Representation and Knowledge Transfer for Health-related Rumour Detection

Rosa Sicilia, Luisa Francini, and Paolo Soda
Unit of Computer Systems and Bioinformatics
Department of Engineering
Università Campus Bio-Medico di Roma

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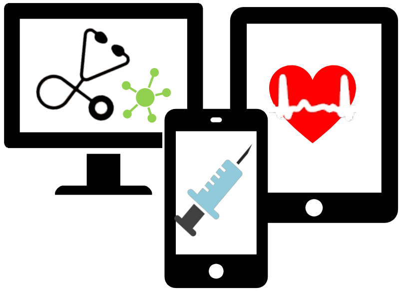
Index

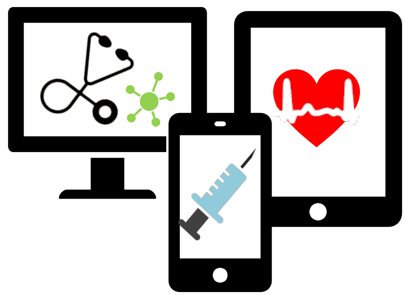
Health-related Rumour Detection



More than 180 mln users all over the world

Health-related Rumour Detection

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



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Index

The Problem

Contributions

Materials and Methods

Experimental Results

Conclusions and Future Work

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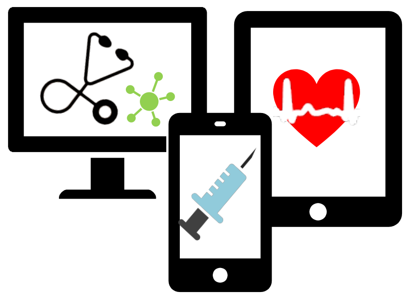

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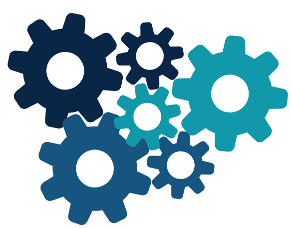
Lung cancer

Zika virus

Heart failures



Automatic Rumour Detection system

Index
The Problem
Contributions
Materials and Methods
Experimental Results
Conclusions and Future Work

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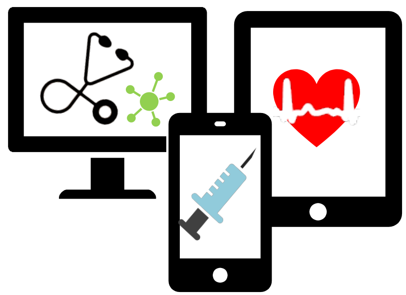

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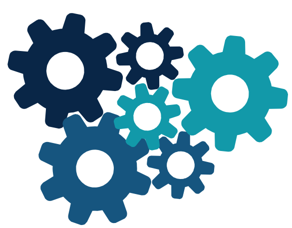


Vaccine ?

What if we have a tweet of a new topic, unseen by that system?

Index

The Problem

Contributions

Materials and Methods

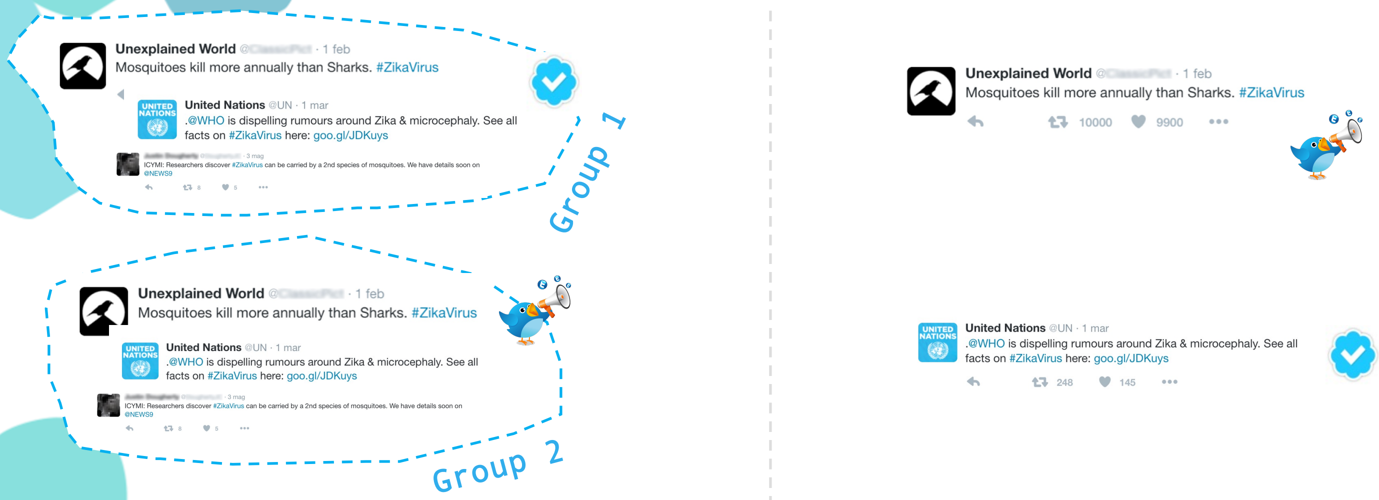
Experimental Results

Conclusions and Future Work

Transferring knowledge between topics

Most of the literature:

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



Macro-level | **Micro-level**

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

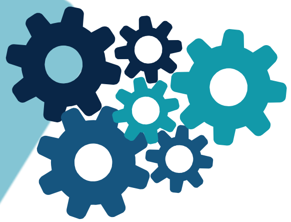
Index
The Problem
Contributions
Materials and Methods
Experimental Results
Conclusions and Future Work

Contributions

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

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

Index
The Problem
Contributions
Materials and Methods
Experimental Results
Conclusions and Future Work

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

Dataset	rumour	non-rumour	unknown
Zikavirus	54%	30%	16%
Vaccine	28%	42%	30%

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Dataset		rumour	non-rumour	~~unknown~~
Zikavirus	694	54%	30%	~~16%~~
Vaccine	990	28%	42%	~~30%~~

Index
The Problem
Contributions
Materials and Methods
Experimental Results
Conclusions and Future Work

Handcrafted representations

User-Network (UN) [1]

24

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]

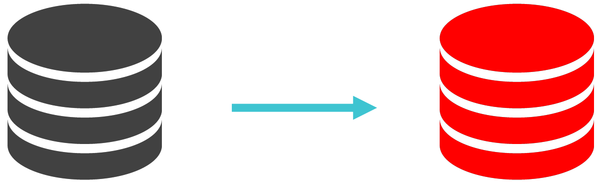
12

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

[1] Sicilia, R., Giudice, S. L., Pei, Y., Pechenizkiy, M., & Soda, P. (2018). Twitter rumour detection in the health domain. Expert Systems with Applications, 110, 33-40.
[2] Zubiaga, A., Liakata, M., & Procter, R. (2017, September). Exploiting context for rumour detection in social media. In International Conference on Social Informatics (pp. 109-123). Springer, Cham.

Transfer learning competitors

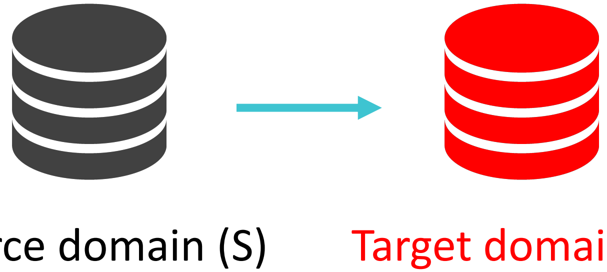


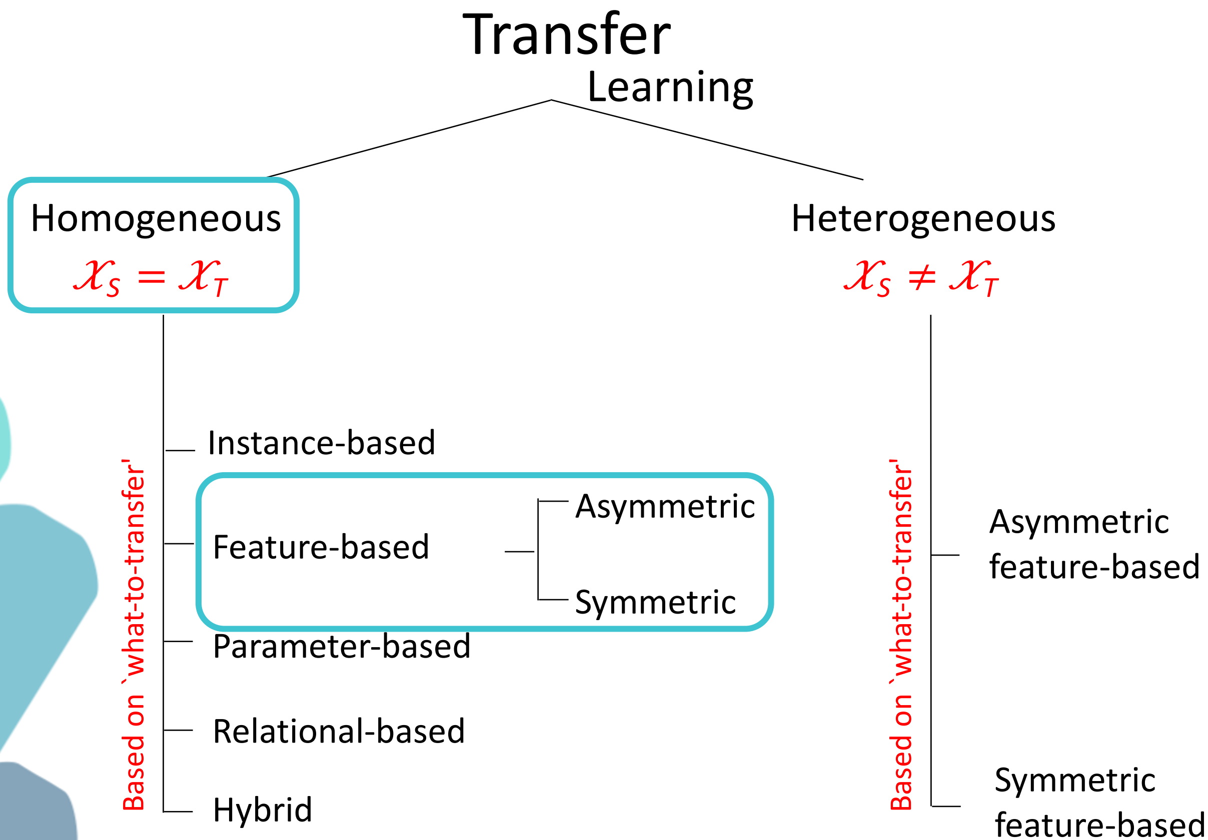
Source domain (S) — Target domain (T)

Transfer Learning

- Homogeneous $\mathcal{X}_S = \mathcal{X}_T$
  - Based on `what-to-transfer'
    - Instance-based
    - Feature-based
      - Asymmetric
      - Symmetric
    - Parameter-based
    - Relational-based
    - Hybrid
- Heterogeneous $\mathcal{X}_S \neq \mathcal{X}_T$
  - Based on `what-to-transfer'
    - Asymmetric feature-based
    - Symmetric feature-based

Transfer learning competitors





Index
The Problem
Contributions
Materials and Methods
Experimental Results
Conclusions and Future Work

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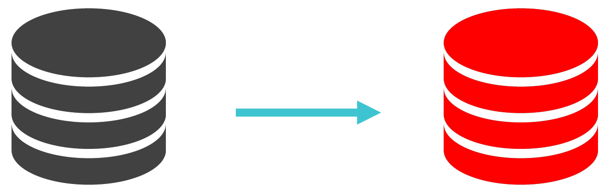
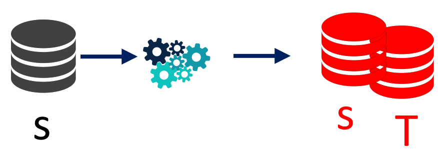


Source domain (S) Target domain (T)

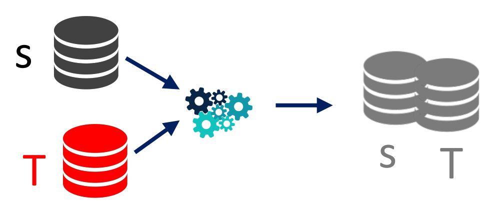
Asymmetric feature-based TL



Adaptation Regularization-based Transfer Learning (ARTL)

Transfer Kernel Learning (TKL)

Symmetric feature-based TL



Graph co-regularized Transfer Learning (GTL)

Index
The Problem
Contributions
Materials and Methods
Experimental Results
Conclusions and Future Work

Representation comparison

Representation		#Vaccine (S) - #Zikavirus (T)				#Zikavirus (S) - #Vaccine (T)			
		Acc	F1	Rec R	Prec R	Acc	F1	Rec R	Prec R
UN	kNN	0.36	0.26	0.00	0.00	0.40	0.29	1.00	0.40
	SVM (rbf)	0.36	0.26	0.00	0.00	0.40	0.29	1.00	0.40
	SVM (linear)	0.36	0.26	0.00	0.00	0.39	0.29	0.98	0.39
	DT	**0.82**	**0.81**	**0.82**	**0.90**	**0.45**	**0.44**	**0.38**	**0.33**
	RF	0.64	0.64	0.50	0.88	0.39	0.38	0.67	0.36
SC + CRF	**W2V 20**	0.40	0.37	0.43	0.40	**0.43**	**0.38**	**0.50**	**0.50**
	W2V 50	0.40	0.38	0.38	0.38	0.41	0.32	0.50	0.50
	W2V 100	0.66	0.60	0.62	0.70	0.40	0.30	0.50	0.47
	W2V 200	**0.72**	**0.70**	**0.70**	**0.72**	0.41	0.31	0.51	0.62
	W2V 300	0.67	0.62	0.63	0.69	0.40	0.30	0.50	0.59

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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

TL Methods	#Vaccine (S) - #Zikavirus (T)				#Zikavirus (S) - #Vaccine (T)			
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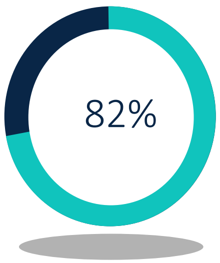
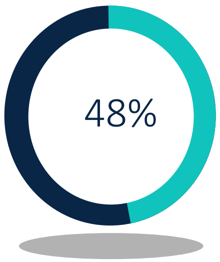
ARTL	0.36	0.26	0.00	0.00	0.40	0.29	1.00	0.40
TKL	0.36	0.26	0.00	0.00	0.40	0.29	1.00	0.40
GTL	**0.42**	**0.35**	**0.25**	**0.52**	**0.48**	**0.38**	**0.76**	**0.39**



Maximum Accuracy without TL

Negative transfer



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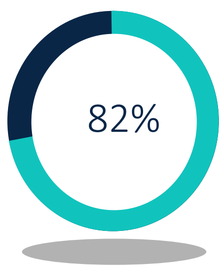

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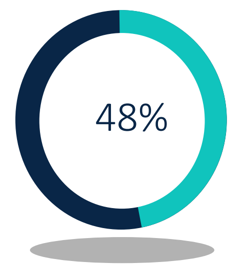


Maximum Accuracy with TL

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

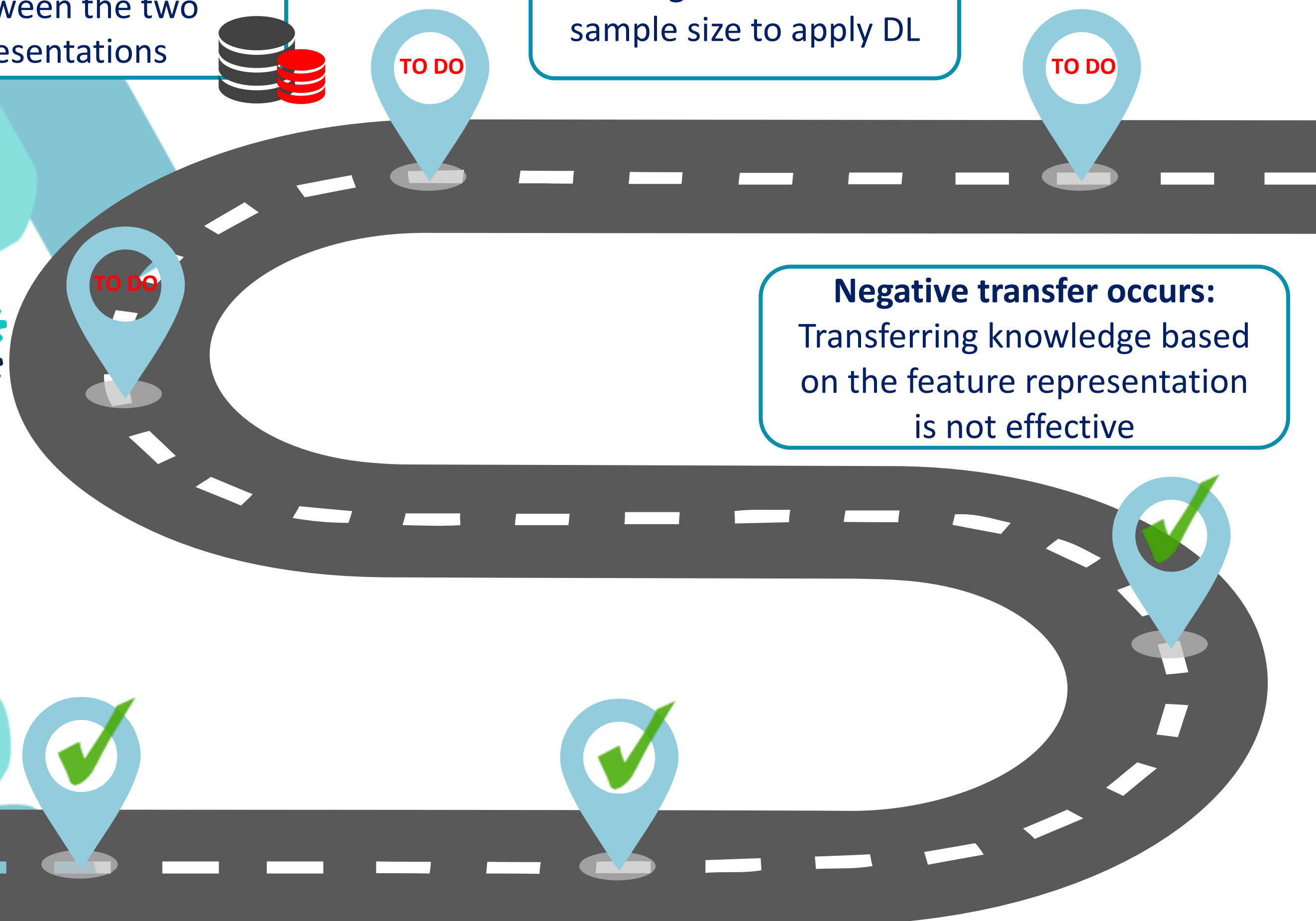
Index
The Problem
Contributions
Materials and Methods
Experimental Results
Conclusions and Future Work

Conclusions and Future Work

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

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

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Thank you for the attention