Nowcasting the Stance of Social Media Users in a Sudden Vote:

The Case of the Greek Referendum

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The Alan Turing Institute

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Introduction

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- Demographic/OSM bias (Morstatter et al., 2013; Miranda Filho et al., 2015)
- Train on opinion polls? (Lampos et al., 2013; Tsakalidis et al. 2015)
- Evaluation: 5-10 instances

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What about major/sudden electoral cases in which we have no historical evidence?

Greek crisis in a nutshell

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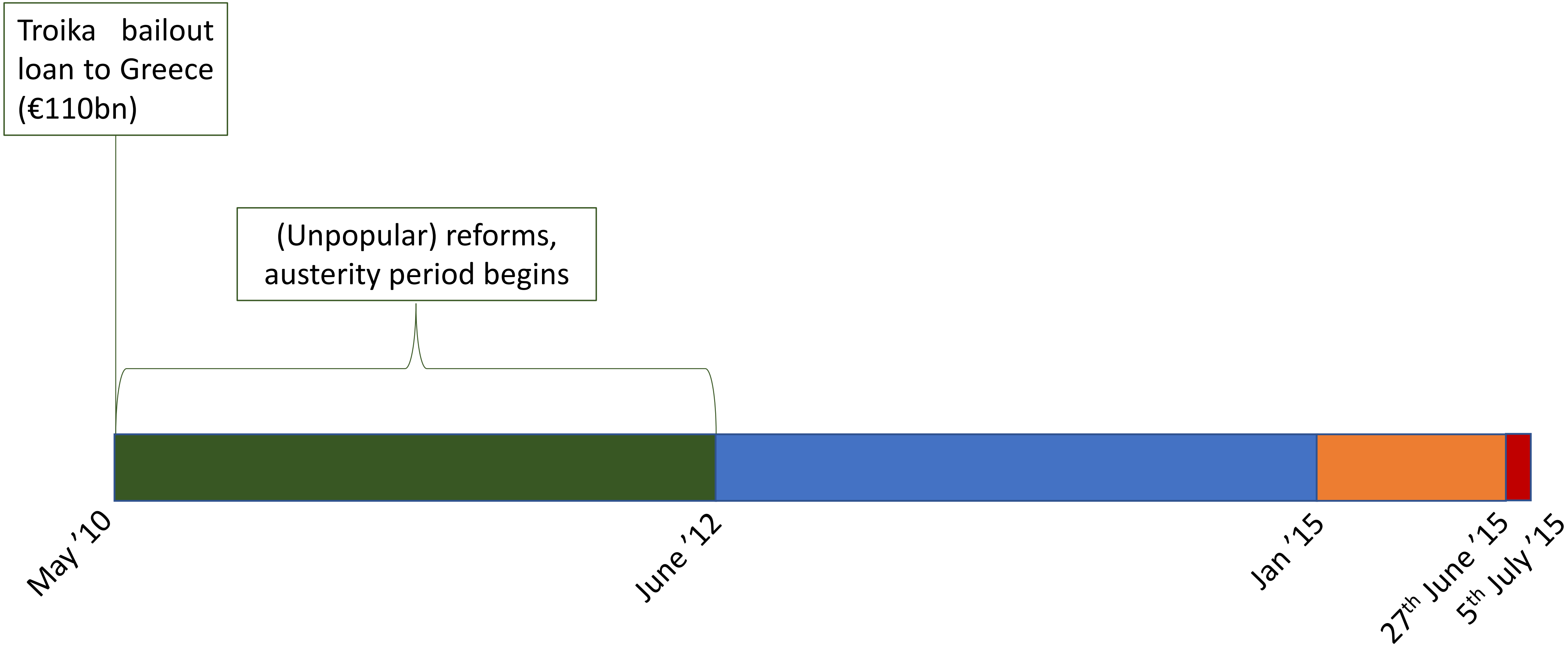

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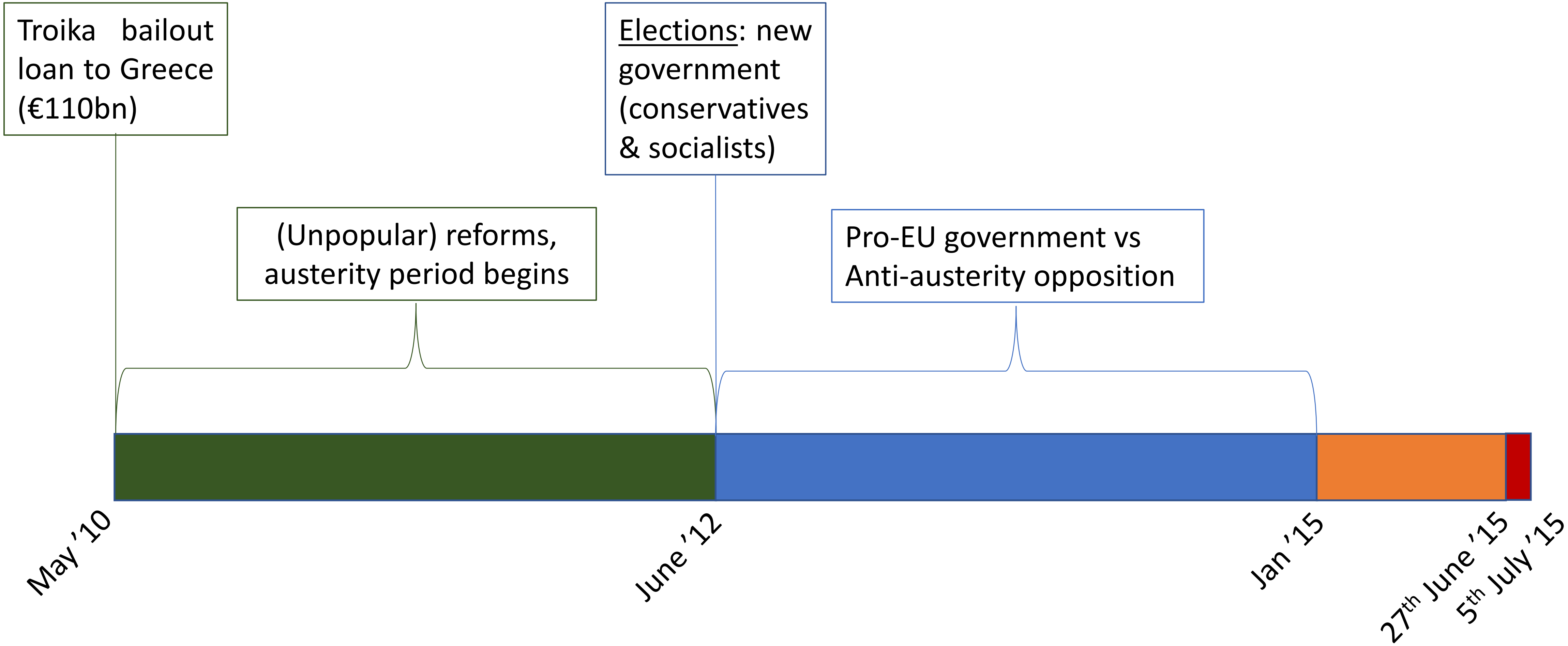

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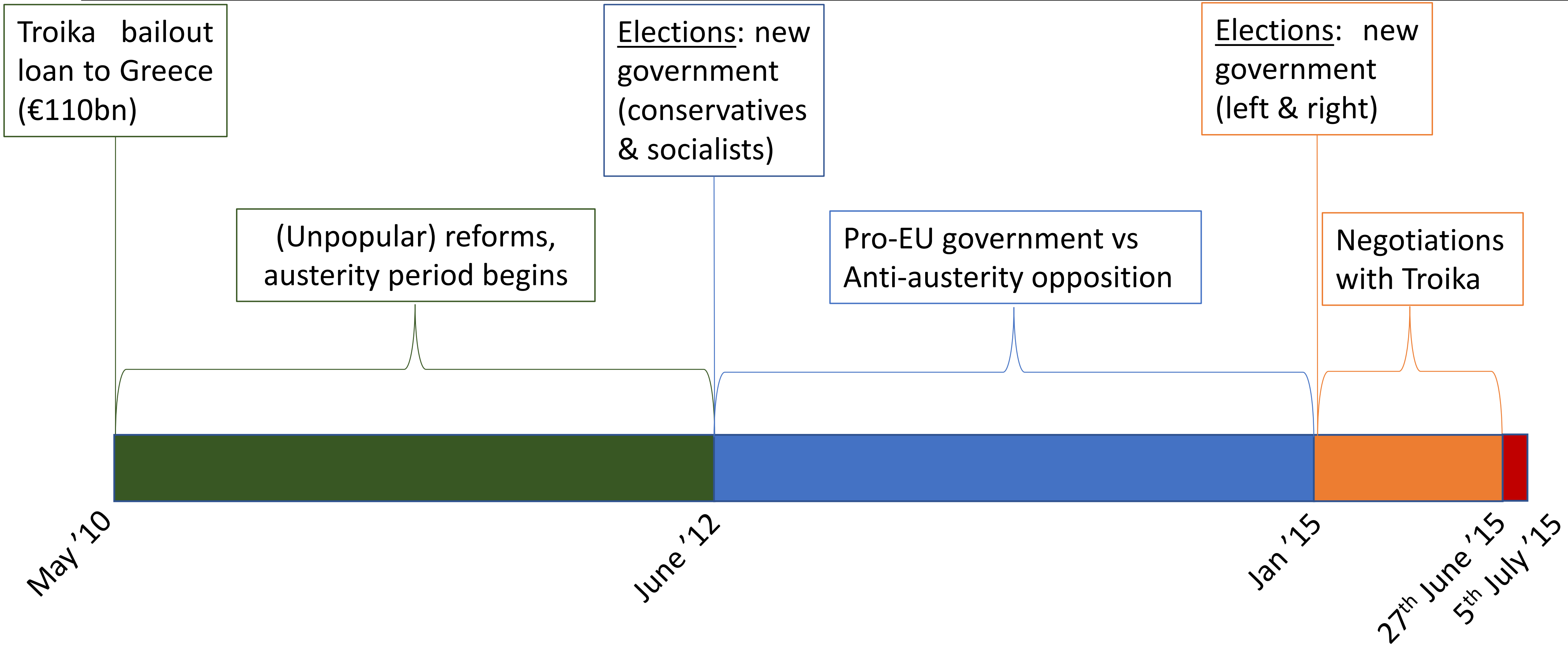

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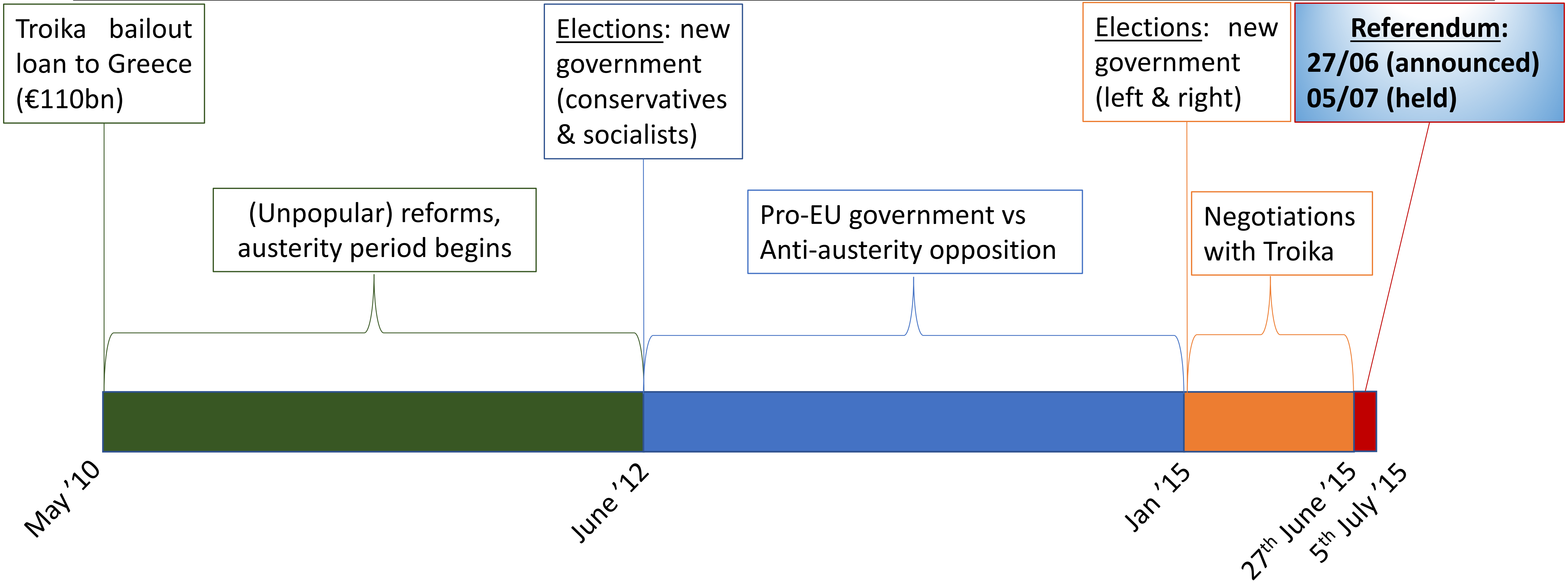

<u>27th June-5th July</u> extreme polarisation, demonstrations, capital controls…

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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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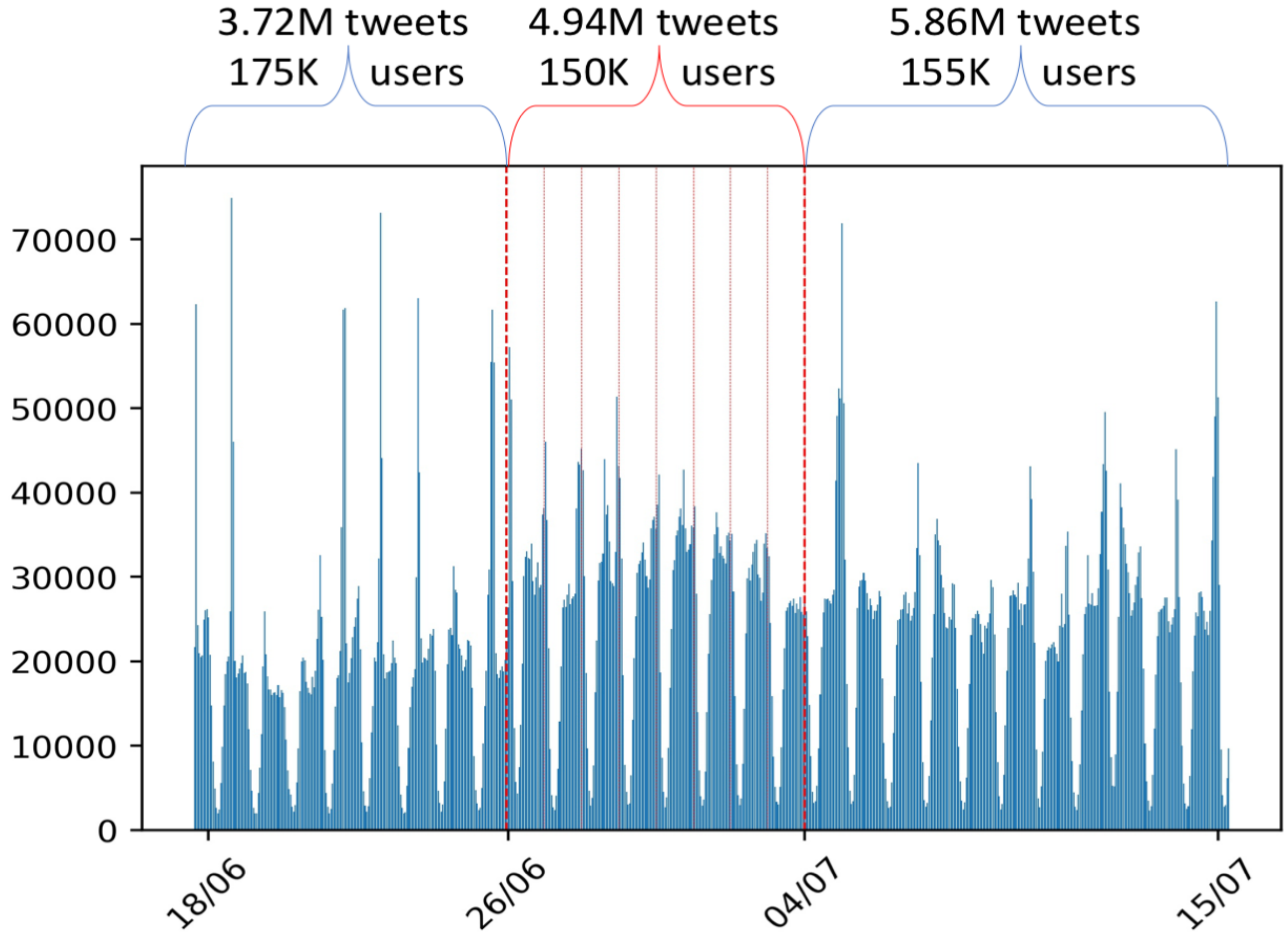


Dataset

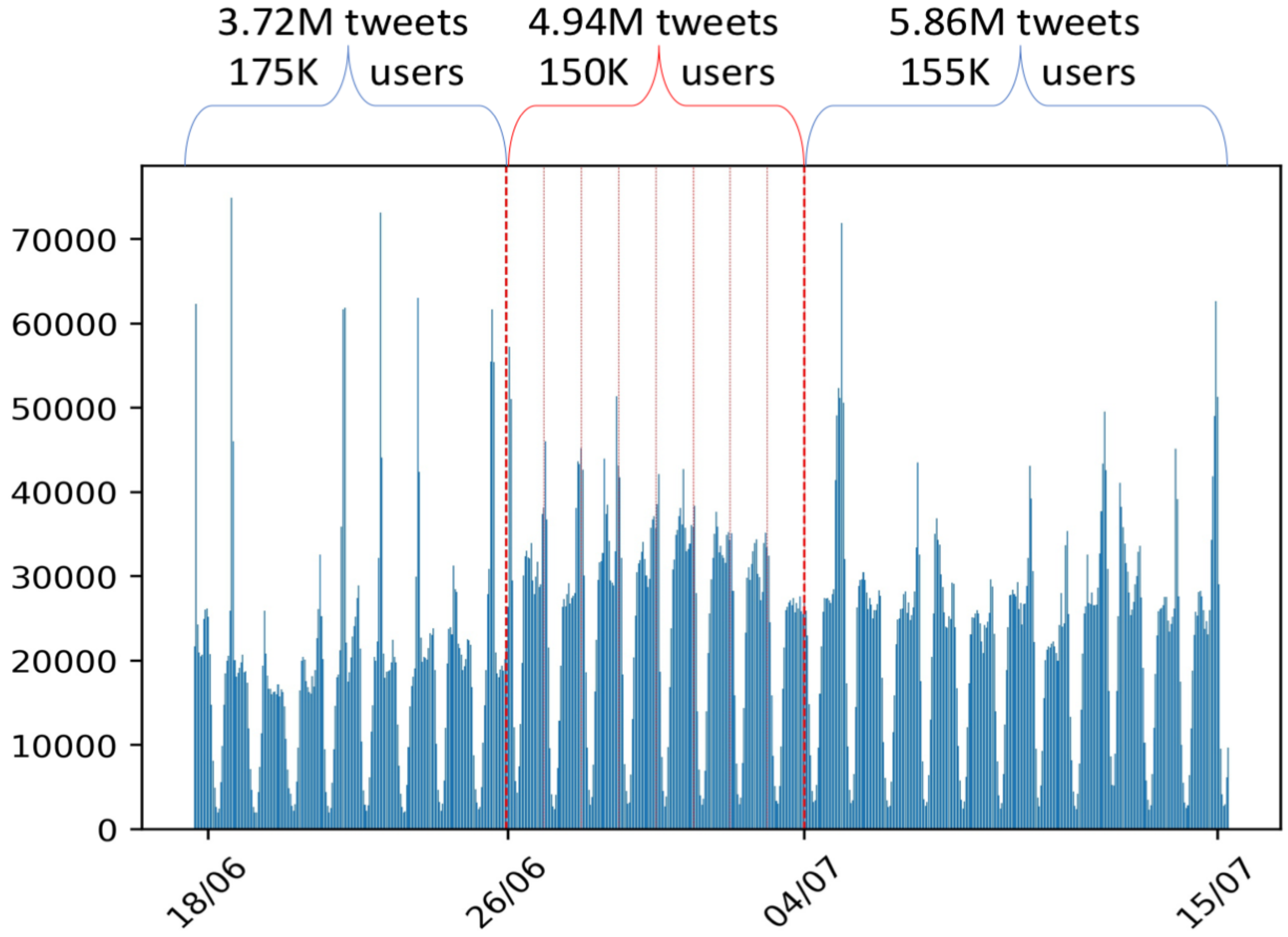
Twitter Streaming API (Greek stop-words)

- 14.6M tweets
- 304K users

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
- 74/26 NO/YES (result: 61/39)



Training Set

Seed accounts with “known” labels:

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

$\left.\right\}$ 148/119 YES/NO

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

Threshold t

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YES/NO

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

Threshold t

$scores[u] > t \Rightarrow YES$

965 YES

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

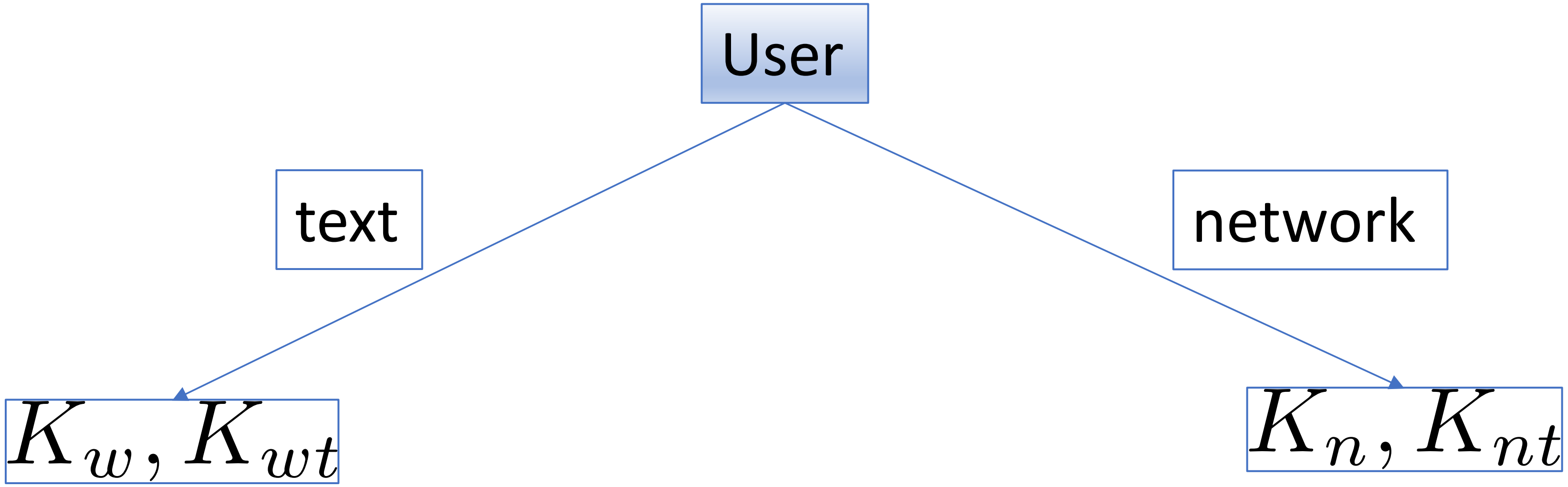
1,165 NO

Data (summary)

	#users	#tweets	YES (%)	NO (%)
Train	2,121	867K	45%	55%
Test	2,197	768K	26%	74%

Methodology

Convolution kernels



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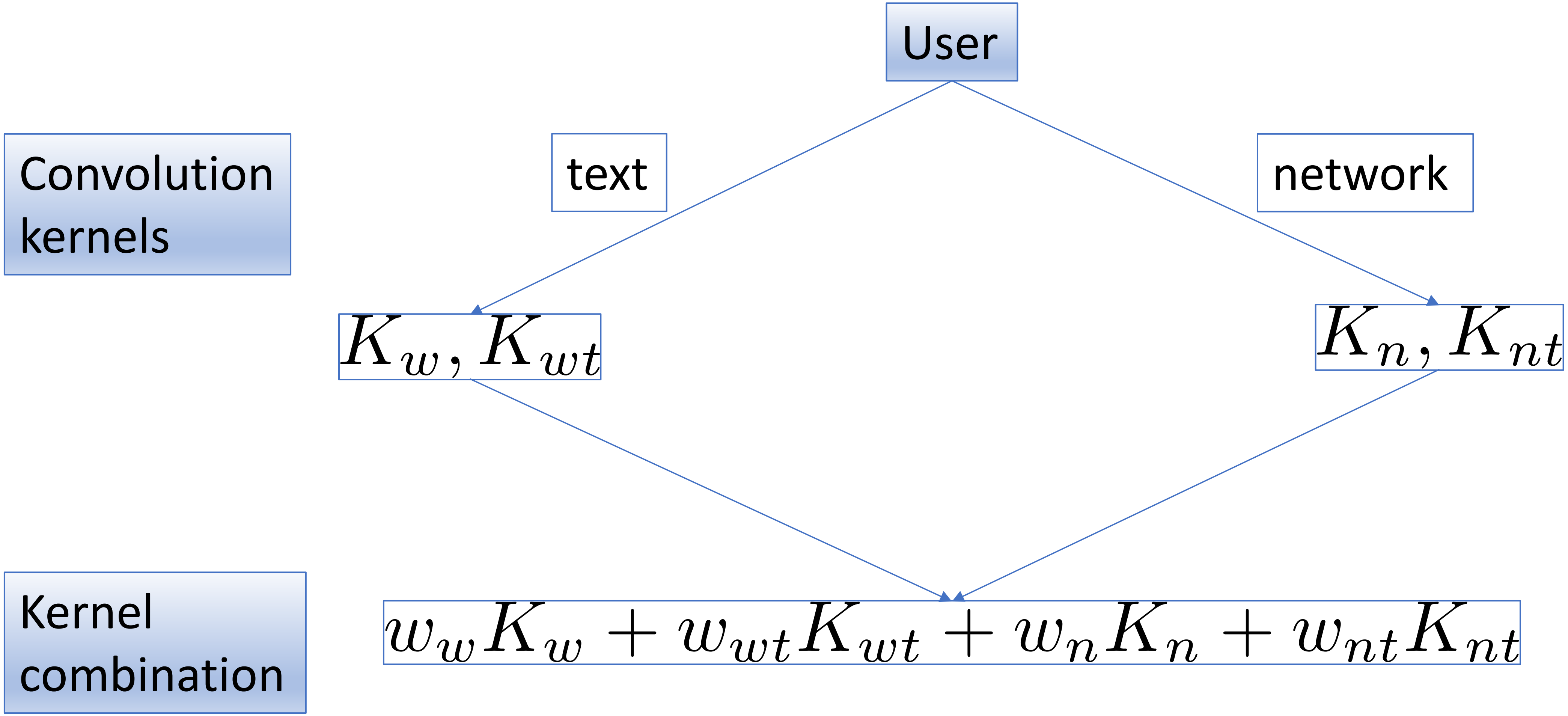

Convolution Kernels

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

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

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TEXT: tweet representation
NET: retweet-based network representation

We can define a convolution kernel as:

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

K_w (TEXT)
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K_w (TEXT)
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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}
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Evaluation

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

Results

	LR	FF	RF	SVM	SVM_f	SVM_{ft}	SVM_+	MCKL
TEXT								
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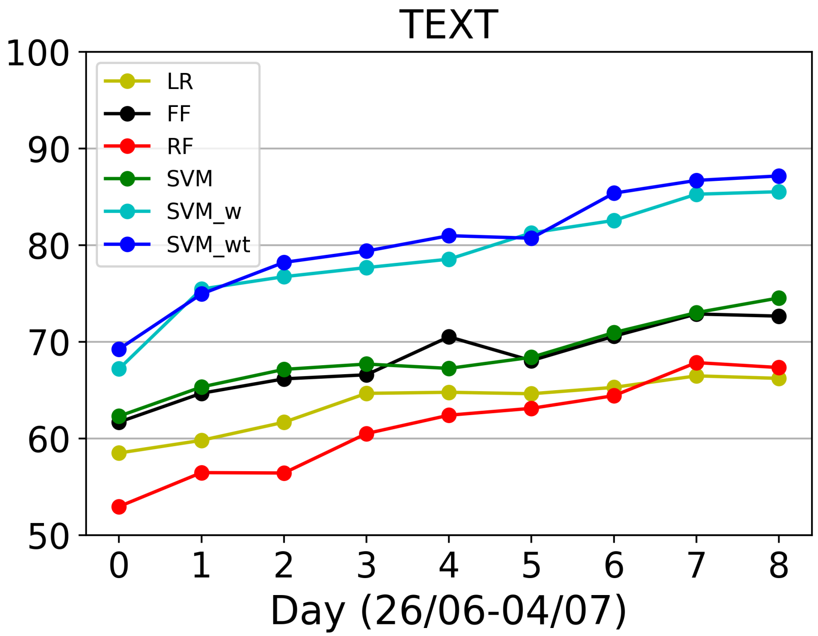

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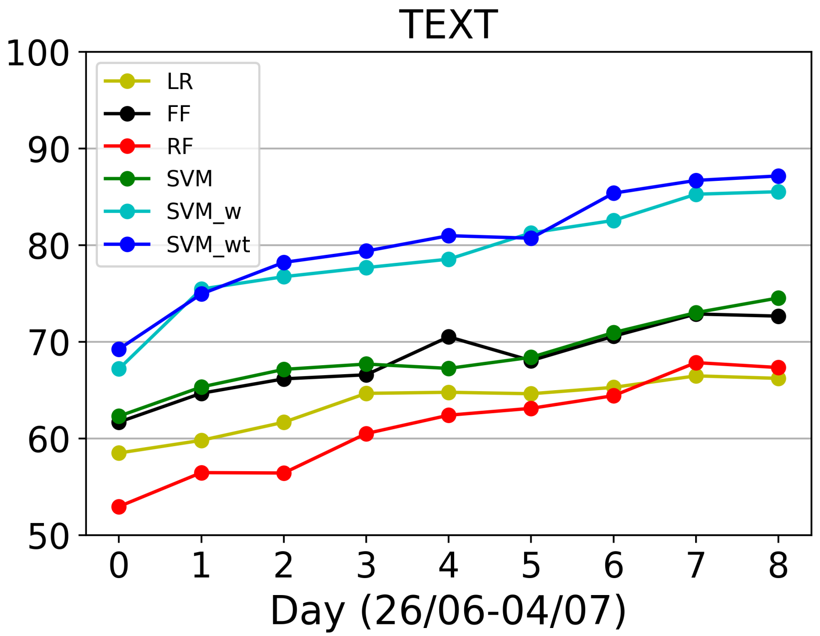

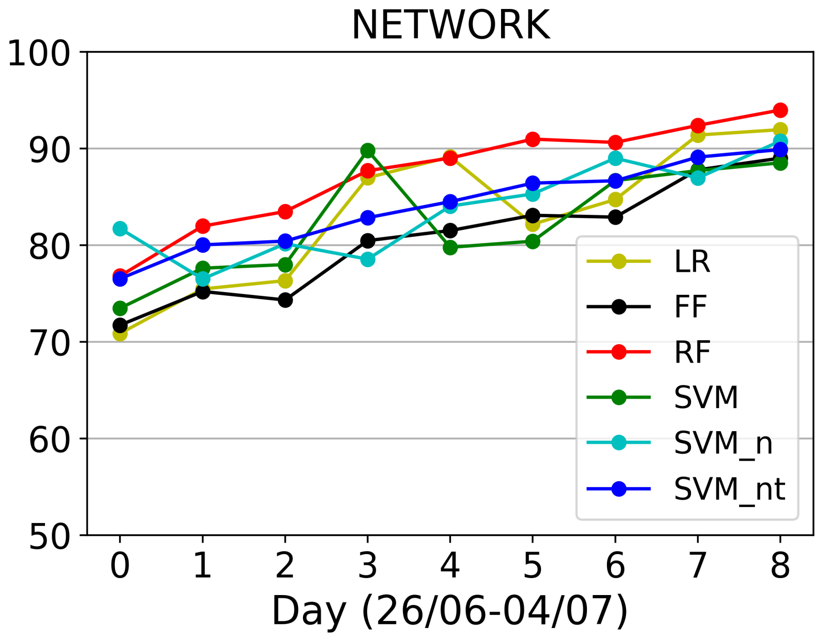

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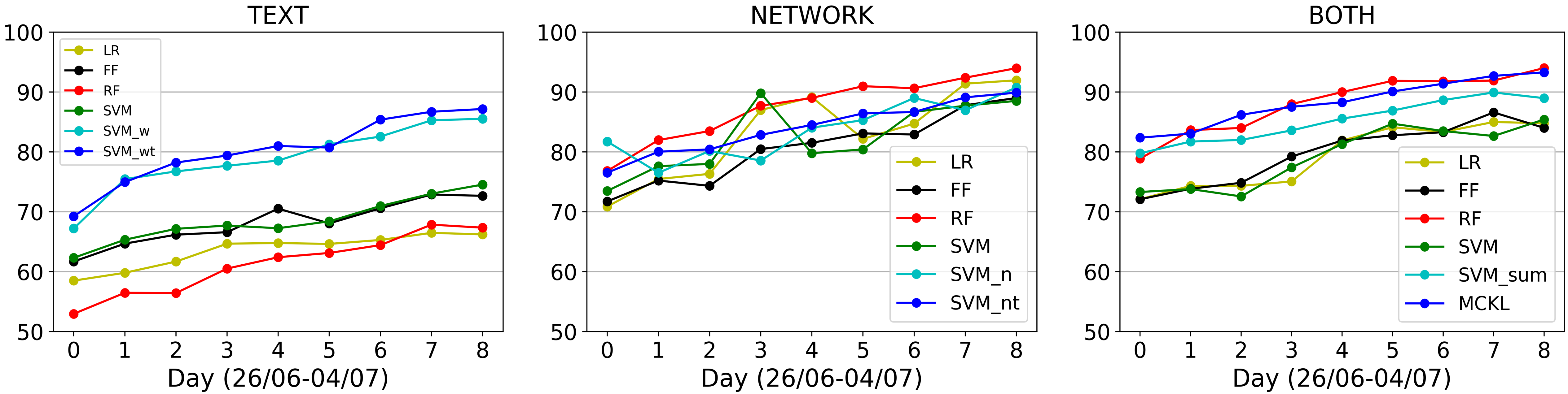

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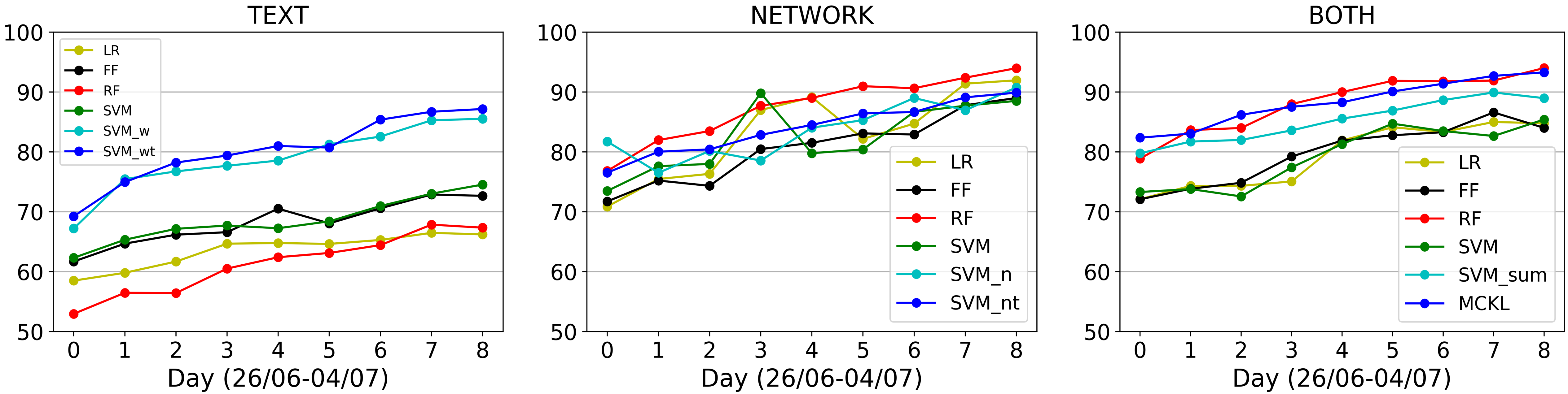

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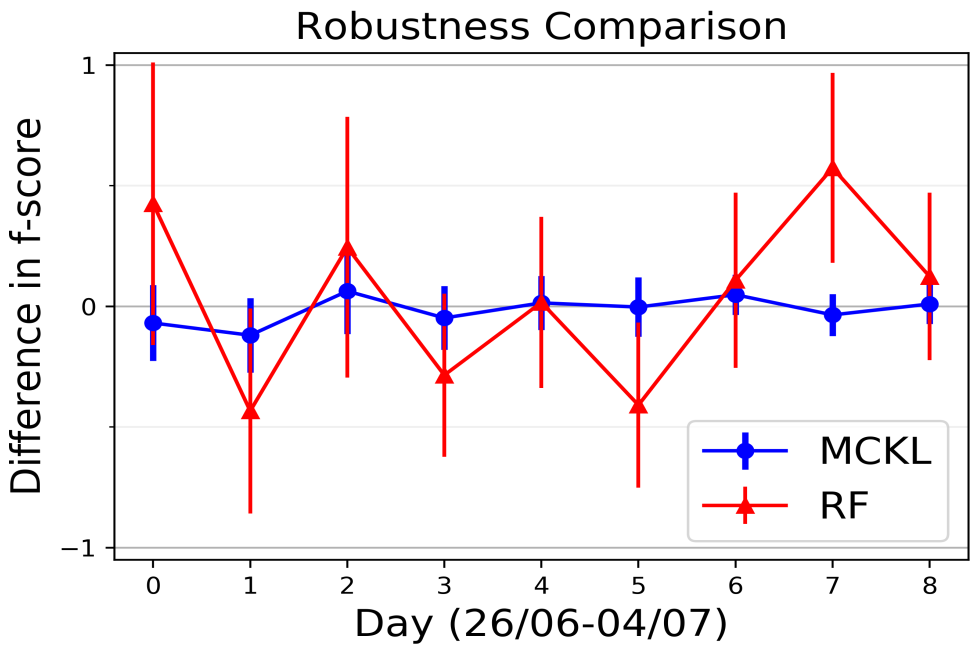
RF vs MCKL: 100 experiments with added noisy features



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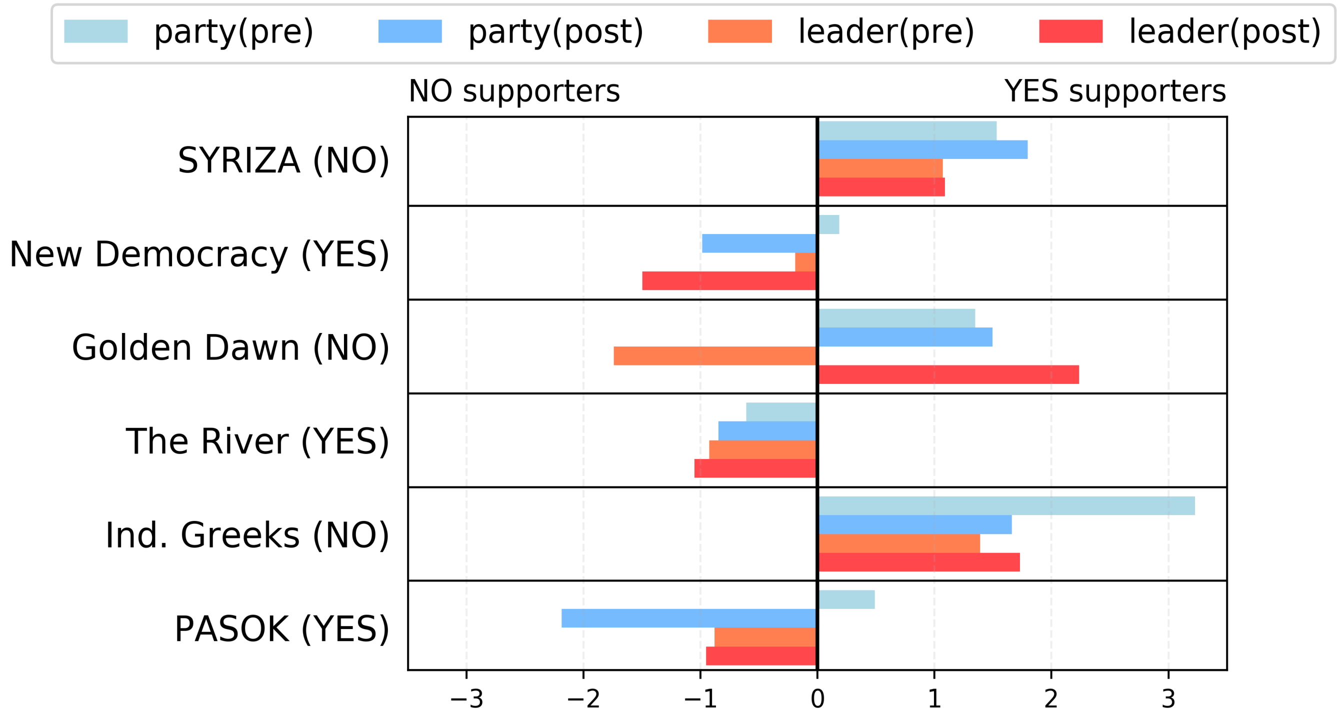

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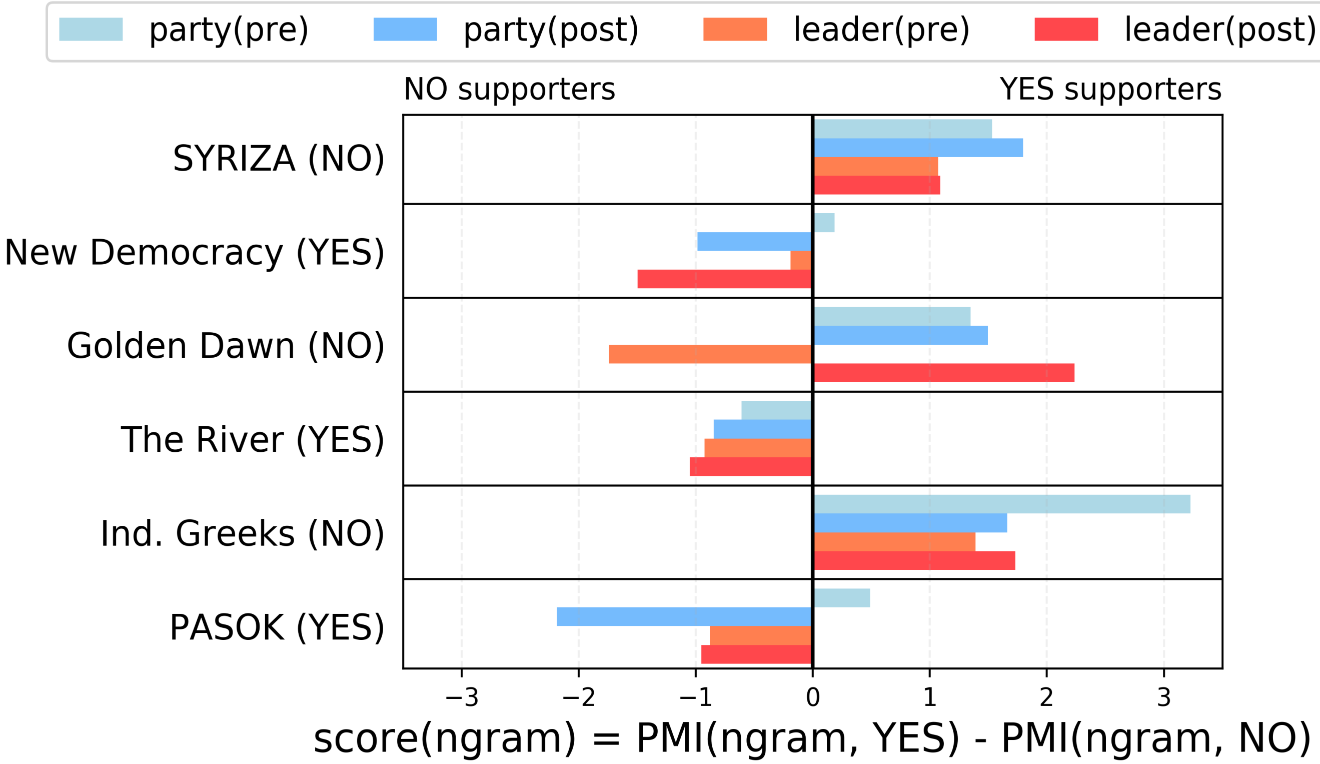

They say that there is a long queue of people in ATMs and they show 6 people waiting; this is not a queue, this is PASOK.

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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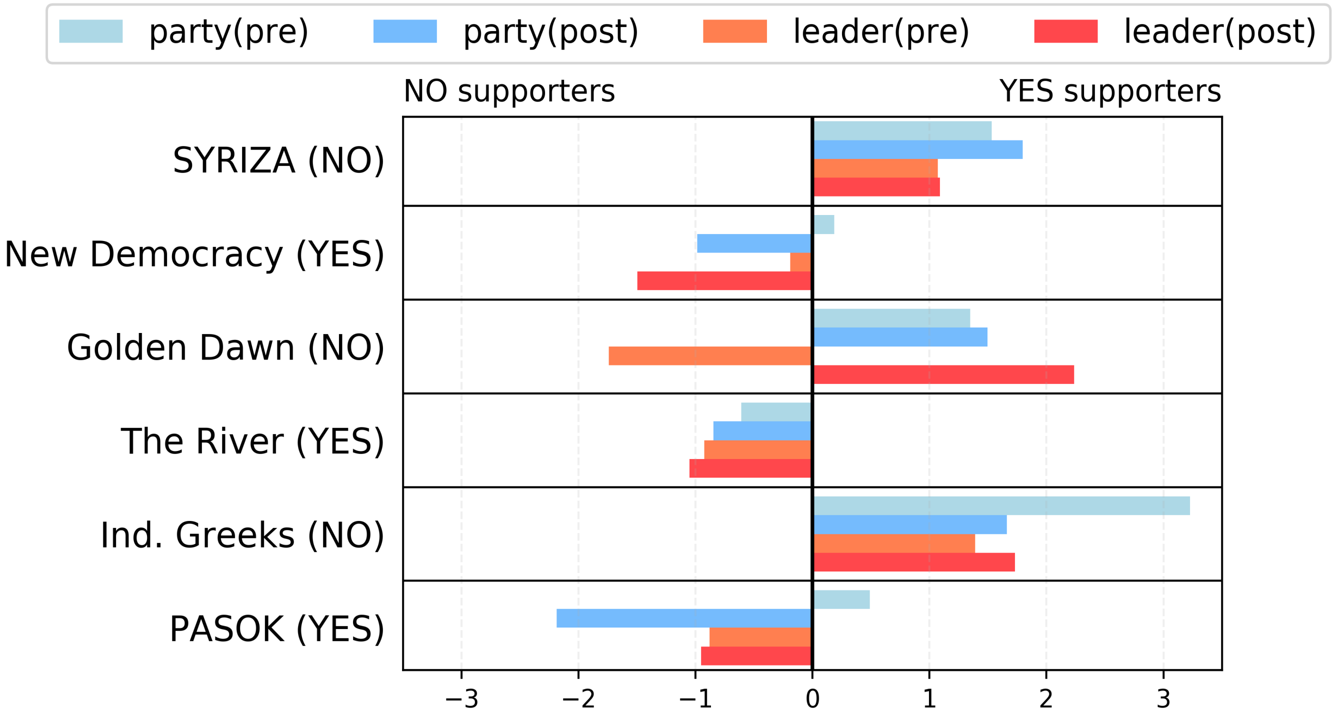

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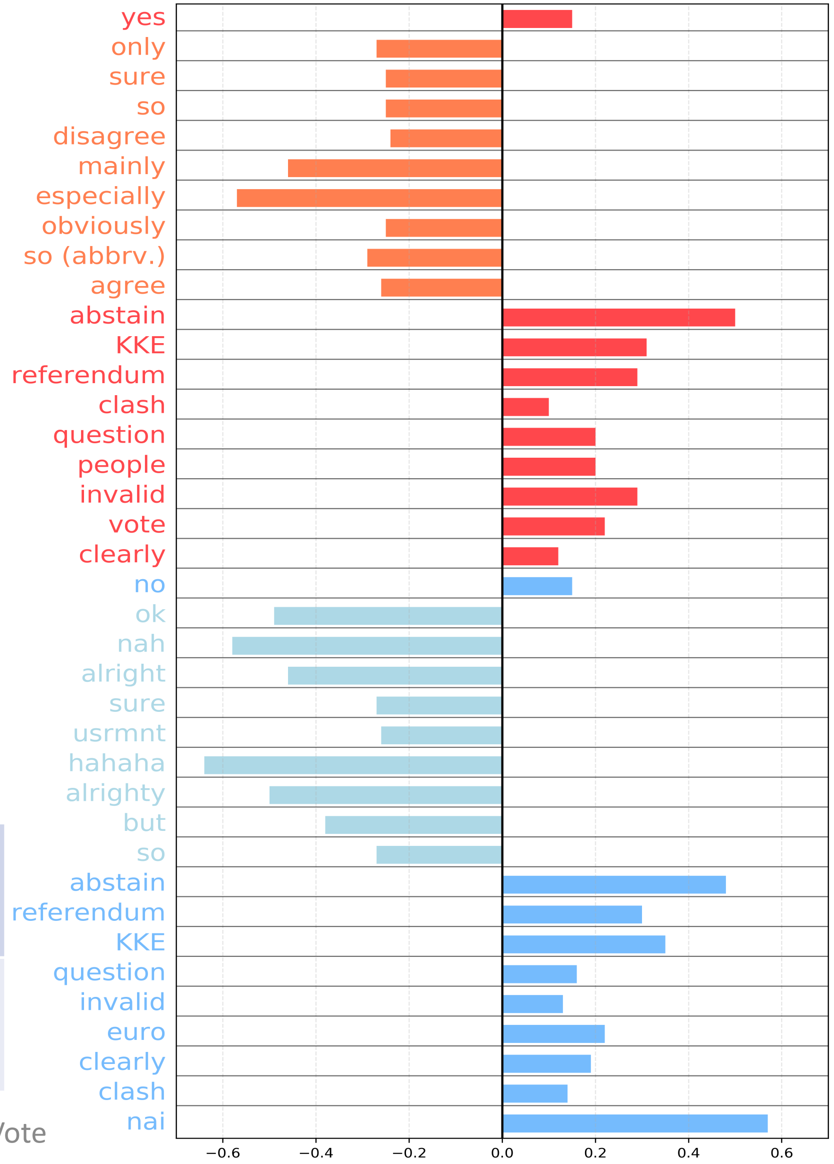

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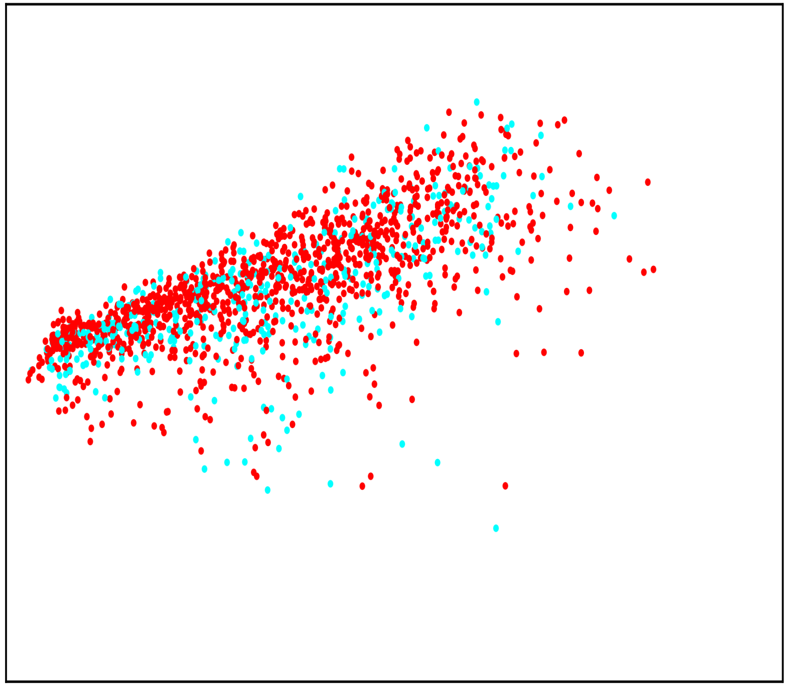
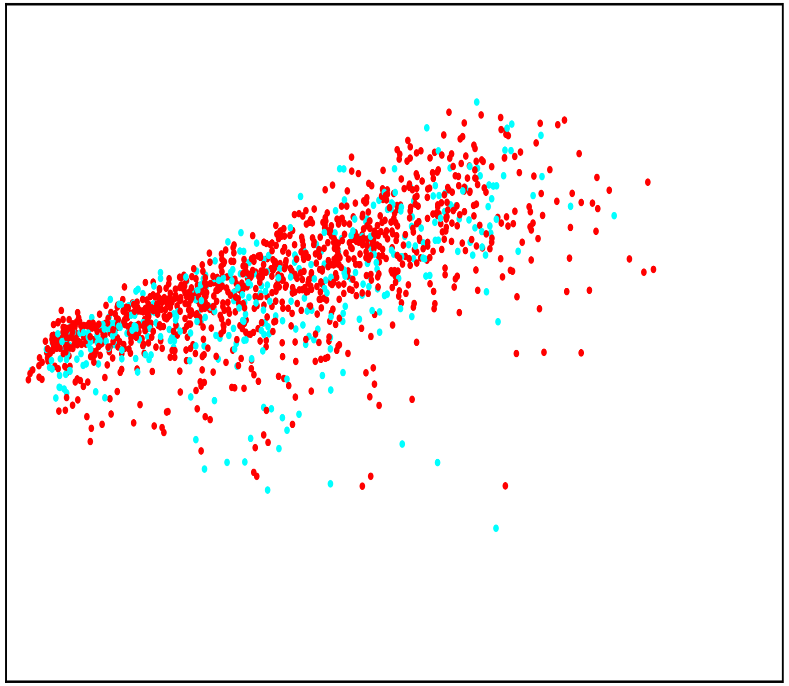


User representations **before** the announcement of the referendum

Discussion (network)



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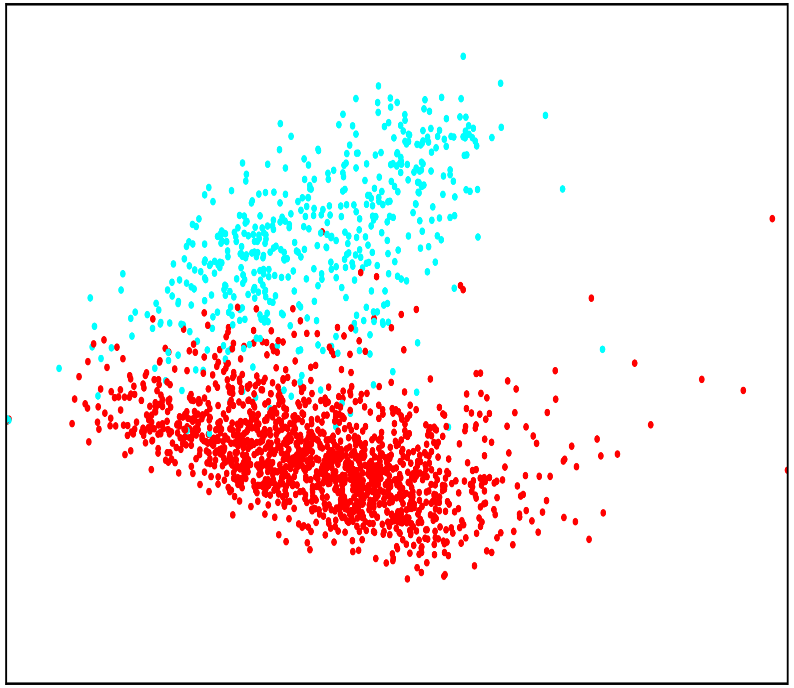

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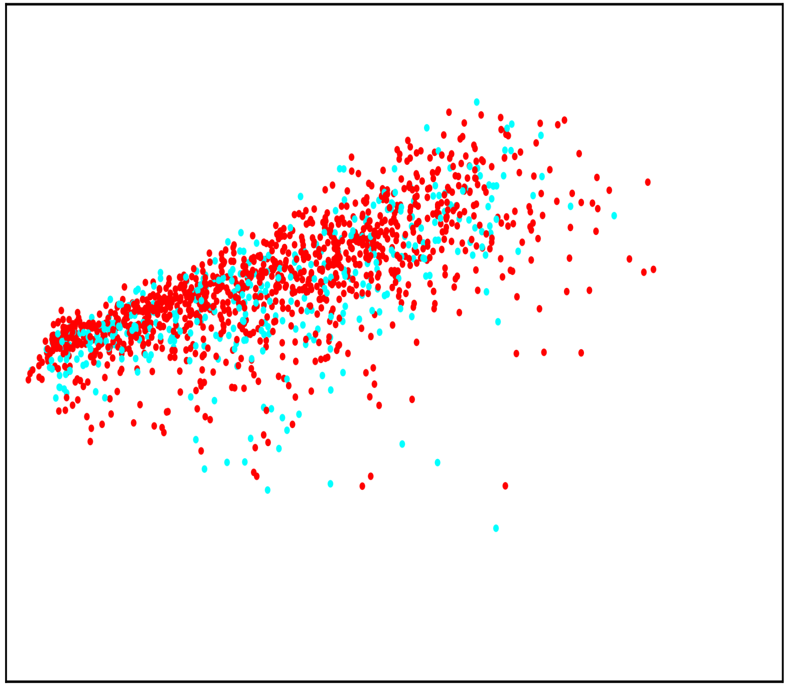

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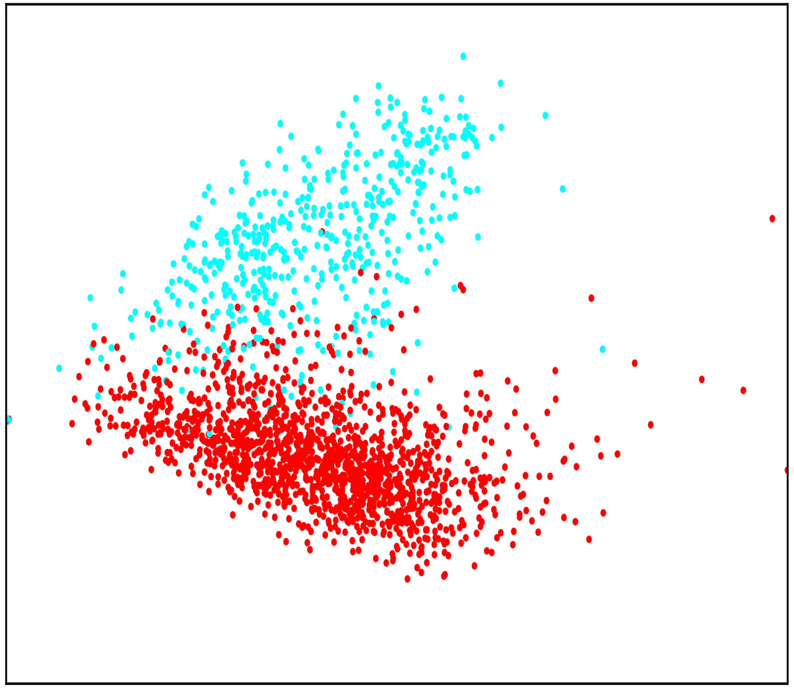

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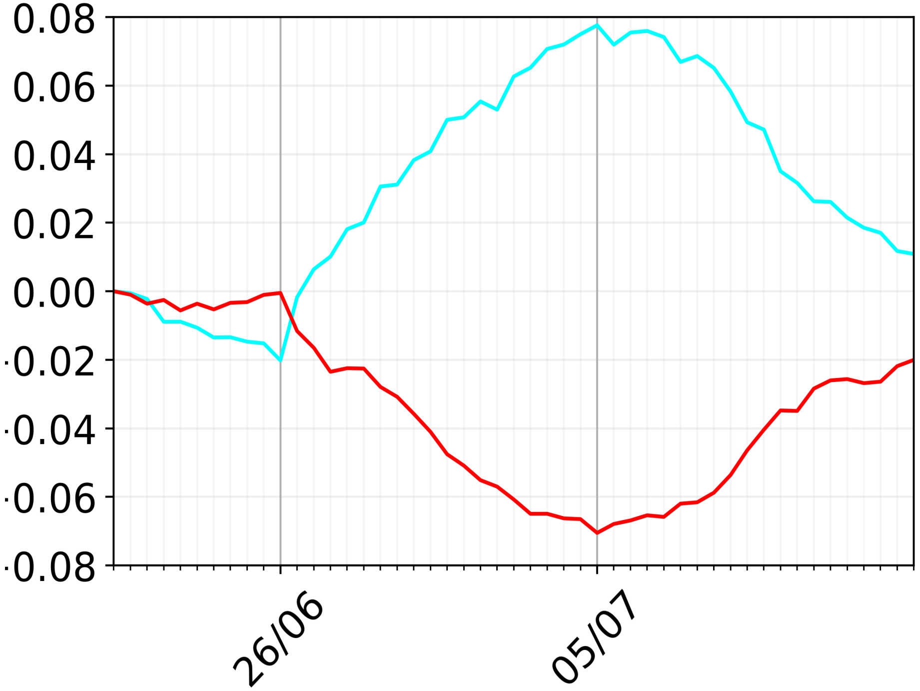

User representations in a sliding window:
sim(YES, YES*)-sim(YES, NO*)
sim(NO, YES*)-sim(NO, NO*)

Conclusion

Nowcasting the voting intention during the Greek Referendum (2015)

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Temporal modelling: highly important (text)
Network structure: most predictive

MCKL boosts performance of weaker kernels/models in a robust way

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Future work:

- Random sample of test users
- Longer lasting electoral races
- More modalities (e.g., location, user profile)

Thank you!

Any questions?

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