Representation and Knowledge Transfer for Health-related Rumour Detection

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- Contributions
- Materials and Methods
- Experimental Results
- Conclusions and Future work
More than 180 mln users all over the world
Health-related Rumour Detection

A *rumour* is an unverified and instrumentally relevant statement in circulation

More than 180 mln users all over the world
A *rumour* is an unverified and instrumentally relevant statement in circulation.

More than 180 mln users all over the world.

Lung cancer  
Zika virus  
Heart failures

Automatic Rumour Detection system

Rumour

Non-rumour

The Problem

Materials and Methods

Experimental Results

Conclusions and Future Work
Health-related Rumour Detection

A *rumour* is an unverified and instrumentally relevant statement in circulation.

More than 180 mln users all over the world

What if we have a tweet of a new topic, unseen by that system?
Most of the literature:

- *Does not* explore health-related topics
- Focuses on *macro-level* rumour detection

The literature exploits *deep learning techniques* to transfer knowledge which are trained on *huge public datasets for macro-level rumour detection not health related*.
Contributions

We analyse feature knowledge transfer between two health-related topics with shallow machine learning

A comparison of two state-of-the-art handcrafted representations

A comparison of three feature-based transfer learning approaches

Small sample size available for health-related micro-level rumour detection
Health-related Twitter Datasets

#Zikavirus
2079 posts between April and May 2016

#Vaccine
1870 posts in June 2018

Manually annotated at the micro-level

On the #Vaccine dataset:

- 1409 samples blindly annotated by 3 Twitter users
- Gold standard computation

<table>
<thead>
<tr>
<th>Dataset</th>
<th>rumour</th>
<th>non-rumour</th>
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<tbody>
<tr>
<td>Zikavirus</td>
<td>54%</td>
<td>30%</td>
<td>16%</td>
</tr>
<tr>
<td>Vaccine</td>
<td>28%</td>
<td>42%</td>
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Health-related Twitter Datasets

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- 2079 posts between April and May 2016
- Manually annotated at the micro-level

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Handcrafted representations

User-Network (UN) [1]
- Influence Potential
  Power of causing an effect in indirect ways
- Personal Interest
  Reaction of people to a specified news, opinion
- Network characteristics
  Catch the propagation structure of retweet and replies graphs

Social-Content (SC) [2]
- Content-based
  Model the difference between rumours and non-rumours in terms of semantic and syntactic structures
- Social features
  Model user behaviour and his/her reputation in the network

Transfer learning competitors

Source domain (S)  Target domain (T)

Transfer Learning

Homogeneous
\[ X_S = X_T \]

Heterogeneous
\[ X_S \neq X_T \]

Based on ‘what-to-transfer’

Instance-based

Feature-based

Parameter-based

Relational-based

Hybrid

Asymmetric

Symmetric

Asymmetric feature-based

Symmetric feature-based
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Based on 'what-to-transfer'

- Asymmetric
- Symmetric feature-based

The Problem

- Source domain (S)
- Target domain (T)

Experimental Results

Contributions and Future Work
Transfer learning competitors

Source domain (S)  Target domain (T)

Asymmetric feature-based TL
- Adaptation Regularization-based Transfer Learning (ARTL)
- Transfer Kernel Learning (TKL)

Symmetric feature-based TL
- Graph co-regularized Transfer Learning (GTL)
## Representation comparison

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**Best performance achieved by UN + DT**
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**Best performance achieved by UN + DT**

**Vaccine dataset used as training conveys higher performance**
## Transfer Learning results

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Maximum Accuracy without TL: 82%

Maximum Accuracy with TL: 48%

**Negative transfer**
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- **Maximum Accuracy without TL**: 48%
- **Maximum Accuracy with TL**: 82%

**Negative transfer**

- Small sample size
- The transformations applied for transferring knowledge are not appropriate for this domains
- UN is already designed to be topic independent
Conclusions and Future Work

**Comparison of two state-of-the-art representations** for micro-level rumour detection in health

**Investigation of three feature-based transfer learning approaches** in an unsupervised scenario

**Experiment heterogeneous TL between the two representations**

**Enlarge the datasets sample size to apply DL**

**Investigate other shallow TL techniques**

**Negative transfer occurs:** Transferring knowledge based on the feature representation is not effective

**TO DO**

**TO DO**

**TO DO**

**The Problem**

**Contributions**

**Materials and Methods**

**Experimental Results**

**Conclusions and Future Work**
Thank you for the attention.