

Election Campaign Dynamics

Updates, Website

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OUTLINE

1. Updates

Updates

UPDATES

- Refining the Twitter Corpus
 - Requests from clients
 - New candidate: Koenig
 - Retreated/Eliminated candidates: Montebourg, Larrouturou, Bertrand
 - New features: Separate date and hours

emojicons	time	time_Y_M_D	time_H_M_S
None	2022-02-02 16:35:18	2022-02-02	16:35:18
:green_square:, :scroll:, :green_square:, :gre...	2022-02-02 11:04:25	2022-02-02	11:04:25
:green_square:, :notebook:, :green_square:, :s...	2022-02-02 10:53:58	2022-02-02	10:53:58
:France:, :megaphone:, :green_square:, :scroll...	2022-02-02 10:49:05	2022-02-02	10:49:05
	2022-		

CANDIDATE TOPIC RELATION OVER TIME

```
similarity = {'dates':[], 'sim':[]}
for ind in candid_1_topics_r.index:
    candid_1_t = candid_1_topics_r.topic[ind]
    candid_2_t = candid_2_topics_r.topic[ind]
    doc1 = nlp(candid_1_t)
    doc2 = nlp(candid_2_t)
    similarity['dates'].append(ind.date())
    similarity['sim'].append('{:.3}'.format(doc1.similarity(doc2)))
similarity_df = pd.DataFrame.from_dict(similarity, dtype=float)
```

Figure 1: Get the semantic similarity based on time

	dates	sim
0	2022-01-16	0.790
1	2022-01-17	0.836
2	2022-01-18	0.669
3	2022-01-19	0.923
4	2022-01-20	0.681
5	2022-01-21	0.727
6	2022-01-22	0.800

Figure 2: Resulting similarity dataframe

CANDIDATE TOPIC RELATION OVER TIME

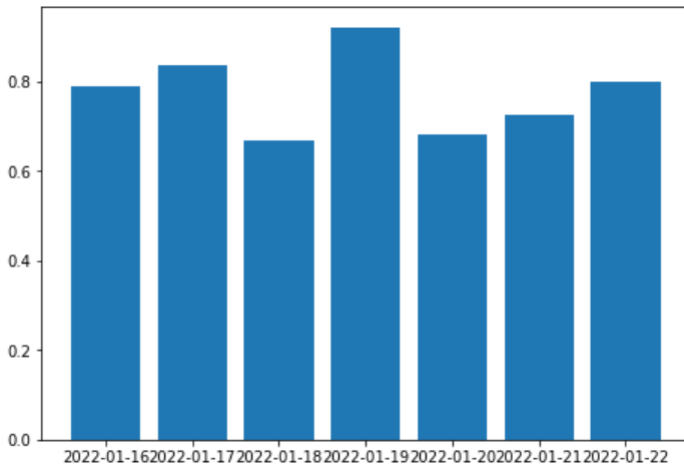
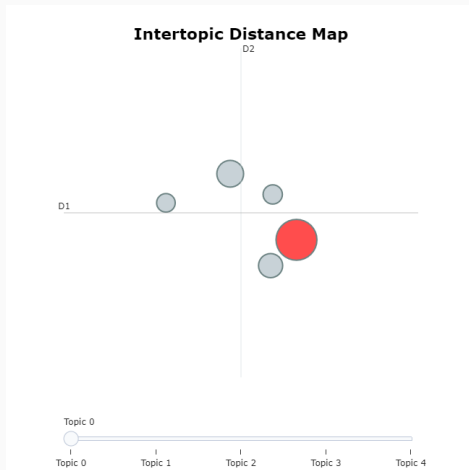


Figure 3: Zemmour and Le Pen's topics similarity over a week

INTER-TOPIC DISTANCE



TOPIC SIMILARITY

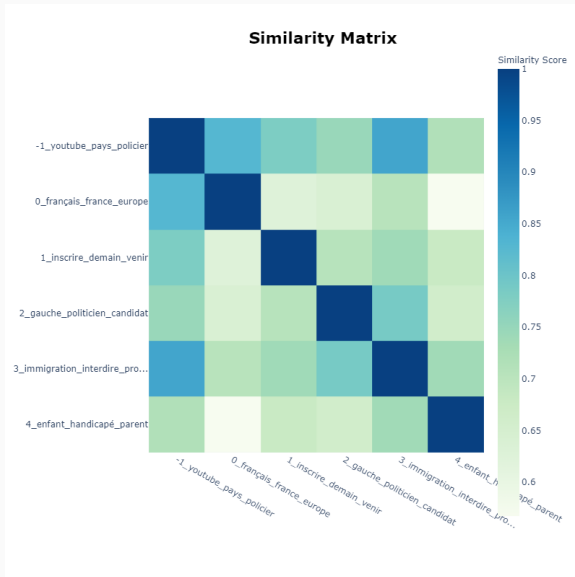
```
In [29]: 1 import fasttext
          2 model = fasttext.load_model("gensim-data\\cc.fr.300.bin\\cc.fr.300.bin")

Warning : `load_model` does not return WordVectorModel or SupervisedModel any more, but a `FastText` object.
```

```
In [30]: 1 import numpy as np
          2
          3 df = pd.DataFrame({"questions":topic_list_1})
          4
          5 df["vecs"] = df["questions"].apply(model.get_sentence_vector)
          6
          7 from scipy.spatial.distance import pdist, squareform
          8 out = pdist(np.stack(df['vecs']), metric="cosine")
          9 cosine_similarity = squareform(out)
         10 print(cosine_similarity)

[[0.          0.56311359 0.45381749 0.6564606  0.64648623 0.59208383]
 [0.56311359 0.          0.57012764 0.53140708 0.60120124 0.56137877]
 [0.45381749 0.57012764 0.          0.50060046 0.59027854 0.519126  ]
 [0.6564606  0.53140708 0.50060046 0.          0.62654354 0.68910435]
 [0.64648623 0.60120124 0.59027854 0.62654354 0.          0.58767631]
 [0.59208383 0.56137877 0.519126  0.68910435 0.58767631 0.          ]]
```


TOPIC SIMILARITY



EVALUATION

- Evaluating a topic model is a challenging task
 - unsupervised models
 - The absence of standard measures and well-established tools
- ◇ Normalized Point-wise Mutual Information (NPMI)
- ◇ It measures the topic coherence between high scoring words in the topic
- ◇ Ranges from $[-1, 1]$
- ◇ The higher positive NPMI the better

Thank you!