Nowcasting User Behaviour with Social Media and Smart Devices

Adam Tsakalidis

The Alan Turing Institute

29/11/2018

Invited Talk

Overview

- **Introduction**
- **Part 1: Nowcasting Political Indices Using Social Media**
  - Predicting Election Results with Social Media
  - Nowcasting the Political Stance of Social Media Users
- **Part 2: Nowcasting Mental Health Using Heterogeneous Data**
  - Using Heterogeneous User Generated Content to Sense Well-being
  - Challenges in Assessing Mental Health using User Generated Content
- **Conclusion & Future Directions**

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Urban state monitoring

- Political preferences, health state of population
- Opinion polls, visits to doctors…
- Time consuming, manual effort, sparse…

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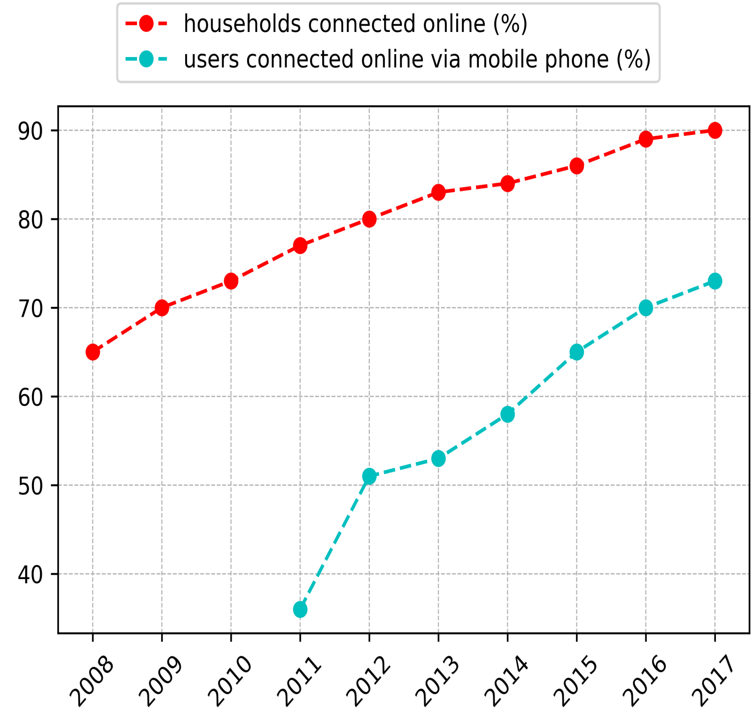
User-Generated Content (UGC)

- Large volumes in real-time
- Social media, smart devices

	Facebook	Twitter	Instagram	Sina Weibo	LinkedIn
Users	2.2B	0.3B	1.0B	0.4B	0.3B



➢ UGC: Real time "sensors"

Goal & Challenges

Aim: "nowcast" real-world and user-specific indices using UGC

- Macro-level (population)
- Micro-level (individual)

Longitudinal, asynchronous, heterogeneous data sources

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Challenges

Generalise to new domains

Work under a real-world setting

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Predicting Elections Using Social Media

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Methodology

- Datasets: keyword-based (Twitter)
- Algorithms: LR, GP, SMO (average)
- Ground Truth: Opinion Polls
- Features: *(a)* past opinion polls *(b)* count-based *(c)* sentiment-based

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Real-world

Twitter-based

Results

	Past Work			Polls	Websites		Time Series Models		
	CB1	**CB2**	**SB**	**Polls**	**MP**	**PW**	**PB**	**CPB**	**TPB**
MAE	4.87	5.19	2.59	1.57	1.39	1.73	1.40	1.38	**1.35**

PB: No Twitter Features
CPB: No Sentiment Features
TPB: All Features

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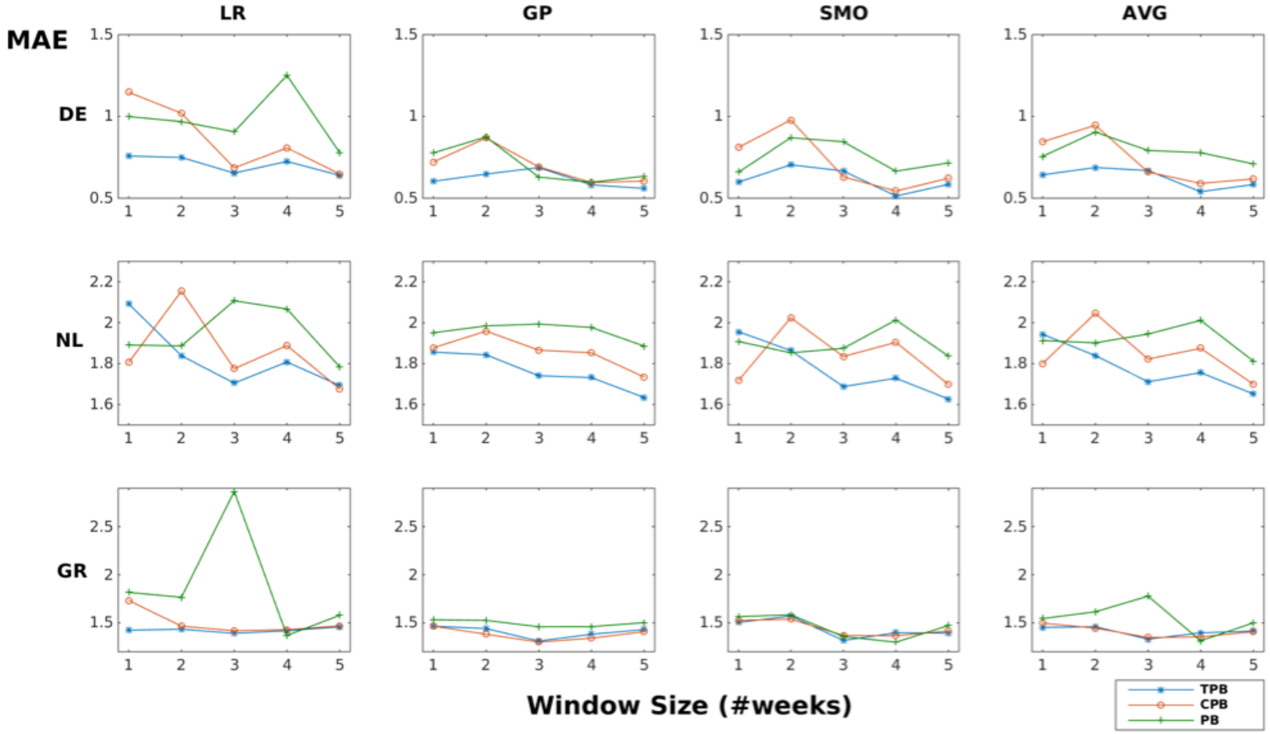

TPB vs PB:
significant differences (.05)

TPB vs CPB:
significant differences (.05)
except for SMO

Issues

Reference: Tsakalidis, Adam, et al. "Predicting elections for multiple countries using Twitter and polls." *IEEE Intelligent Systems* 30.2 (2015): 10-17.

Issues

Further experiments

- 2015 General Elections (Greece): better estimates than *all* opinions polls

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- Sudden/major political debates?
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→ **Greek Bailout Referendum (2015)**

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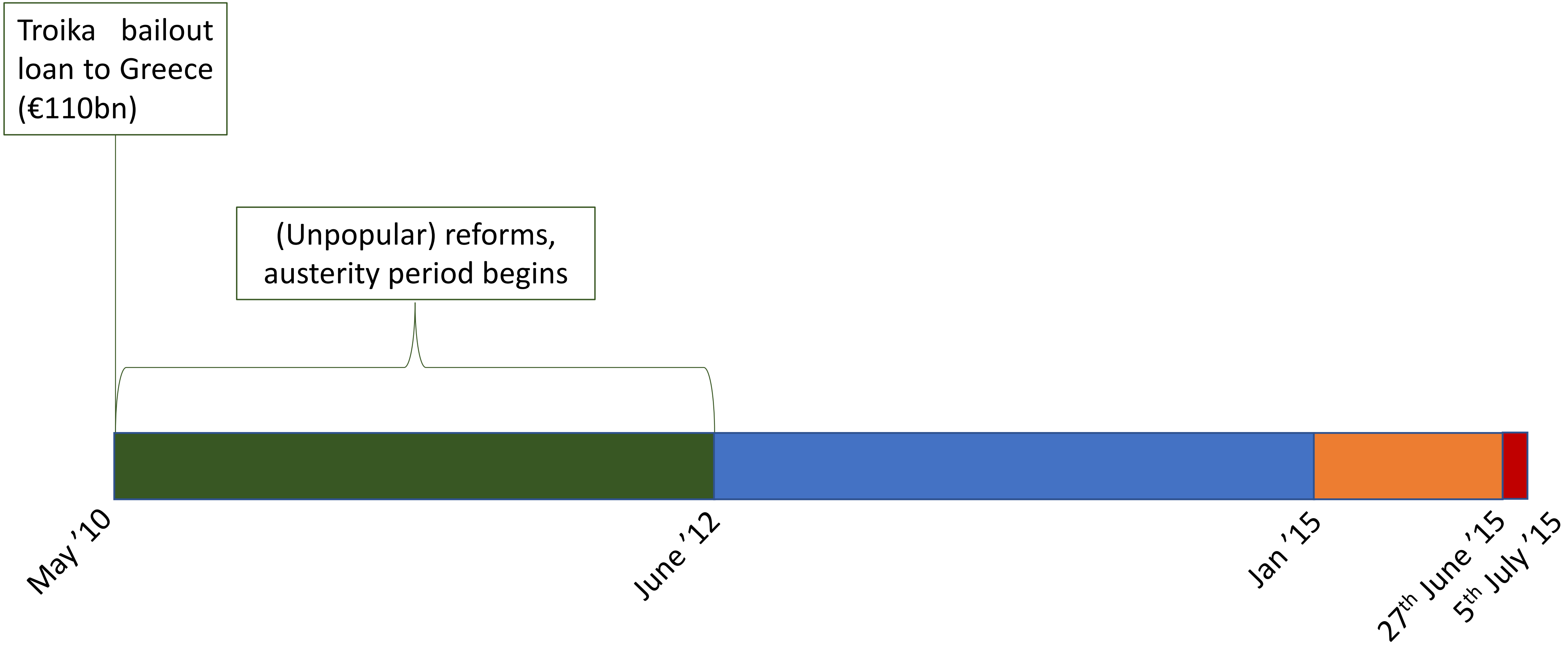

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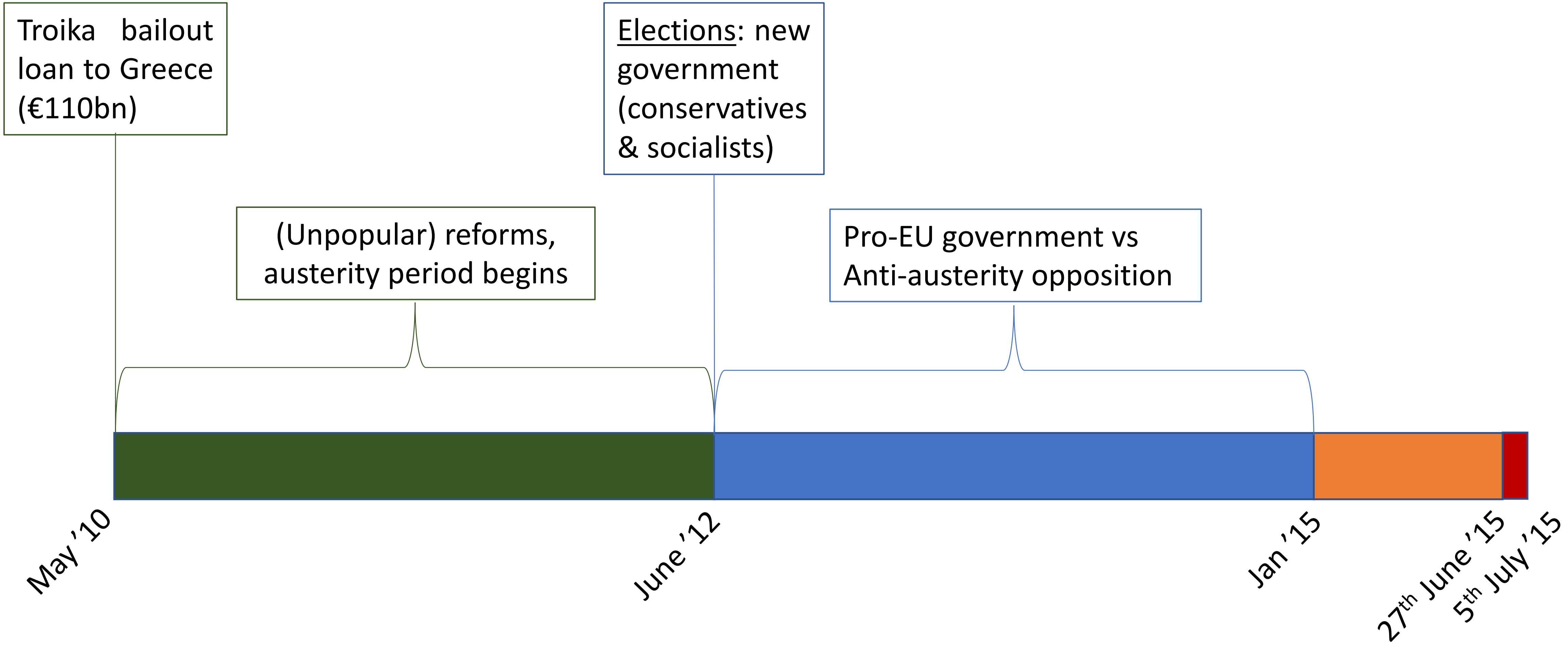

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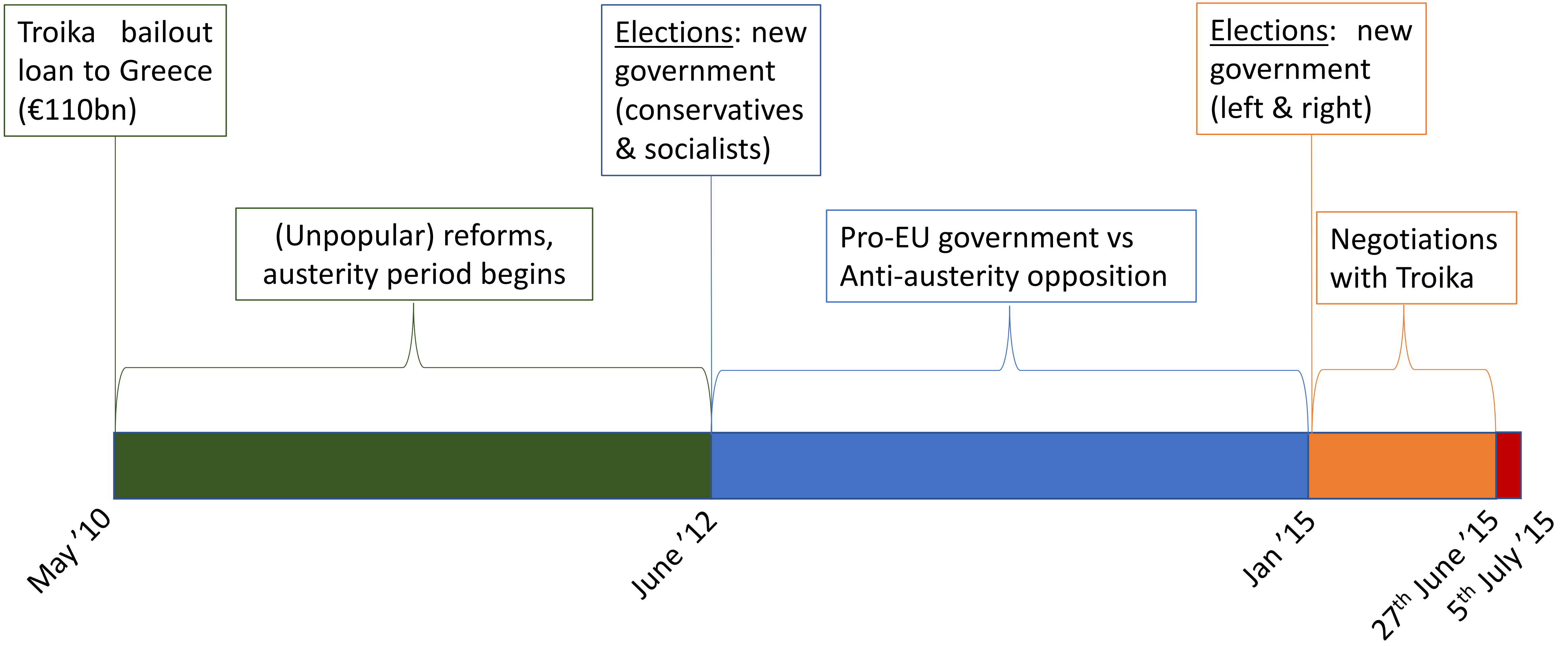

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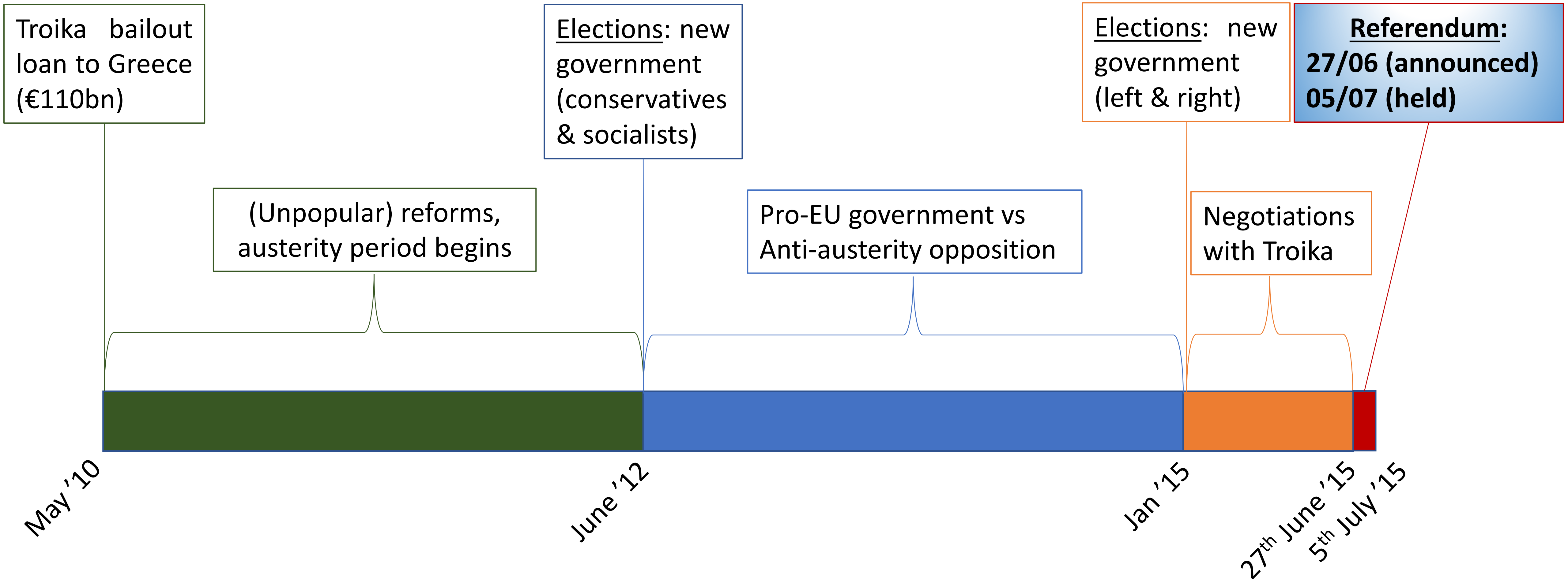

27th June-5th July extreme polarisation, demonstrations, capital controls…

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Aim: *nowcast the stance (YES/NO) of social media users* (binary task over time)

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For *t* in [0, 1, …, 8]: *#[26/06-04/07]*

1. Assume training set of *n* users at *t*:
2. Learn a function at *t*:
3. Evaluate performance on test users at *t*

$$D_t = \{(x_t^{(1)}, y^{(1)}), \ldots, (x_t^{(n)}, y^{(n)})\}$$
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Challenges:

- real-world application; no manual effort – training set?
- combine *asynchronous* and *time sensitive* information sources?

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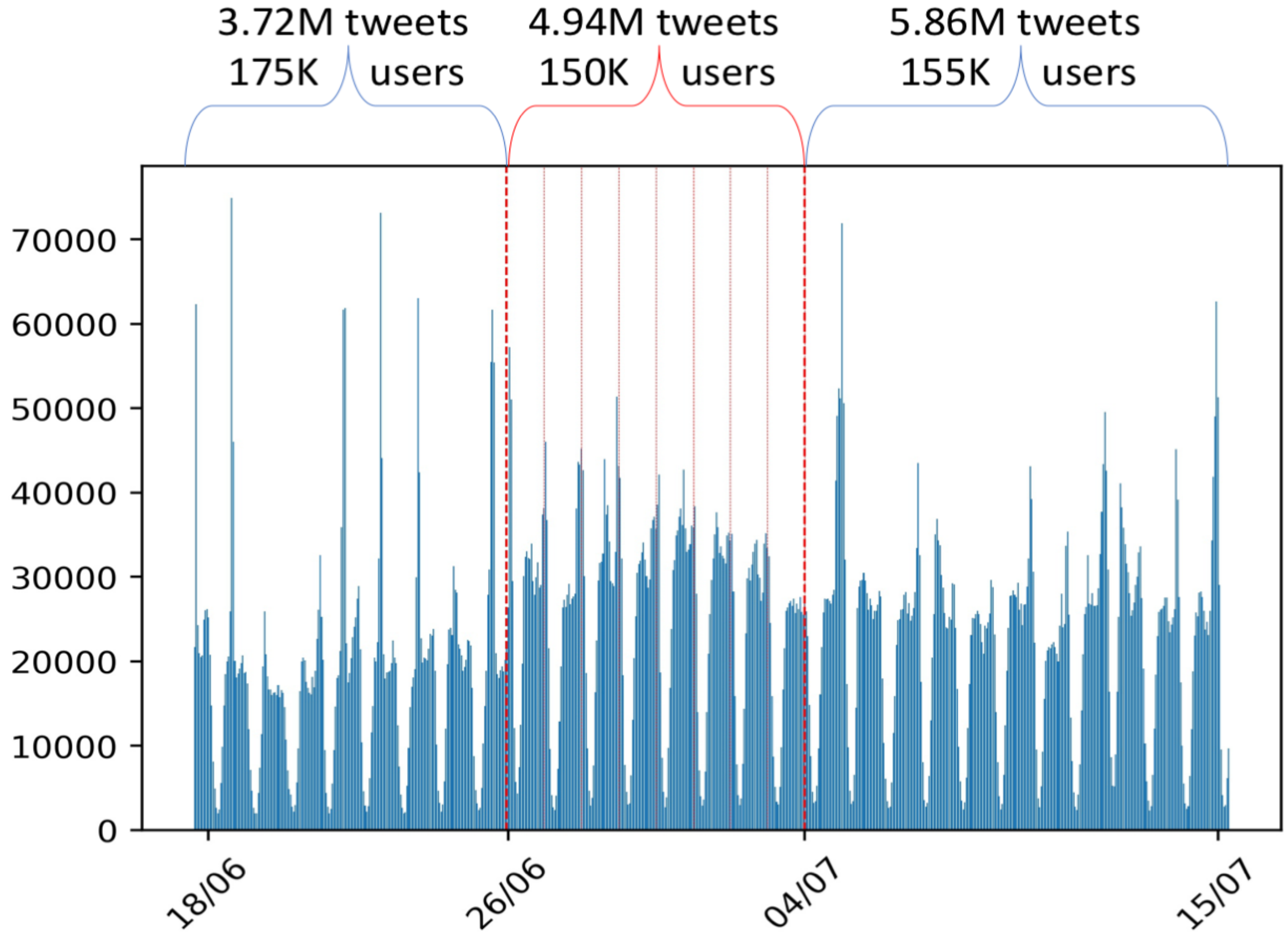

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- 14.6M tweets
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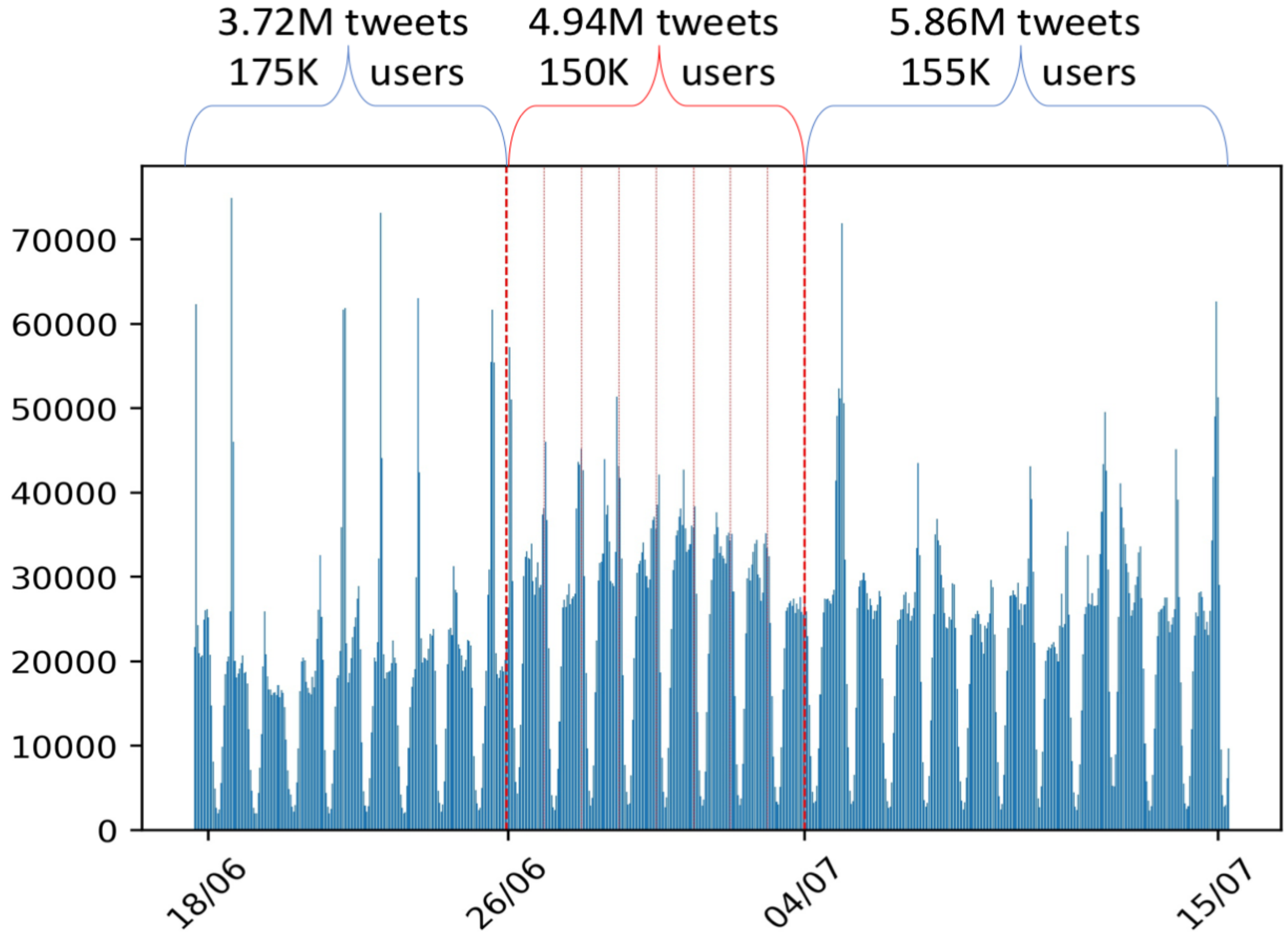
Test set: annotate 2.7K users

- >10 tweets; >3 polarised hashtags
- Annotation: YES/NO (or N/A)
- Cohen's κ: .98 (.74)

- Final set: 2,197 users
- 77/23 NO/YES (result: 61/39)



Training Set

Seed accounts with "known" labels:

- political parties (pro-EU vs anti-austerity)
- MPs
- keyword-based profile search

148/119
YES/NO

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$$scores = [PMI(u, YES) - PMI(u, NO), \forall u]$$

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YES/NO

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$$scores[u] > t \Rightarrow YES$$

965 YES

$$scores[u] < -t \Rightarrow NO$$

1,165 NO

Data (summary)

	#users	#tweets	YES (%)	NO (%)
Train	2,121	867K	45%	55%
Test	2,197	768K	23%	77%

Methodology

User

Convolution kernels

text

network

K_w, K_{wt}

K_n, K_{nt}

Kernel combination

$$w_w K_w + w_{wt} K_{wt} + w_n K_n + w_{nt} K_{nt}$$

Convolution Kernels

Z_i: user representations (based on text or network structure) over times T_i:

$$Z_a = \{z_a^1, \ldots, z_a^N\} \qquad T_a = \{t_a^1, \ldots, t_a^N\}$$

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Convolution kernel(s):

$$K_z(a,b) = \frac{1}{|Z_a|\,|Z_b|} \sum_{i,j} k_z(z_a^i, z_b^j)$$

K_w (TEXT)
K_n (NET)

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Account for time (Lukasik & Cohn, 2016):

$$K_{zt}(a,b) = \frac{1}{|Z_a|\,|Z_b|} \sum_{i,j} k_z(z_a^i, z_b^j) k_t(t_a^i, t_b^j)$$

K_{wt} (TEXT)
K_{nt} (NET)

Kernel Combination

Kernel summation:

$$K(a,b) = \sum_{k=1}^{|K|} K_k(a,b)$$

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Multiple (convolution) kernel learning (Sonnenburg et al., 2006):

$$K(a,b) = \sum_{k=1}^{|K|} w_k K_k(a,b)$$

$$f(x) = sign\left(\sum_{i=1}^{N} a_i K(x, x_i) + b\right)$$

Experiments

Features

- TEXT: word2vec (Mikolov et al., 2013); 50 dim; trained on 15M tweets
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Our models

- Single modality: SVM_w , SVM_{wt} , SVM_n , SVM_{nt}
- Combinations: SVM_+ , MCKL

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Evaluation

- macro-average F-score
- *nine* evaluation time points (every midnight)

Results

	LR	FF	RF	SVM	SVM_n	SVM_{nt}	SVM_+	MCKL
TEXT								
NET								
BOTH								

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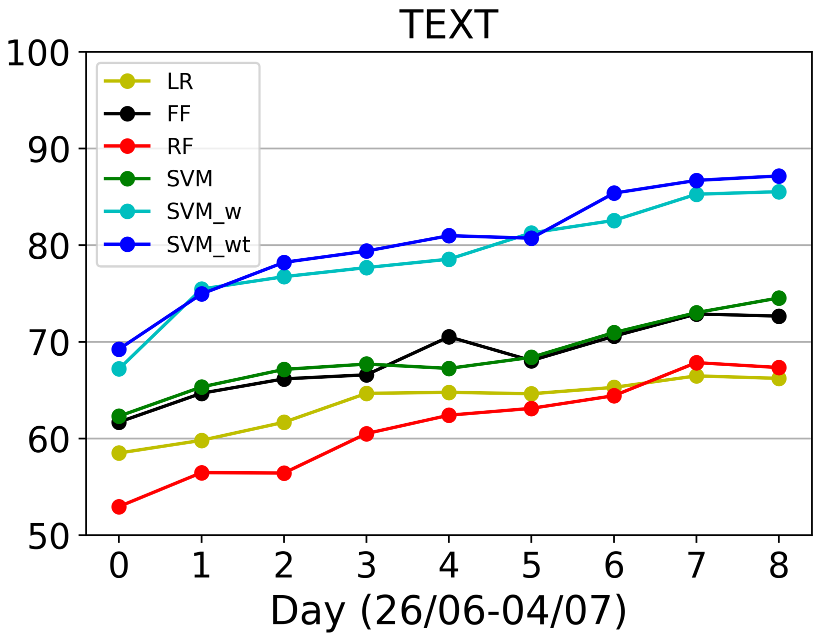

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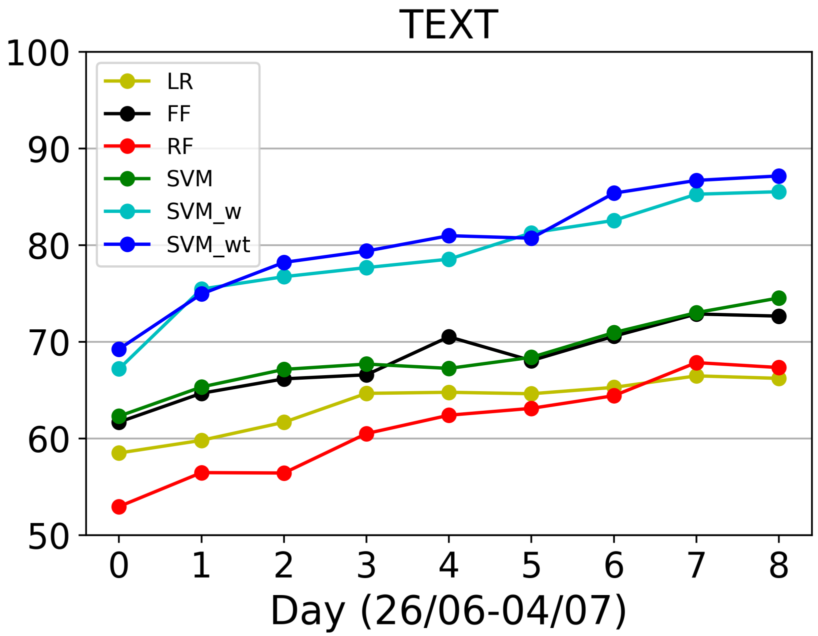

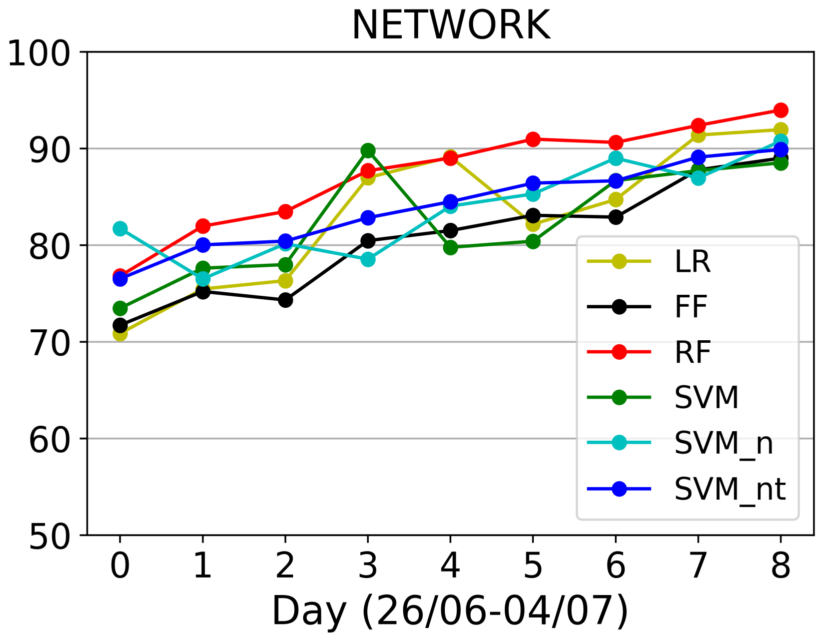

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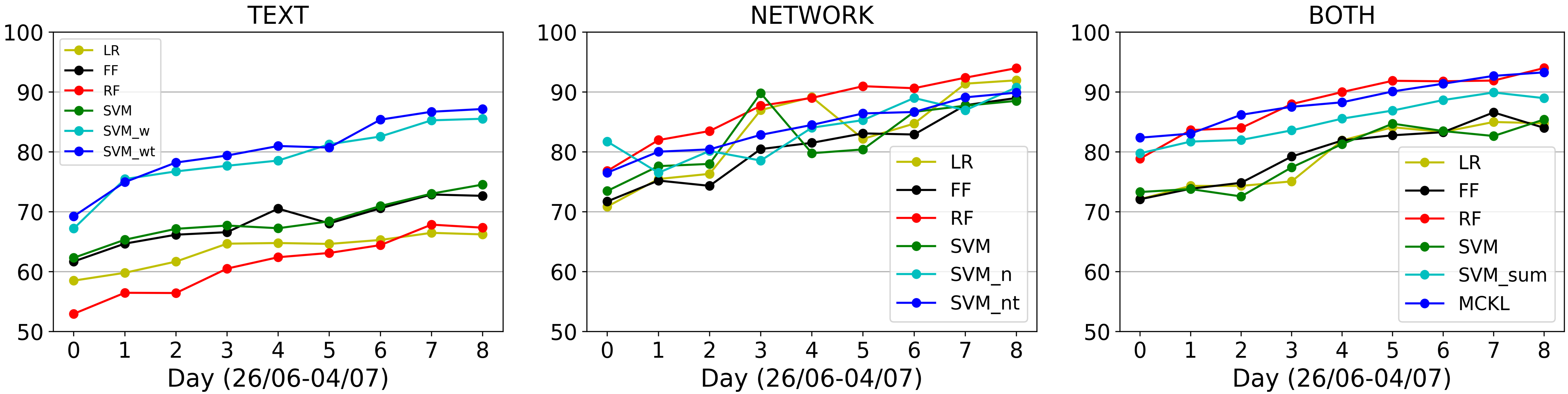

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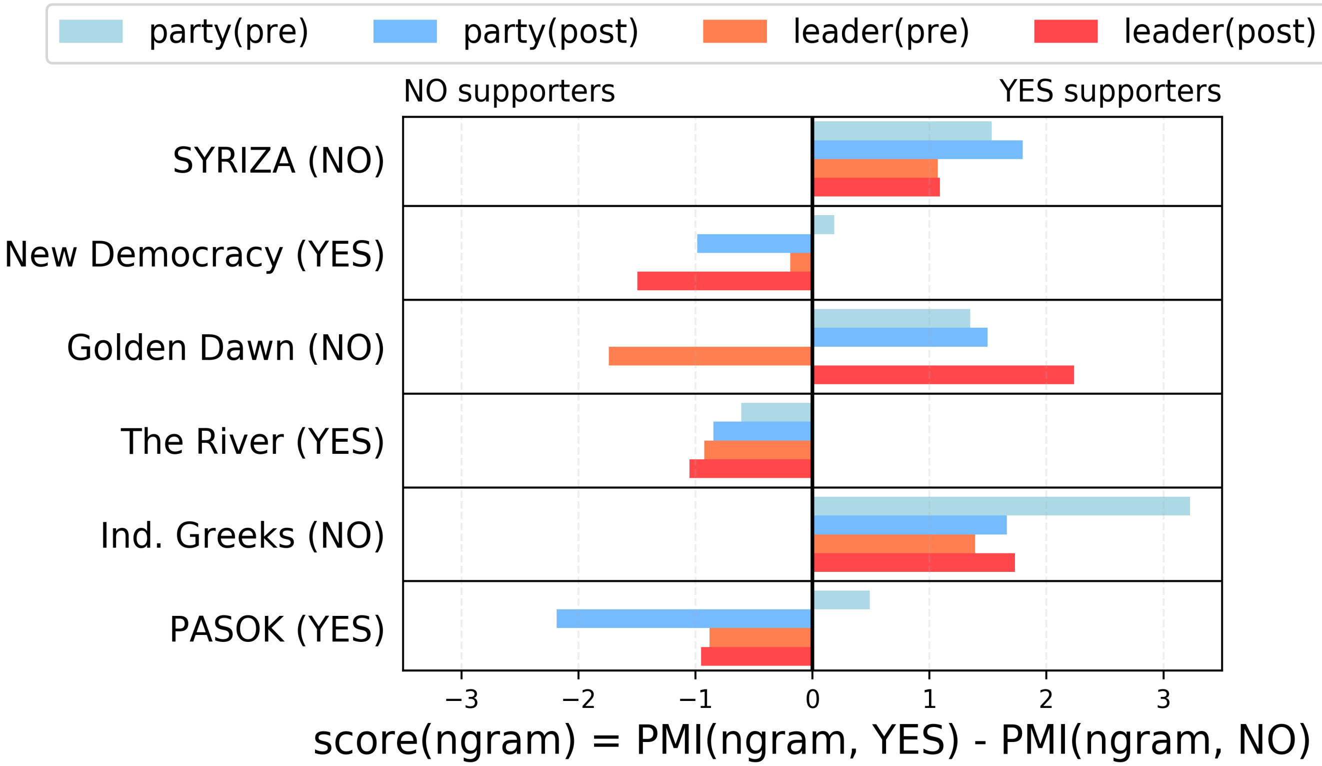

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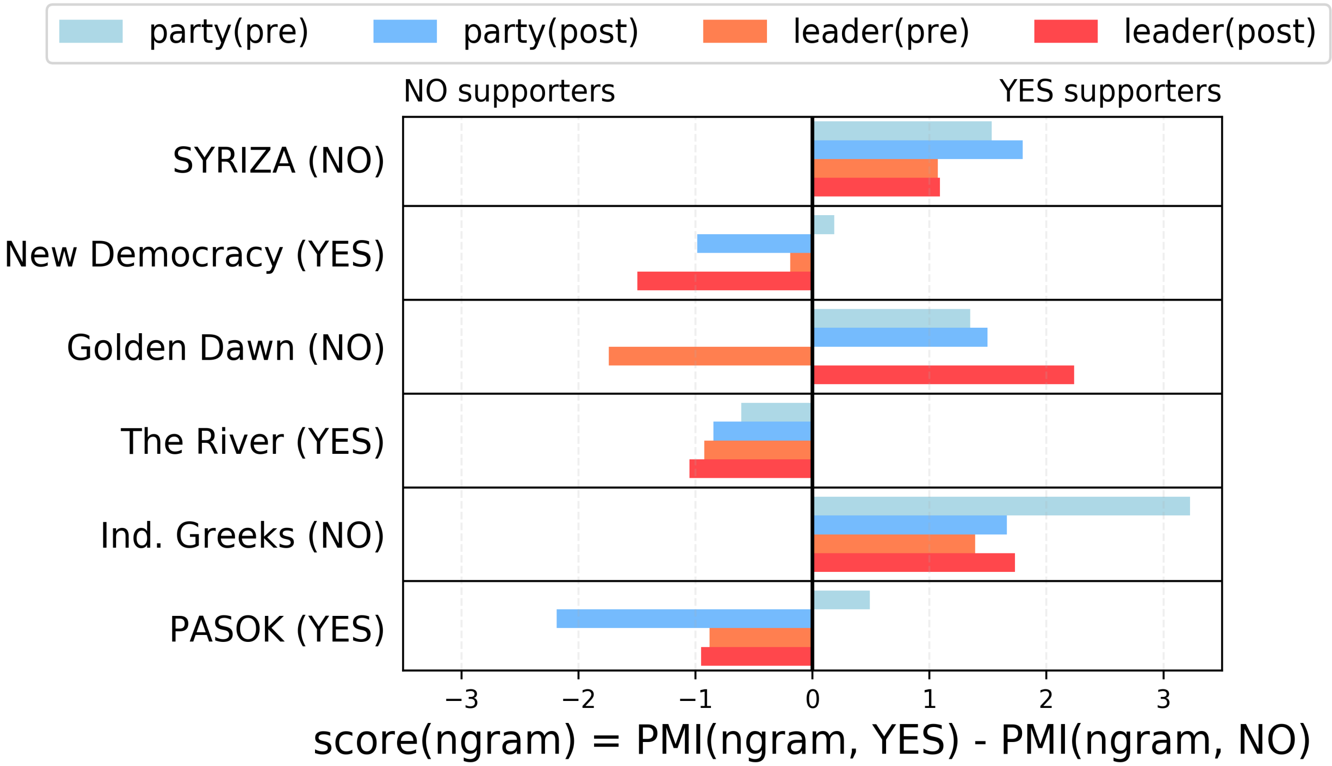

They say that there is a long queue of people in ATMs and they show 6 people waiting; this is not a queue, this is PASOK.

I want to write something funny regarding the statements made by Kammenos, but I cannot find something funnier than the statements made by Kammenos.

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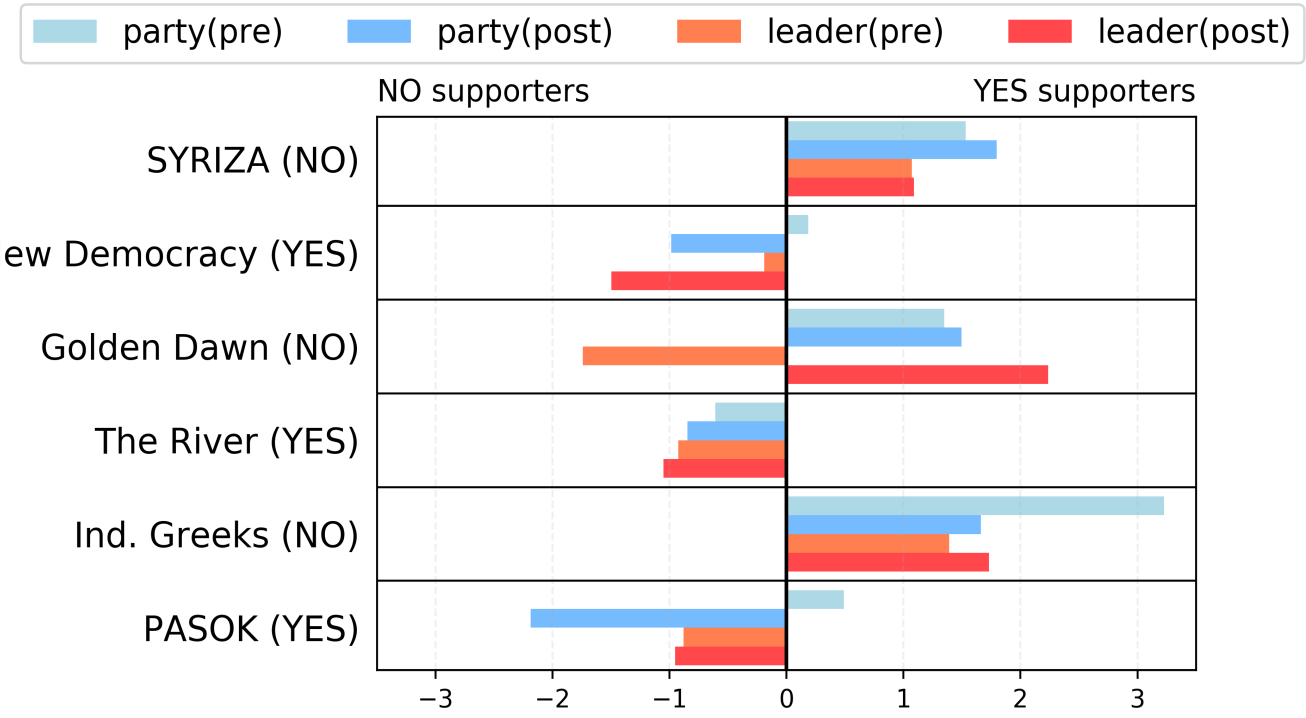
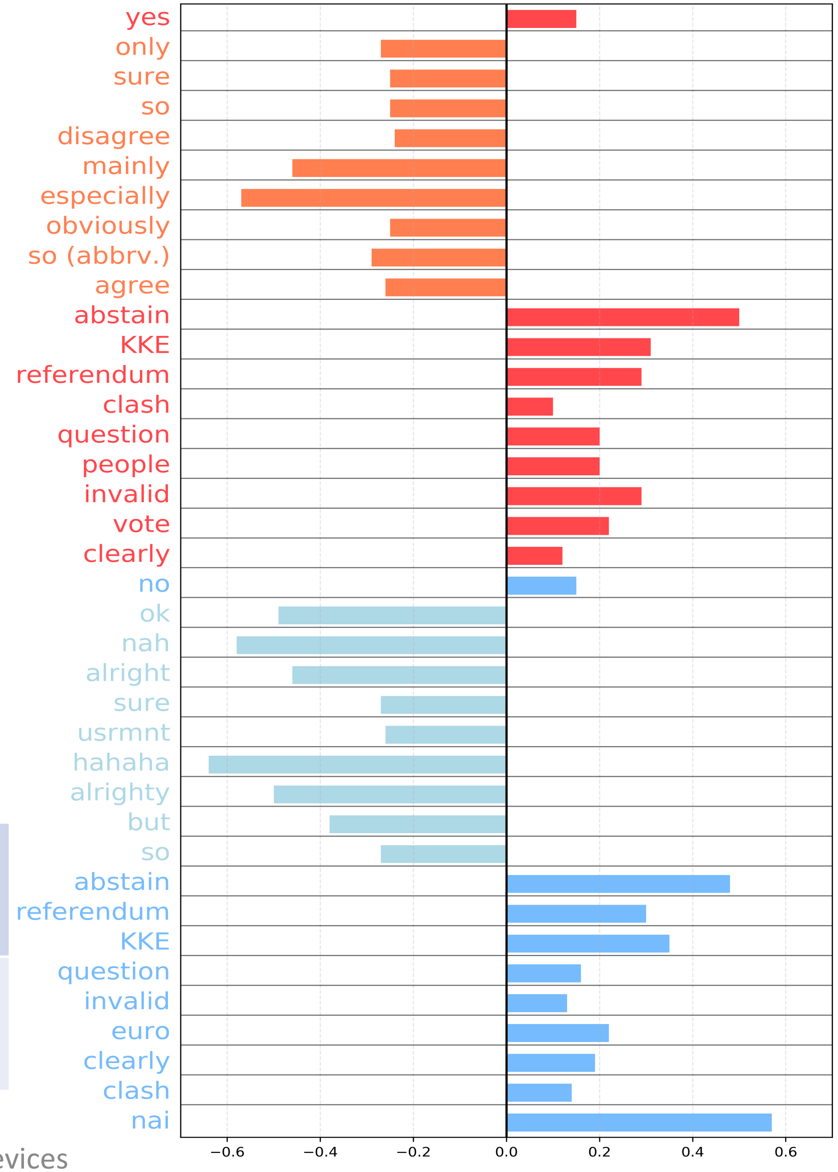


score(ngram) = PMI(ngram, YES) - PMI(ngram, NO)



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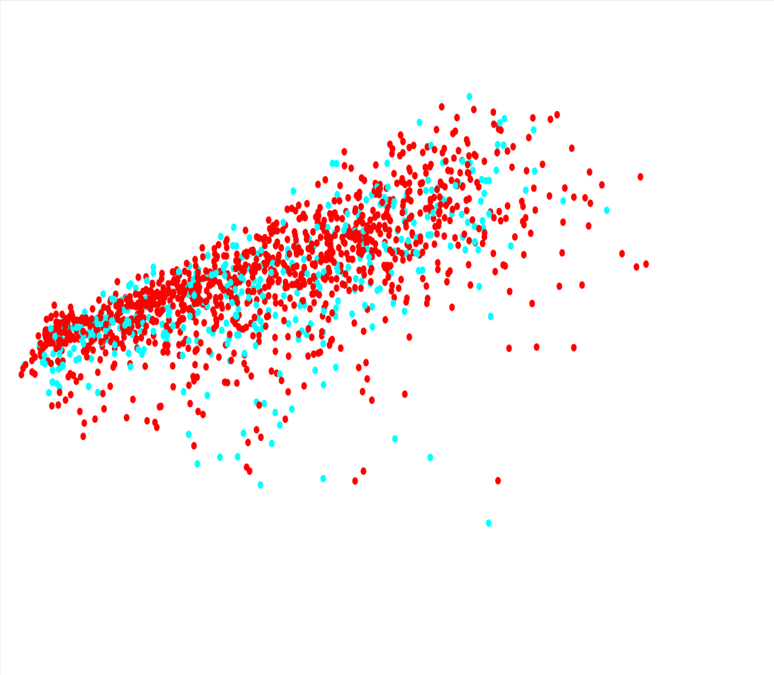

User representations **before** the announcement of the referendum

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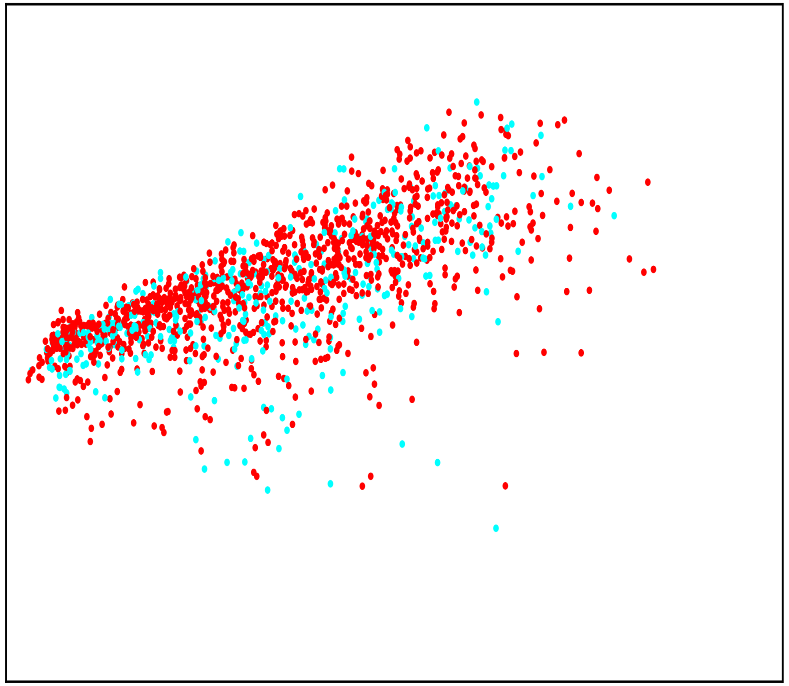

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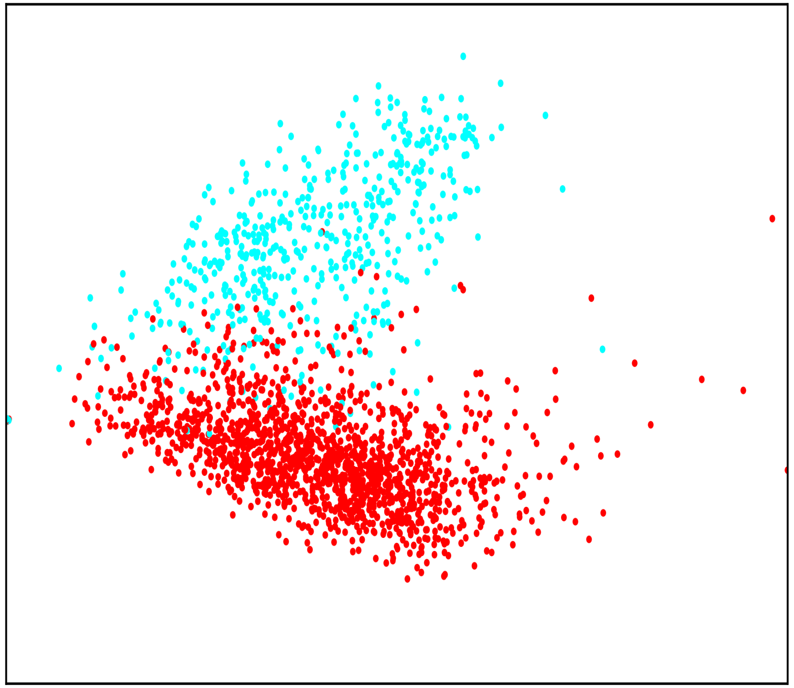

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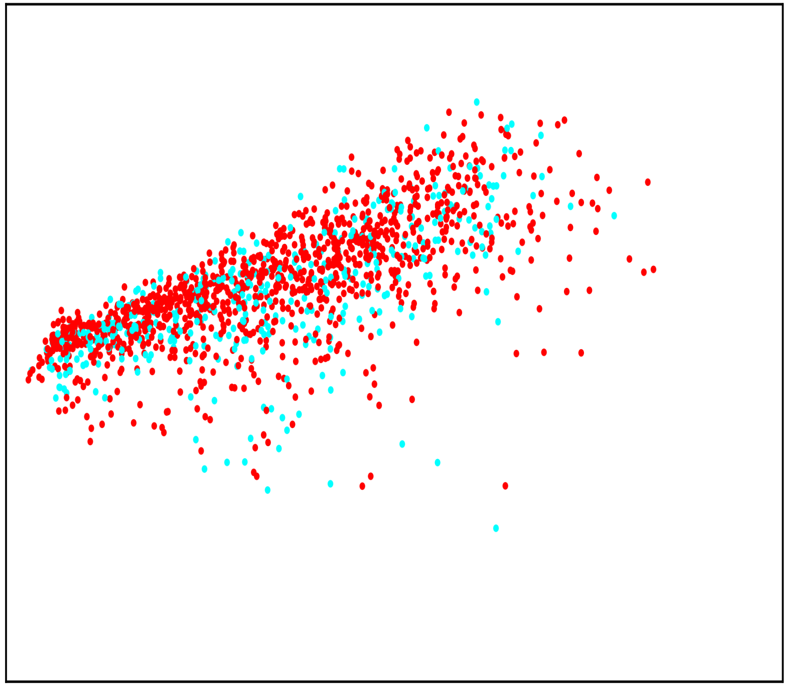

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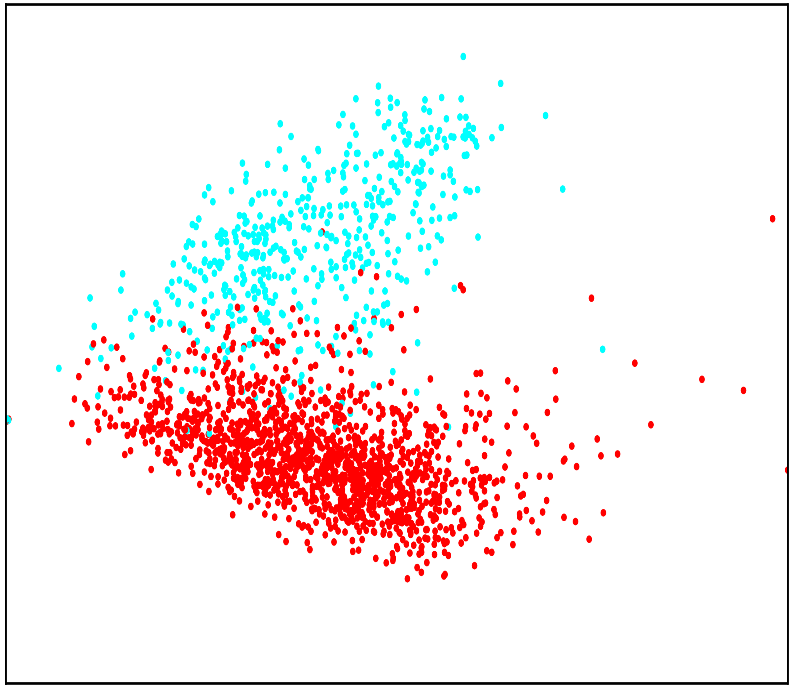

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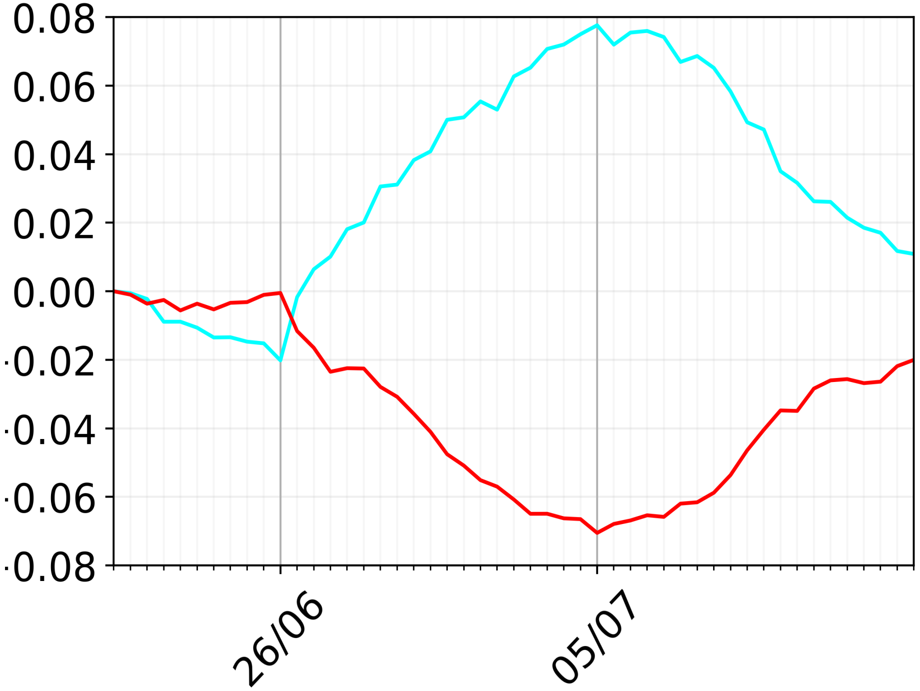

User representations in a sliding window:
sim(YES, YES*)-sim(YES, NO*)
sim(NO, YES*)-sim(NO, NO*)

Summary

Contributions

- Effective/robust MCKL approach (asynchronous, longitudinal)
- Importance of temporal modelling
- Real-time simulation framework

Challenges

- **Time-varying target?**
- **Heterogeneous information?**

Reference: Tsakalidis, Adam, et al. "Nowcasting the Stance of Social Media Users in a Sudden Vote: The Case of the Greek Referendum." *Proceedings of the 27th ACM International Conference on Information and Knowledge Management*. ACM, 2018.

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Continuous Sensing for Mental Heath Assessment

Mental Health Assessment

- Self-reports (time-consuming) → real-time?

Social Media & Smart Devices

- Real-time sensors: location, text, moving patterns…
- Relation to mental health?

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Our goal: combine heterogeneous data

Task & Dataset

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29 users, ~4 months: social media/SMS | DA data   mental health scores

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29 users, ~4 months: social media/SMS | DA data

mental health scores

Target: daily self-assessed {positive, negative, wellbeing} scores (2,436)

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TEXT (>110K)

- ngrams
- lexicons
- word embeddings
- topics
- others (count-based)

DA (>42GB)

- locations
- wifi
- calls
- others (headphones, charging, ...)

RQ3: Experiment & Results

5-fold CV | MKL vs {LASSO, SVR, RF}

		positive	negative	wellbeing
DA	LASSO			
	RF			
	SVR			
	MKL			
TEXT	LASSO			
	RF			
	SVR			
	MKL			
DA+TEXT	LASSO			
	RF			
	SVR			
	MKL			

RQ3: Experiment & Results

5-fold CV | MKL vs {LASSO, SVR, RF}

		positive	negative	wellbeing
DA	LASSO	.31	.11	.30
	RF	.69	.43	.75
	SVR	.58	.35	.62
	MKL	.61	.38	.65
TEXT	LASSO	.53	.23	.55
	RF	.70	.45	.74
	SVR	.60	.32	.62
	MKL	.62	.36	.65
DA+TEXT	LASSO	.49	.18	.54
	RF	.71	.46	.76
	SVR	.60	.34	.62
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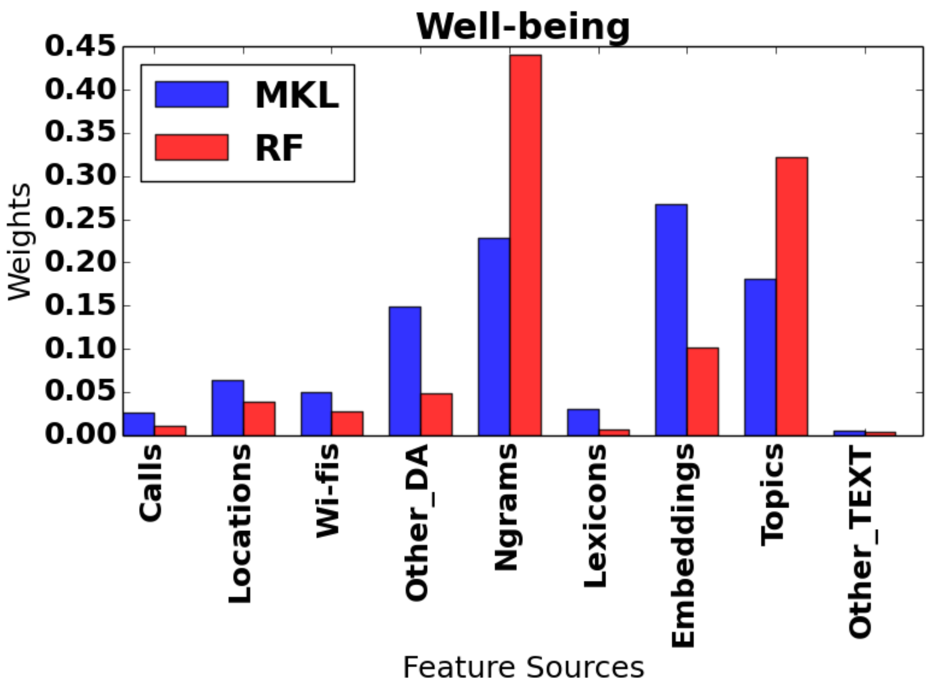

Reference: Tsakalidis, Adam, et al. "Combining heterogeneous user generated data to sense well-being." *Proceedings of COLING 2016, the 26th International Conference on Computational Linguistics: Technical Papers*. 2016.

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Does this evaluation framework follow a real-world setting?

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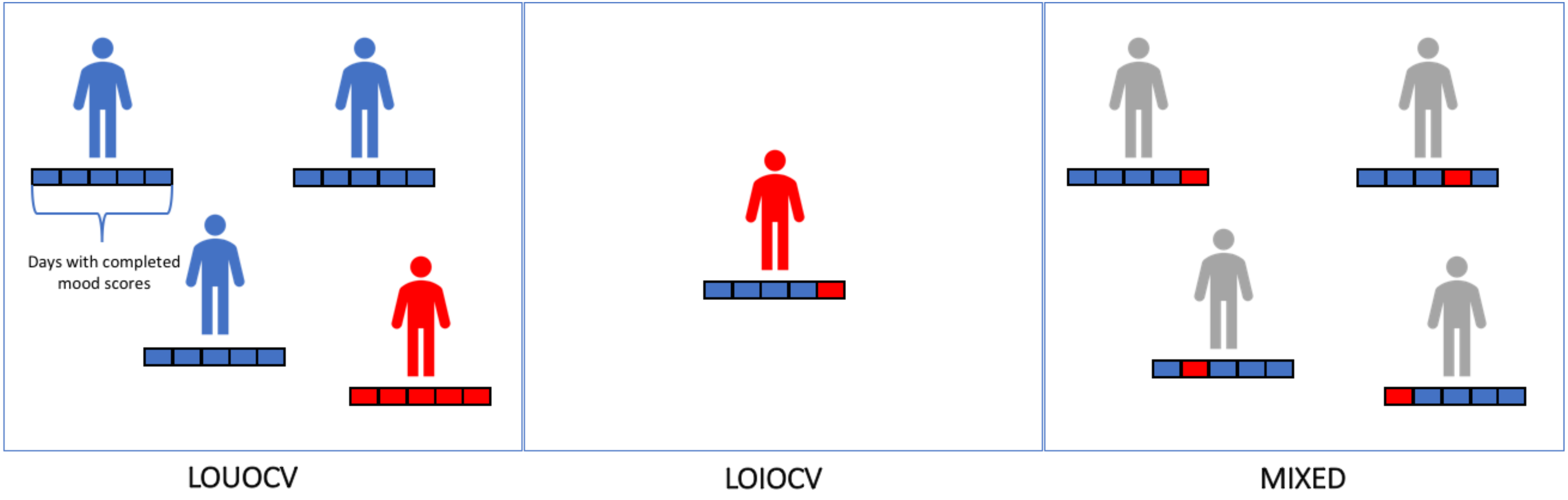
Overview

- Introduction
- Part 1: Nowcasting Political Indices Using Social Media
  - Predicting Election Results with Social Media
  - Nowcasting the Political Stance of Social Media Users
- **Part 2: Nowcasting Mental Health Using Heterogeneous Data**
  - Using Heterogeneous User Generated Content to Sense Well-being
  - **Challenges in Assessing Mental Health using User Generated Content**
- Conclusion & Future Directions

Types of Evaluation



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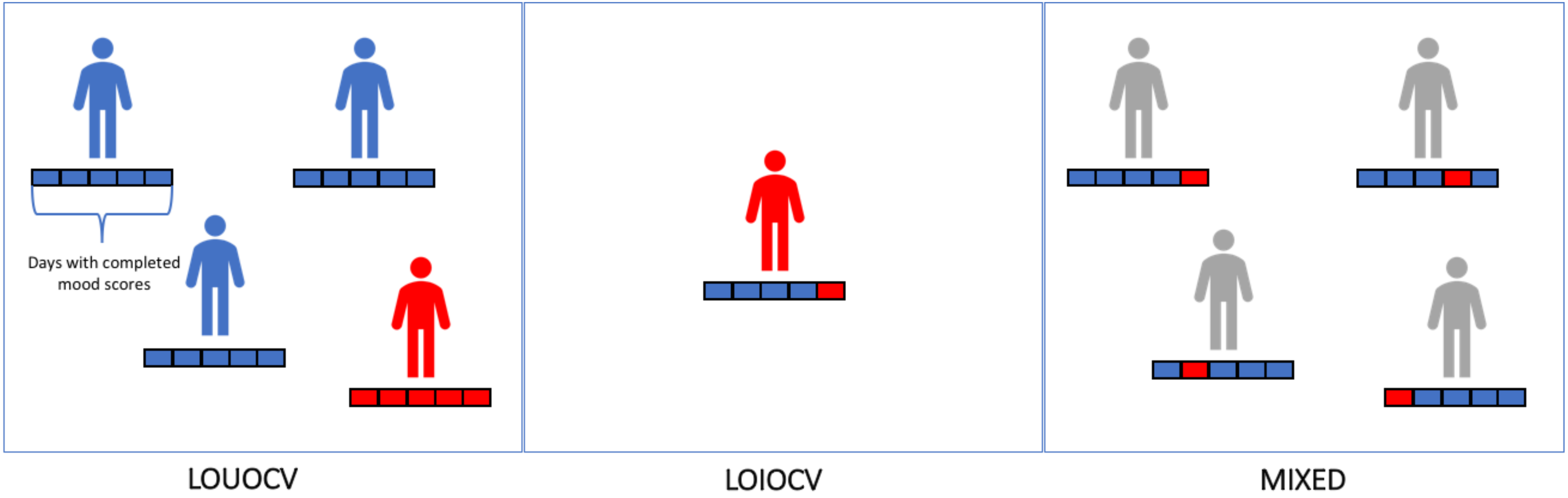

Goal: Generalise to new users

Problem: few users…

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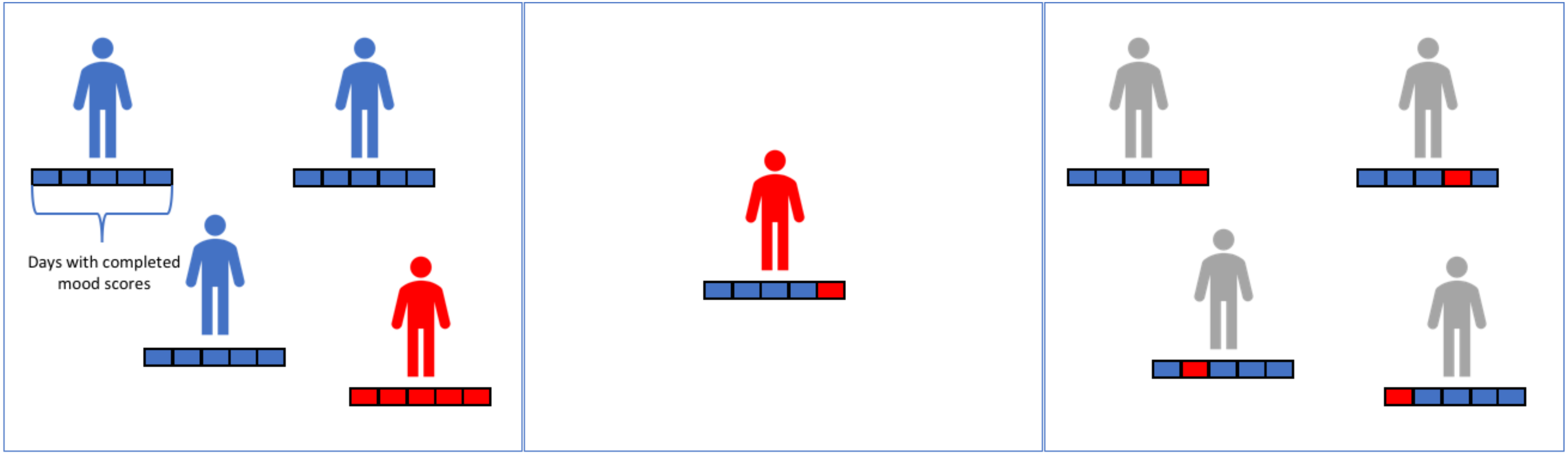

LOUOCV LOIOCV MIXED

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Goal: Personalised models

Problem: few instances…

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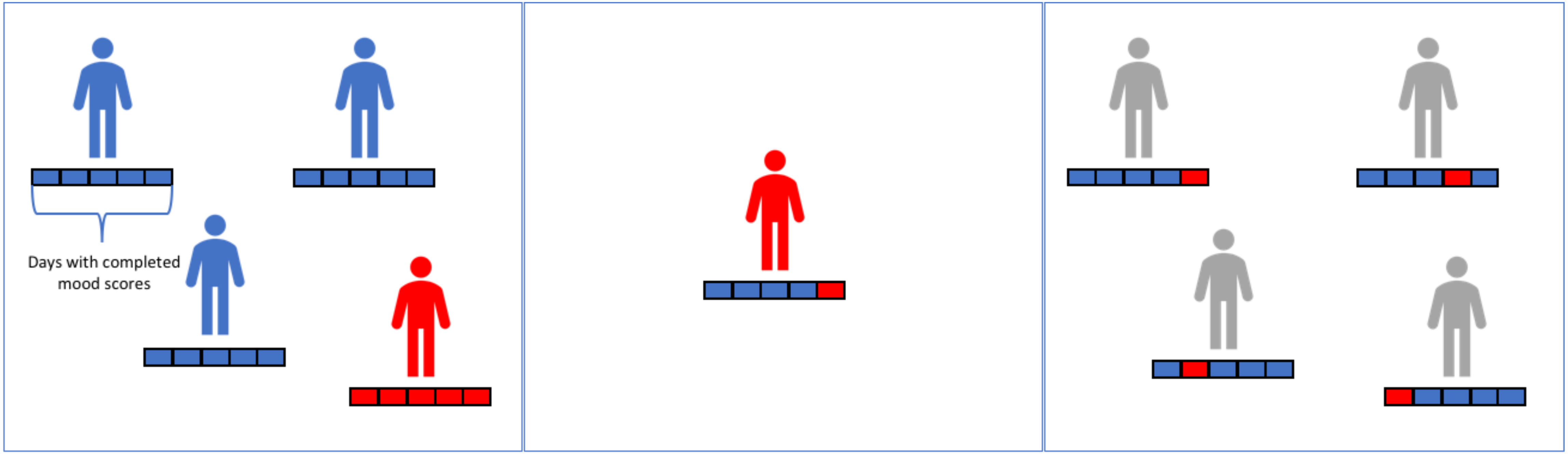

LOUOCV LOIOCV MIXED

Goal: Generalise to new users

Problem: few users…

Goal: Personalised models

Problem: few instances…

Goal: Generalise to certain users only

Problem: identify the user & infer his/her “average” score

Bias in SOTA

Training on past values of the target

1	2	3	4	5	6	7

Bias in SOTA

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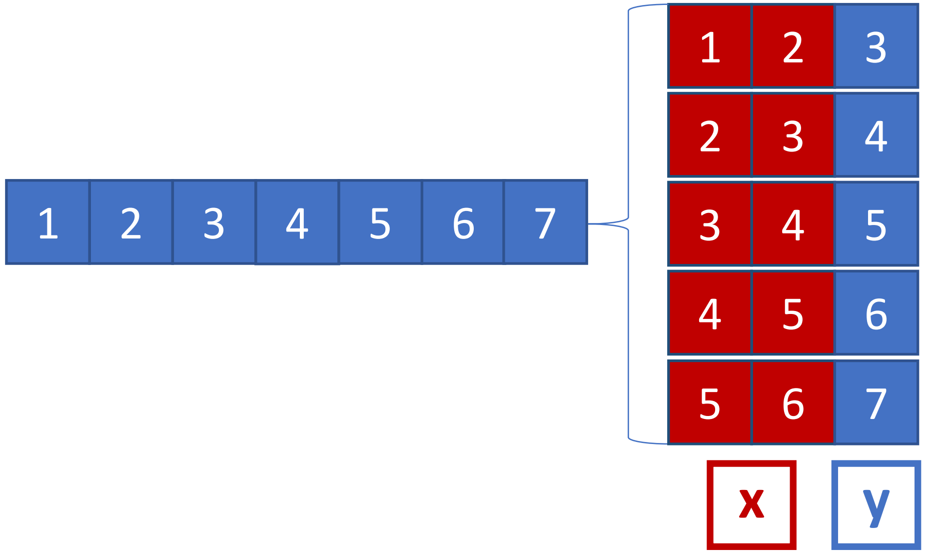

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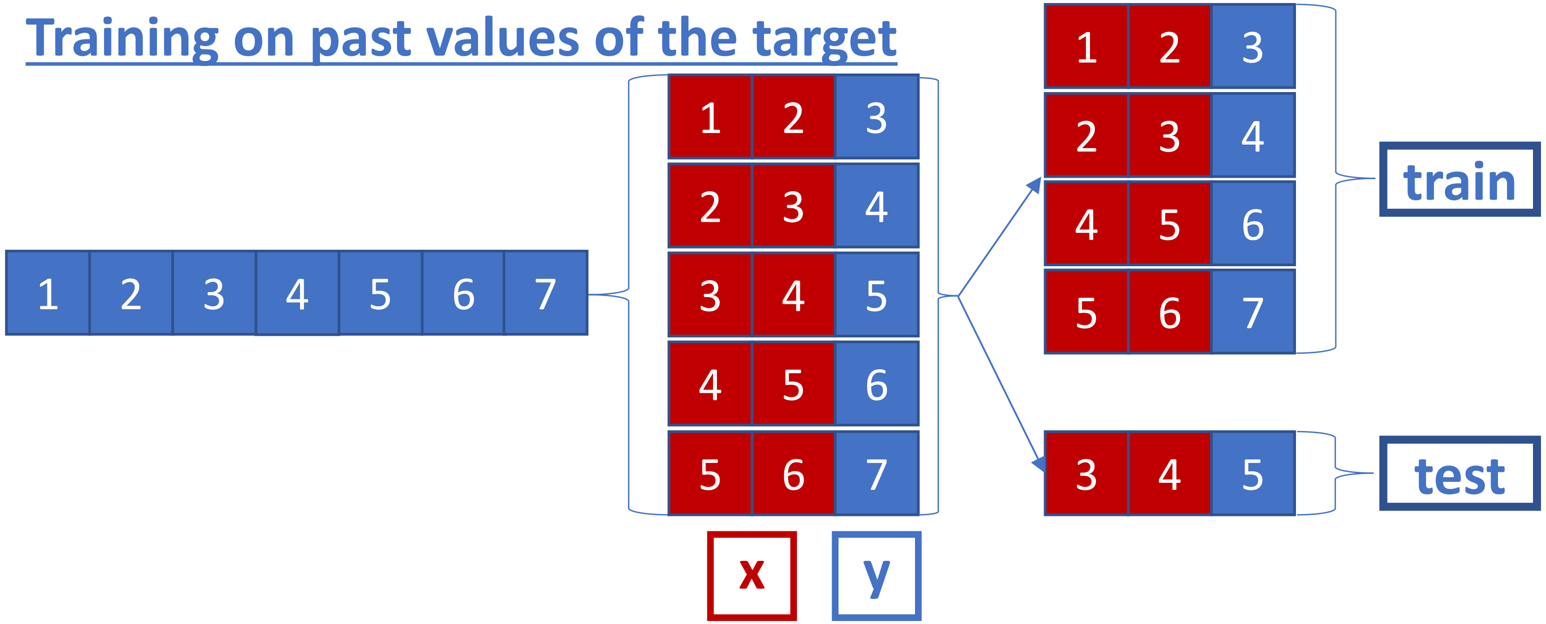

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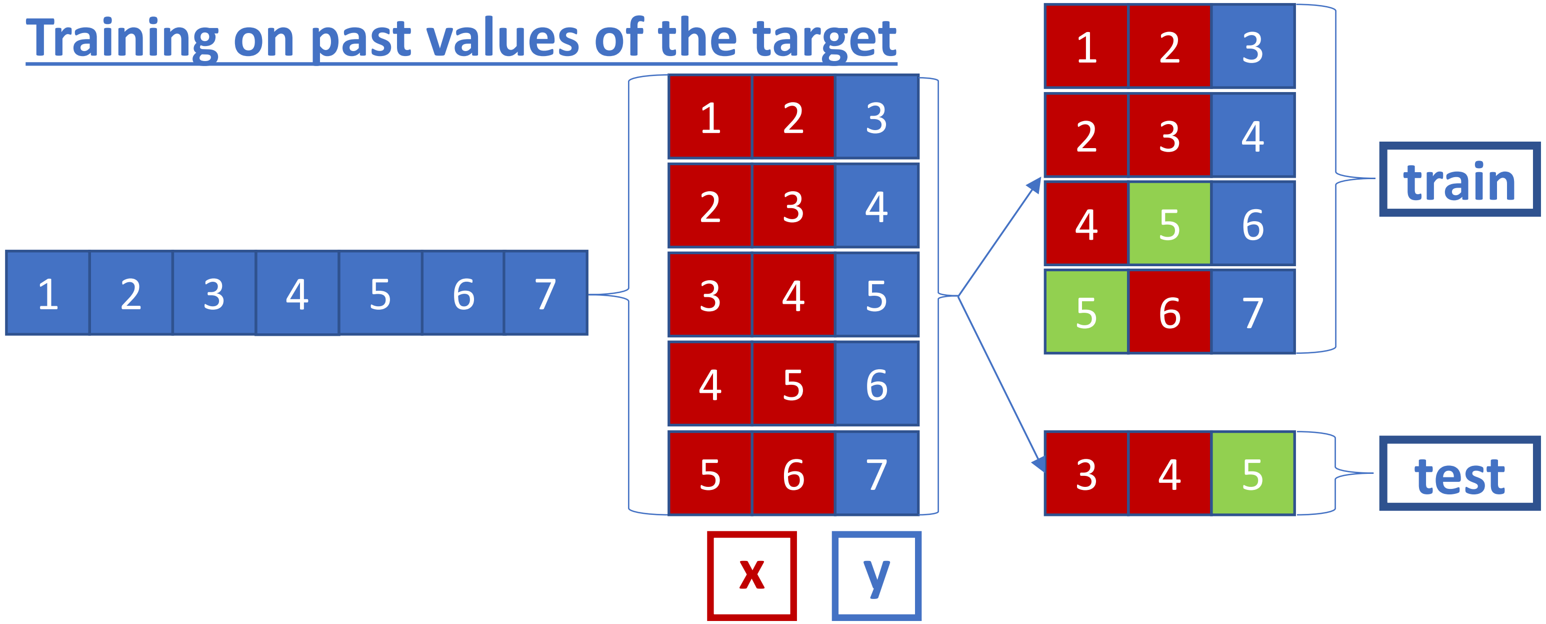

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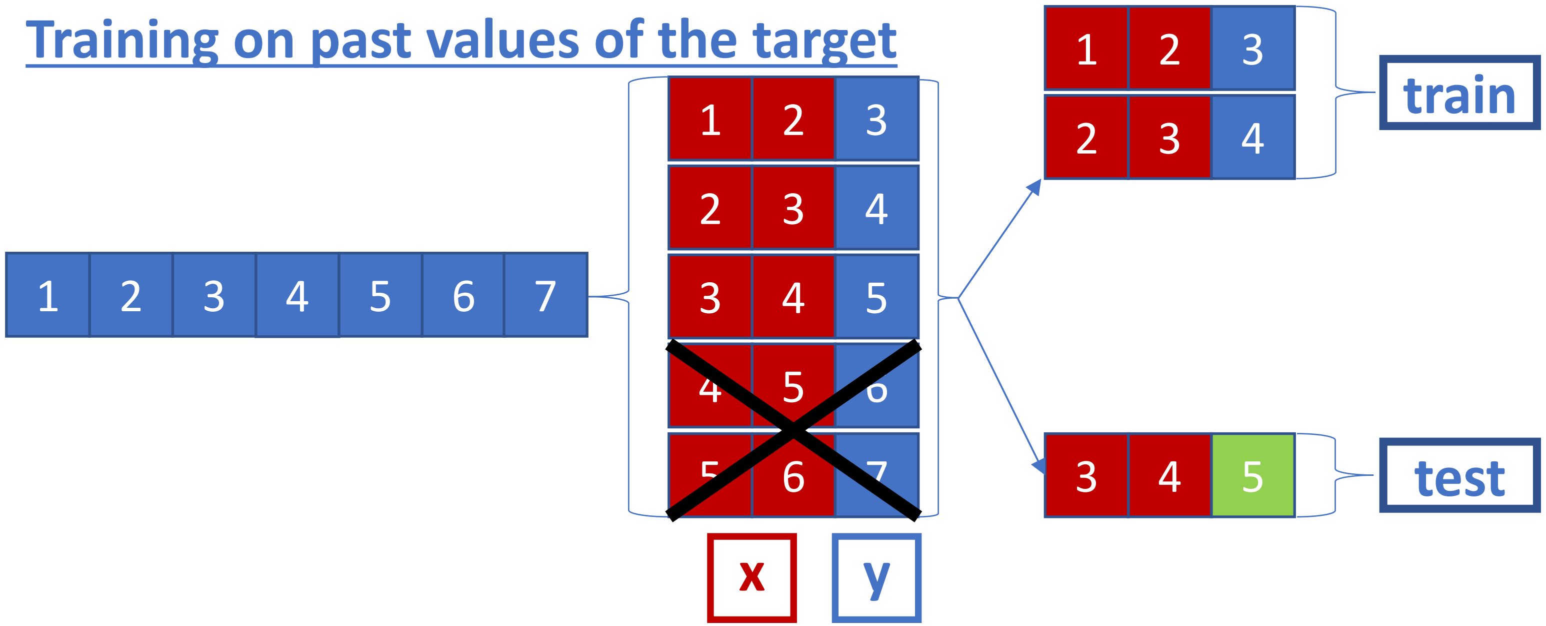

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	positive	negative	wellbeing	stress
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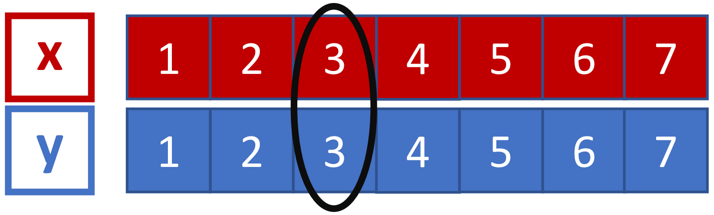

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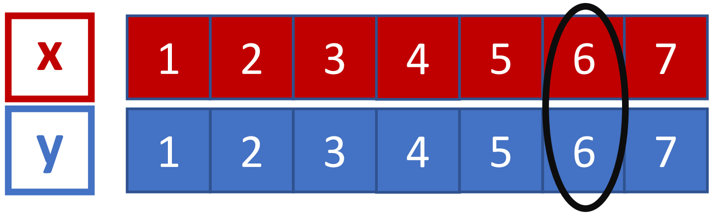

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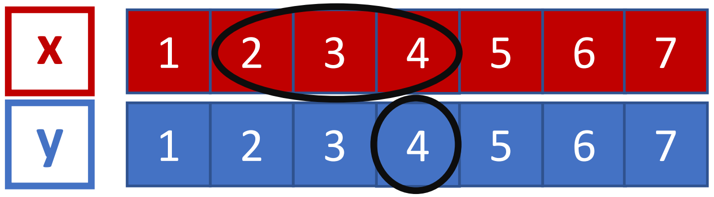

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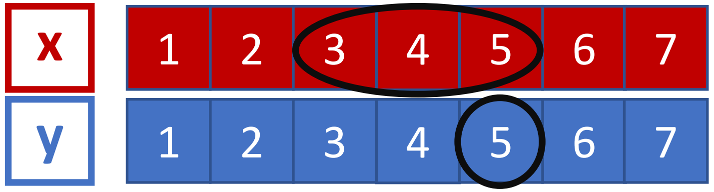

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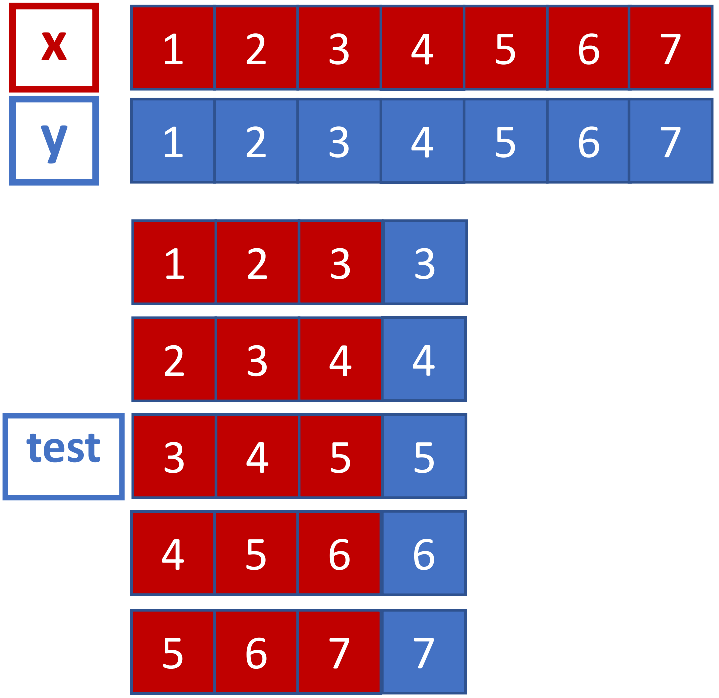

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	x	x	x	y
	1	2	3	3
	2	3	4	4
test	3	4	5	5
	4	5	6	6
	5	6	7	7

67% of the input is the same!

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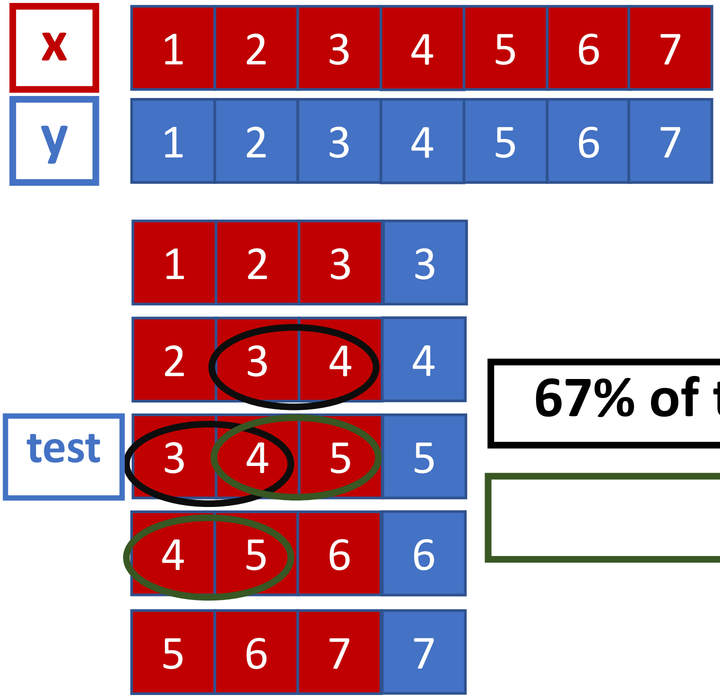

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Again!

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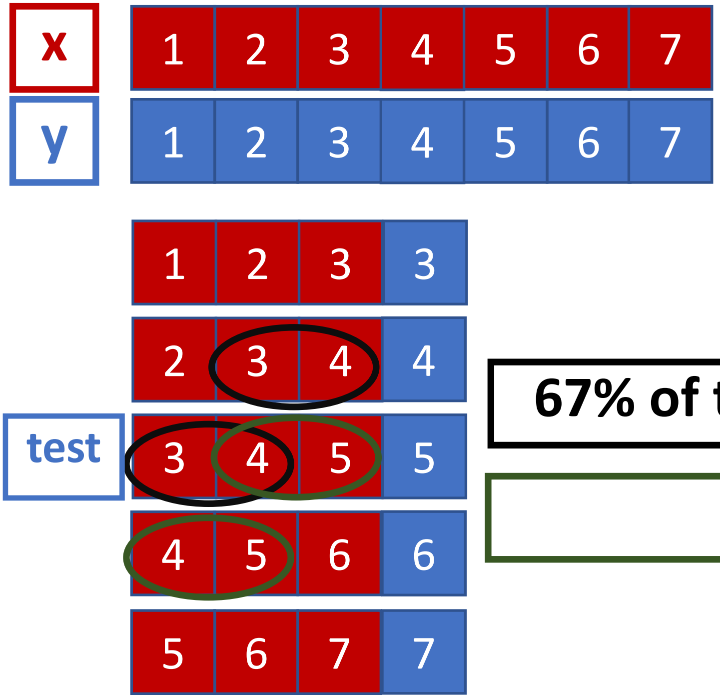

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	2	3	4	4
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Again!

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A: Artificially easy task – unrelated to mental health!

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- Overlapping instances (input)
- What if the target is also correlated?

	positive	negative	wellbeing	stress
MODEL	64.02	60.03	65.06	45.86
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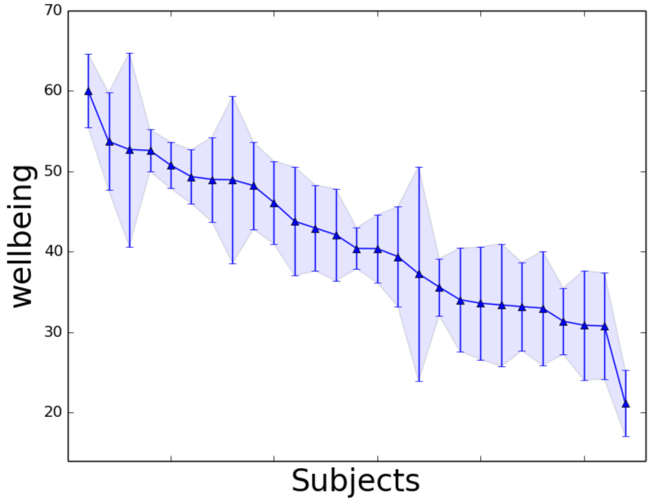
Predicting users instead of mood scores (MIXED)

- identify the user?



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	positive	negative	wellbeing	stress
LOIOCV	15.96	11.64	20.94	1.07
LOUOCV	36.77	31.99	51.08	0.81
AVG	29.89	27.80	41.14	0.70
-mood	113.30	75.27	138.67	1.08

Inferring test set labels (LOIOCV)

- Overlapping instances (input)
- What if the target is also correlated?

	positive	negative	wellbeing	stress
MODEL	64.02	60.03	65.06	45.86
Random	64.22	60.88	64.87	45.79

Predicting users instead of mood scores (MIXED)

- identify the user?

	positive	negative	wellbeing	stress
MIXED	0.43	0.25	0.48	0.02
LOIOCV				
LOUOCV				

Bias in SOTA

Training on past values of the target

- LOUOCV: new user?
- LOIOCV: test set target: feature in train set!

	positive	negative	wellbeing	stress
LOIOCV	15.96	11.64	20.94	1.07
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LOIOCV	-0.03	-0.04	-0.03	-0.08
LOUOCV	-4.19	-1.09	-4.66	-0.67

Reference: Tsakalidis, Adam, et al. "Can We Assess Mental Health through Social Media and Smart Devices? Addressing Bias in Methodology and Evaluation." (to appear in *ECML PKDD '18/ADS*)

Future Directions

Can we assess mental health through UGC…?

Need to re-evaluate mental health models!

- Extremely important for practitioners
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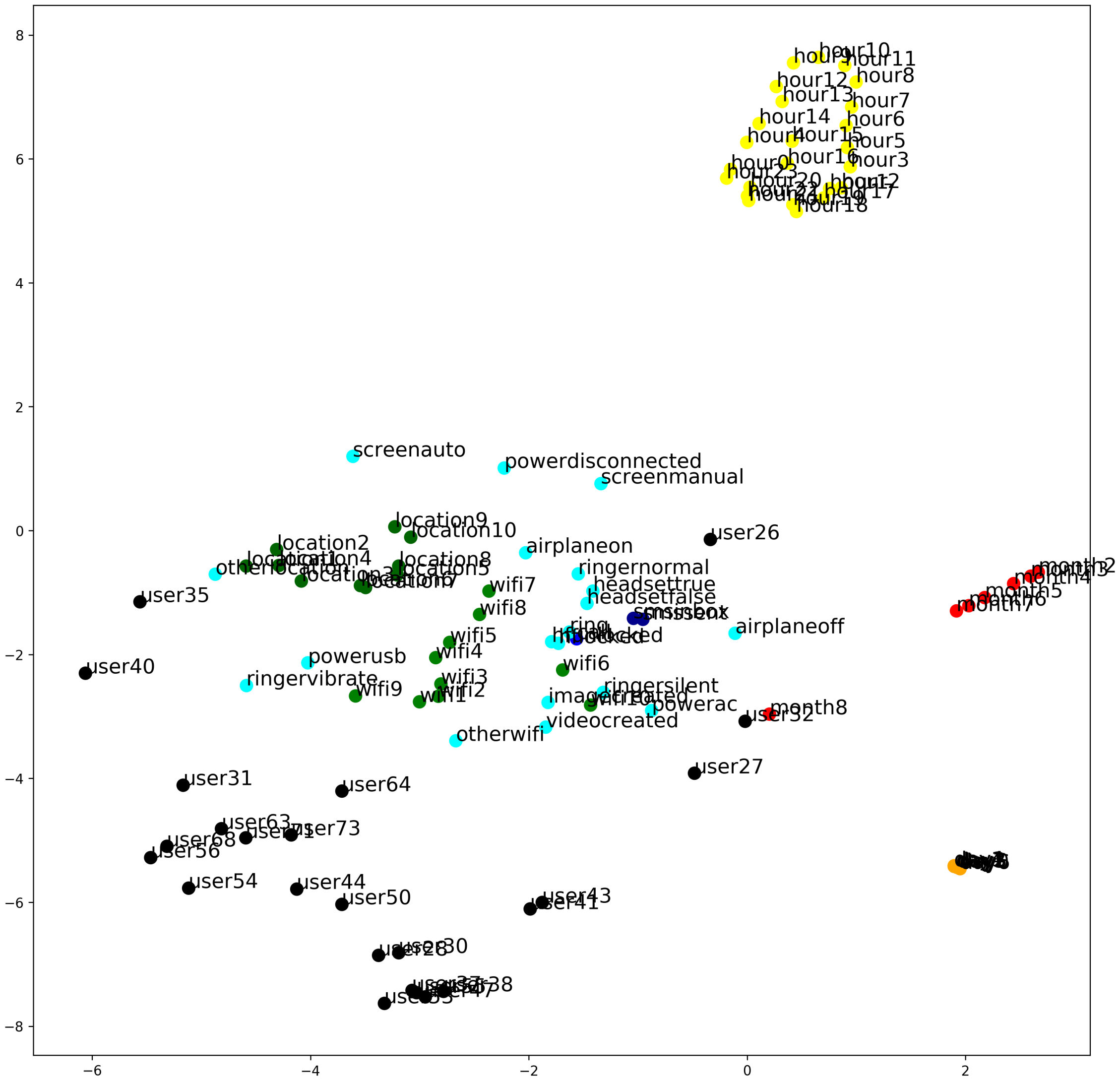

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Latent feature representations:

$$J = \log p_w(D=1|f,h) + \sum_{\tilde{f}\sim Q_{\text{noise}}} \left[\log p_w(D=0|\tilde{f},h)\right]$$

Overview

- **Introduction**
- **Part 1: Nowcasting User Political Stance Using Social Media**
  - Predicting Election Results with Social Media
  - Nowcasting the Political Stance of Social Media Users
- **Part 2: Nowcasting Mental Health Using Heterogeneous Data**
  - Using Heterogeneous User Generated Content to Sense Well-being
  - Challenges in Assessing Mental Health using User Generated Content
- **Conclusion & Future Directions**

Conclusion & Future Directions

Social Media & Smart Devices

- Rich resources of user-specific information
- Real-time sensors of political/health indices?
- Ethical implications?

High importance:

- work under a real-world setting

Future Work

- Heterogeneous data representation
- Asynchronous modelling
- Multi-domain applications

Published Material and Coverage

[1] Tsakalidis, Adam, et al. "Predicting elections for multiple countries using Twitter and polls." *IEEE Intelligent Systems* 30.2 (2015): 10-17.

- Press Release (University of Warwick): *Can we predict our political future?*
- Financial Times (Chris Tighe): *Tweets analysed for clues to UK general election result*
- Motherboard (Victoria Turk): *Attempting to Predict an Unpredictable Election*

[2] Tsakalidis, Adam, et al. "Nowcasting the Stance of Social Media Users in a Sudden Vote: The Case of the Greek Referendum." *Proceedings of the 27th ACM International Conference on Information and Knowledge Management*. ACM, 2018.

- Efimerida ton Syntakton (Kostas Zafiropoulos): Twitter threatens Opinion Polls (Greek)

[3] Tsakalidis, Adam, et al. "Combining heterogeneous user generated data to sense well-being." *Proceedings of COLING 2016, the 26th International Conference on Computational Linguistics: Technical Papers*. 2016.

[4] Tsakalidis, Adam, et al. "Can We Assess Mental Health through Social Media and Smart Devices? Addressing Bias in Methodology and Evaluation." *arXiv preprint arXiv:1807.07351*(2018). (to appear in ECML PKDD 2018/ADS)

Acknowledgements

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Thank you!

Any questions?

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