 0$ : **Forget** previous state, otherwise pass through prev. state.

- Read gate  $q$ :

- Takes previous output  $h_{t-1}$  and current input  $x_t$

$$q_t = \tanh(W_q \cdot [h_{t-1}, x_t] + b_q)$$

# Political Stance Predictor

- Memory Cell gate  $c$ :
  - New values depends on  $f_t$ , its previous state  $c_{t-1}$  and read gate  $q_t$

$$c_t = f_t c_{t-1} + i_t q_t$$

- Output gate  $o_t$  :
  - Will be fed as input into next block

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$

$$h_t = o_t \tanh(c_t)$$

- **Intuition:**
  - We learn when to retain a state, or when to forget it.
  - Parameters are constantly updated as new data arrive

# Political Stance Predictor

- **LSTM without Textual Features**

- We take current user stance label as LSTM input
- We create X and Y pairs, Y sequence is created by one next shift in the sequence
- We reshape the data in LSTM friendly 3D format as (samples, timesteps, features) use categorical crossentropy as loss function and softmax as activation function

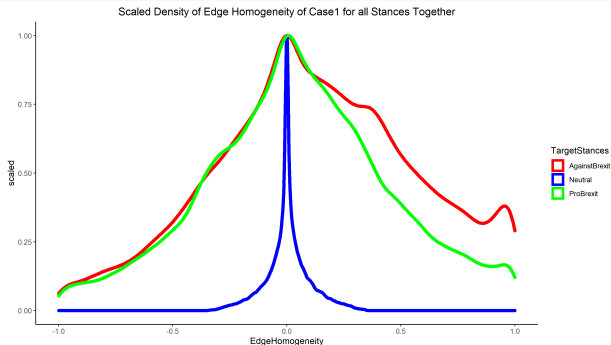
- **LSTM with textual features**

- We take textual features as input
- We label each sequence as one user stance
- We reshape the data in LSTM friendly 3D format as (samples, timesteps, features) use categorical crossentropy as loss function and softmax as activation function

- **Performance metrics is measures with F1 Score, Accuracy, Recall and Precision**

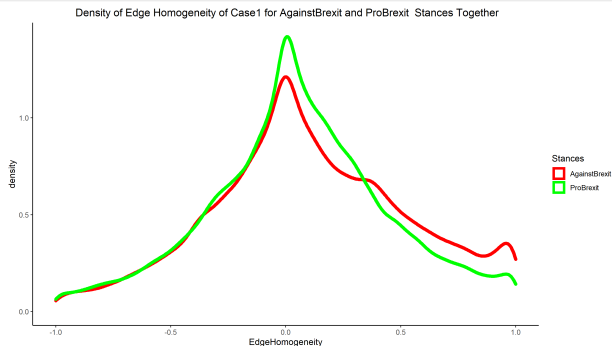
# Results

Probability Density Function of Edge Homogeneity for Case1  
(Source Node is Fixed and Target Node is Combined of All  
Stance)-All the Scenarios



# Results

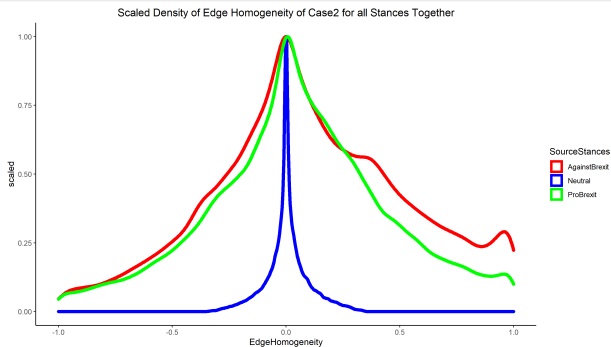
Probability Density Function of Edge Homogeneity for Case1  
(Source Node is Fixed and Target Node is Combined of All  
Stance)-with Against and Pro Brexit Stances





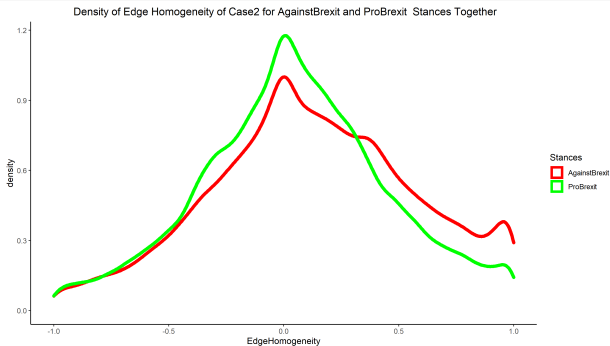
# Results

Probability Density Function of Edge Homogeneity for Case2  
(Target Node is Fixed and Source Node is Combined of All  
Stance)- combined with other scenarios



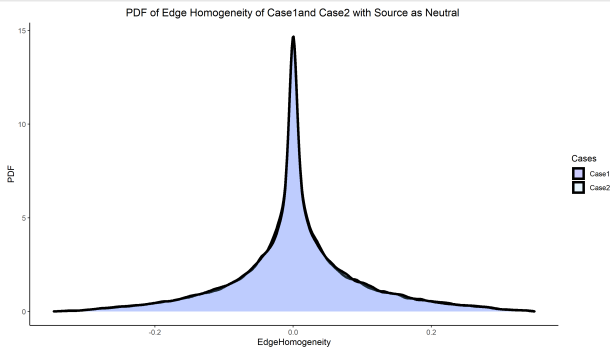
# Results

Probability Density Function of Edge Homogeneity for Case2  
(Target Node is Fixed and Source Node is Combined of All  
Stance)-with Against and Pro Brexit Stances



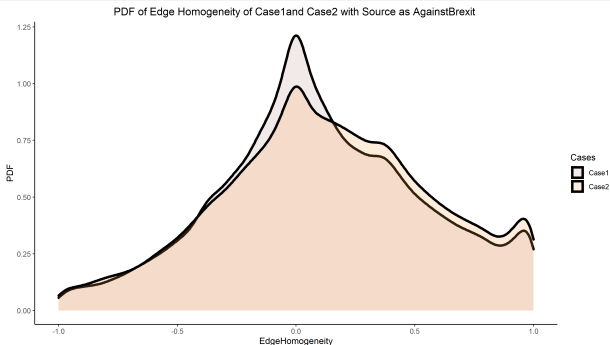
# Results

## Probability Density Function of Edge Homogeneity for Case1 and Case2 For Neutral Stance



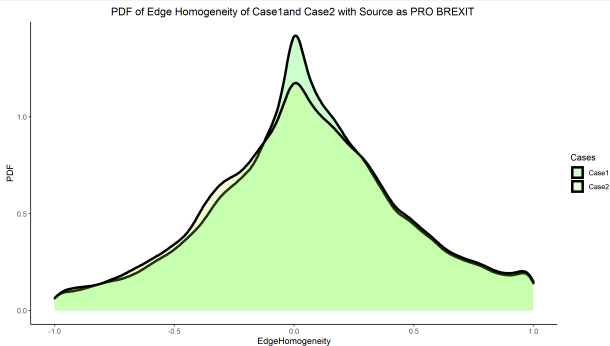
# Results

## Probability Density Function of Edge Homogeneity for Case1 and Case2 For Against Stance



# Results

## Probability Density Function of Edge Homogeneity for Case1 and Case2 For ProBrexit Stance



# Results

## Performance Evaluation of the Political Stance Predictor

**Table:** Confusion Matrix of Actual Stance and Predicted Stance from LSTM model

| <i>Actual — Predicted</i> | <b>Against</b> | <b>Neutral</b> | <b>Brexit</b> |
|---------------------------|----------------|----------------|---------------|
| <b>Against</b>            | 3790           | 5544           | 3354          |
| <b>Neutral</b>            | 5817           | 8174           | 4818          |
| <b>Brexit</b>             | 3857           | 5238           | 3210          |

# Results

**Table:** Performance Metrics for LSTM Model without Textual Features used for predicting user's stance based on their submitted posts.

| Set  | Accuracy | Precision | Recall | F1-Score |
|------|----------|-----------|--------|----------|
| Test | 0.350    | 0.3496    | 0.3496 | 0.3496   |

**Table:** Performance Metrics for LSTM Model with Textual Features used for predicting user's stance based on their submitted posts.

| Set  | Accuracy | Precision | Recall | F1-Score |
|------|----------|-----------|--------|----------|
| Test | 0.430    | 0.4236    | 0.4216 | 0.4236   |

# Conclusion and Future Work

- Edge Homogeneity on Source Node and Target Node around Brexit on reddit dataset
- Prediction of future political stance based on different features defined using the structure online diffusion
- Apply the Model on Dividing the data on different time periods
- Improve the model with adding additional hyper parameters



# Thank You