National Research Council Canada
Conseil national de recherches Canada

EuroGames16: Evaluating Change Detection in Online Conversation

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Change Detection in Online Conversation

Online conversation:

- Stream of docs/messages
- e.g. Follow twitter hashtag

Changes impact conversation

- Volume
- Sentiment
- Topic

We want to detect changes

- when they happen [19:31:31],
- as soon as they happen.

19:30:37	How come no-one is mentioning the blatant foul in the buil
19:30:45	I like #Nainggolan's hair style #WALBEL #Euro2016
19:30:52	That is a top draw save by Courtois. Wales building pressu
19:30:59	#WALBEL @BBCMOTD How many dodgy referee decision
19:31:05	Jordan Lukaku is absolutely dreadful. #WALBEL
19:31:11	Come on #WAL! You can do this. #EURO2016 #WALBEL
19:31:16	How was Kanu not offside? #WALBEL #EURO2016
19:31:21	Tap and dive for Begium #WALBEL
19:31:24	Good game so far, a #wal equaliser is coming #WALBEL
19:31:27	And can we talk about the #referee ? #WALBEL #BELWAL
19:31:31	GOAL!!!!!! Wales 1-1Belgium #WAL #WALBEL
19:31:34	Somehow Belgium players are falling like leaves...get up a
19:31:37	Oh dear Wales who is laughing now #WALBEL
19:31:39	YESSSS WILLIAMS!!!! #WALBEL
19:31:40	RT @AJoToole: Ashley Williams for the equaliser. Come o
19:31:41	GOOOOOOOOOOOOOOOOOOOOOL WILLIAAAAAAAA
19:31:44	Wales 1-1 Belgium (Williams '30) #EURO2016 #WALBEL Fo
19:31:46	Goooooooooooooooooooooal #WALBEL
19:31:48	Wales have equalised!!! 1-1 #WALBEL
19:31:50	ASSSHHHLLLEEEYYY WILLLLIIIAAAMMMSSSS!! #WAL #\

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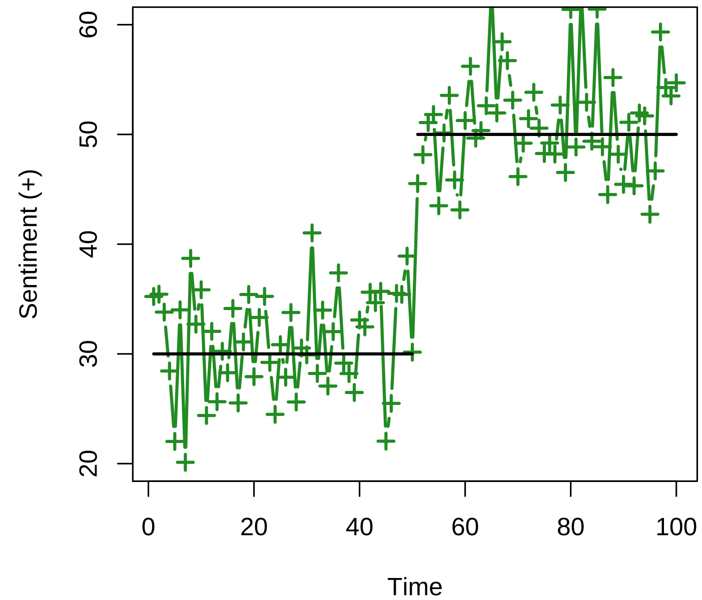
Change Point Detection

Known problem in time series analysis.

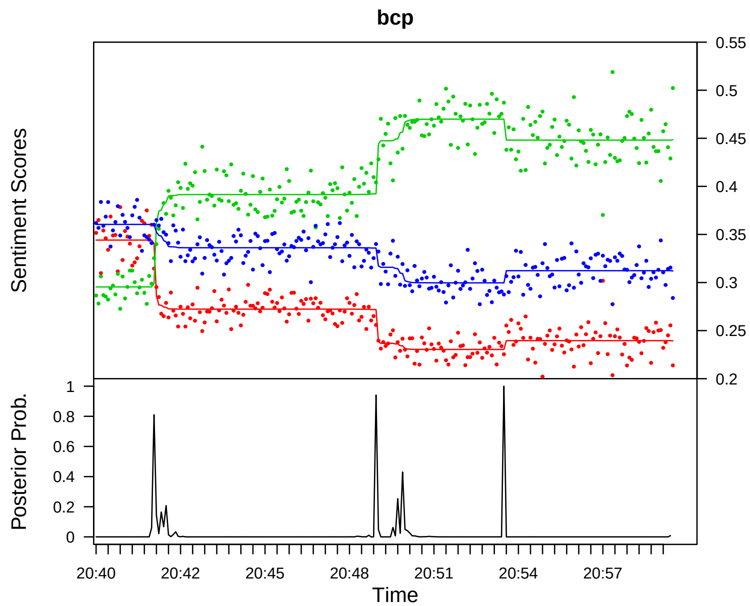
- Assuming time series of sentiment scores:
  - E.g. $s^+(t)$ positive sentiment.
- A Change Point is a location where the underlying stochastic process changes,
  - E.g. go from moderately happy ($s^+ \sim 30\%$) to quite happy ($s^+ \sim 55\%$).



- Various strategies:
  - Batch vs. Online (all data vs. one point at a time)
  - Parametric vs. Non-parametric (e.g. Gaussian vs. no assumption)
  - Univariate vs. Multivariate (e.g. count vs. 3 sent. scores)

Baseline Batch CPD Algorithms

bcp: Bayesian CP detection

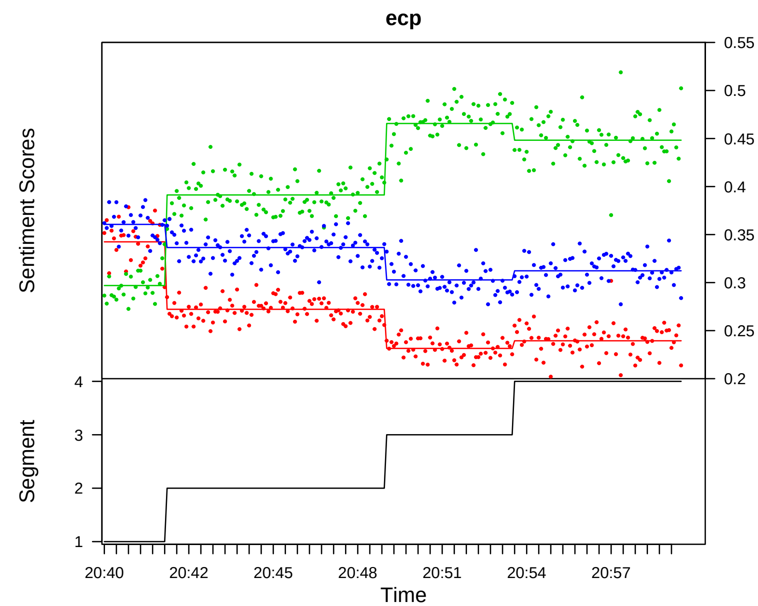


Infering posterior probability of change

- Batch
- Gaussian assumption
- Multivariate

[1] Barry&Hartigan (1993) J.Amer.Stat.Assoc.

ecp: Nonparametric CP analysis



Recursive test of differing distributions

- Batch
- Non parametric (no assumption)
- Multivariate

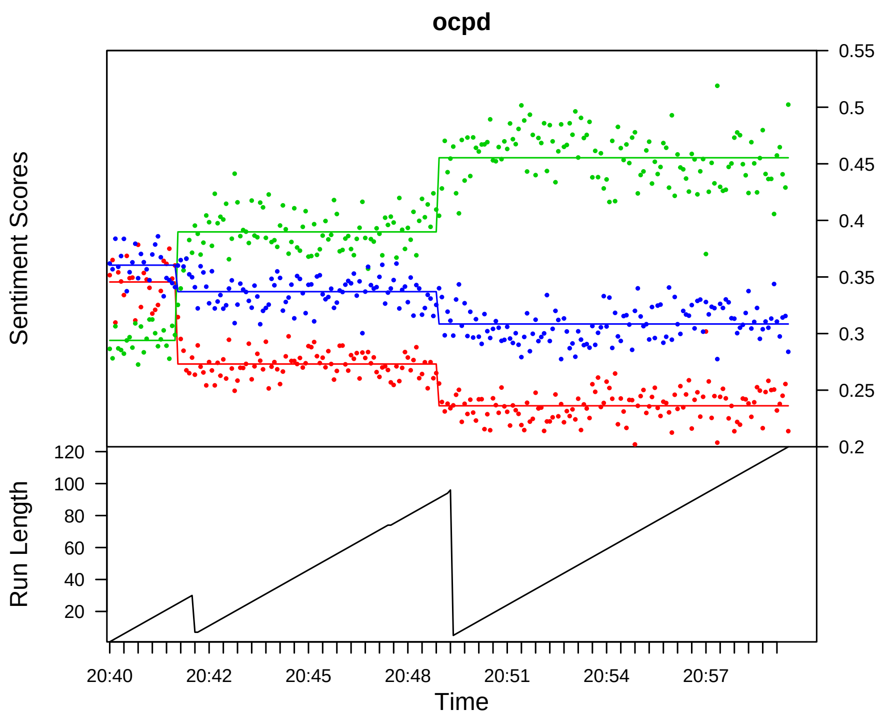
[2] James&Matteson (2014) J. Stat. Soft.

Online Change Point Detection

Model run length, using underlying predictive model (UPM).

E.g.:**ocpd**: Gaussian UPM **ocpd+**: Linear trend + Gaussian noise UPM .

Bayesian inference ⇒ run length distribution.



- Online (one point at a time)
- Gaussian (**ocpd**) or linear (**ocpd+**)
- Multivariate
- `R` package `onlineCPD`

[3] Adams&Mackay (2007) arXiv:0710.3742

Run length drops → change point!

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From Document Streams to Time Series

⋮

$\mathbf{c}_i =$`What the fuck is this ref man #WALBEL`, $[t_i =$19:30:53$]$

⋮

$\mathbf{c}_j =$`Best game of the tournament so far.  #EURO2016`, $[t_j =$19:33:00$]$

⋮

- Compute sentiment (polarity) score:[1]
  - $s_i^+ = .130$, $s_i^0 = .190$, $s_i^- = .681$
  - $s_j^+ = .681$, $s_j^0 = .197$, $s_j^- = .123$
- Average message sentiment over fixed bins (e.g. 5 seconds)
  - $\mathrm{s}[\text{19:30:53}] = (.318, .363, .318)$, $n = 25$
  - $\mathrm{s}[\text{19:32:58}] = (.411, .348, .241)$, $n = 139$
- Three time series of positive/neutral/negative sentiment
- Same framework may yield time series of counts, topics, etc.

[1] Kiritchenko, Zhu, Mohammad (2014) Sentiment analysis of short informal texts. *JAIR* 50:723-762.

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Data Collection: EuroGames16

- 16 games from 2016 UEFA Euro Championship (football/soccer);
- Collected from twitter API during each game +/- a few hours;
- Querying game-specific hashtags (e.g. #FRAPOR #PORFRA);
- Filtering for English + game-specific languages;
- Gold standard events from game reports: goals, on-target, substitutions. . .
- Processed data + gold refs available (find github link in paper).

Game	Hashtag	# Eng.	#Total
-	CROESP	52,953	115k
-	ENGISL	191,384	210k
-	FRAALB	61,748	434k
-	FRAIRL	172,872	665k
-	FRAISL	158,457	721k
-	GERFRA	273,074	496k
-	GERITA	426,381	709k
-	GERPOL	82,132	232k
-	POLPOR	128,079	664k
-	PORAUT	72,644	171k
-	FRAPOR	229,000	1000k
-	PORWAL	287,417	461k
-	RUSWAL	110,165	142k
-	SUIFRA	36,507	468k
-	WALBEL	288,312	379k
-	WALNIR	95,679	115k
Total tweets	-	2.69M	7.04M

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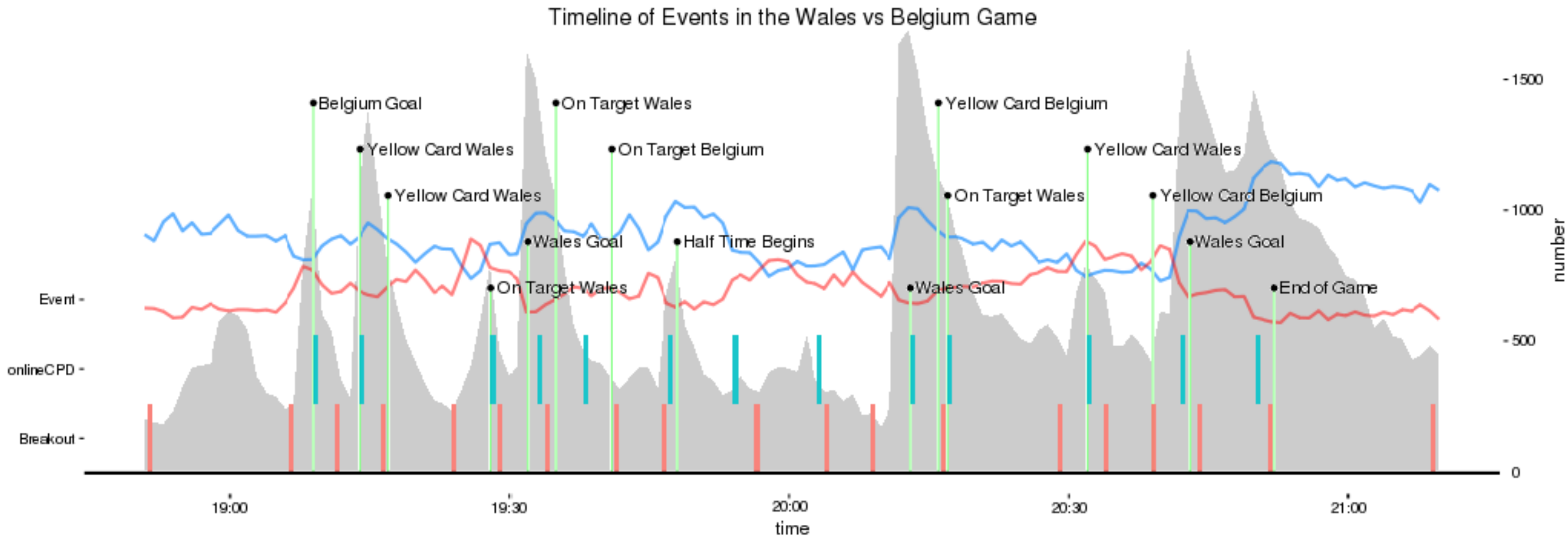
Wales-Belgium Timeline (July 1st Q.final)



volume: number of tweets per 60 seconds,
pos/neg: sentiment score (NRC model),
reference: game events, collected from sports site,
breakout: 'breakout' detection (R package)
onlineCPD: online change-point detection (our work)

Experiments: Overall Scores

- Run 4 CPD algorithms on 16 games/datasets from collection.
  - on raw counts (univariate), sentiment scores (multiv.), and both.
- Compute performance as F-score w.r.t. reference game events.
  - Detected changes within +/- 2 bins of events are correct

Input	**bcp**	**ecp**	**ocpd**	**ocpd+**
Count	.3434	.4645	.4250	**.4725**
Sentiment	.2354	.4315	.3047	**.4428**
+ # references	.3918	**.4860**	.3047	.4380
Count+Sentiment	.4251	.4645	.4010	**.5062**

- **ocpd+** does better overall; **ecp** performs almost as well;
- **bcp**/**ecp** work much better when they know the # references (cheating!).

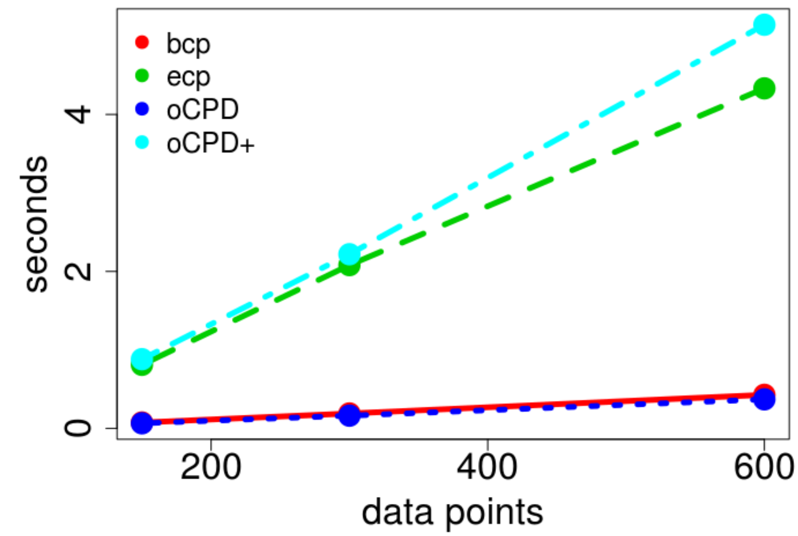
Experiments: Pairwise Comparisons

- Compute wins/ties/losses between pairs of algorithms
  - First number higher when row method wins;
  - Last number higher when column method wins.
- **ocpd+** and **ecp** clearly outperform other two methods;
- Providing correct number of ref. events helps **ecp** a lot (cheating!).

Counts	**ecp**	**ocpd**	**ocpd+**
bcp	2/0/14	5/0/11	2/0/14
ecp	-	11/1/4	**7/1/8**
ocpd	-	-	4/1/11
Sentiment	**ecp**	**ocpd**	**ocpd+**
bcp	1/0/15	5/1/10	0/0/16
ecp	-	12/0/4	**7/1/8**
ocpd	-	-	3/0/13
+ # refs	**ecp**	**ocpd**	**ocpd+**
bcp	0/0/16	4/0/12	0/0/16
ecp	-	14/0/2	**10/0/6**
ocpd	-	-	3/0/13

More Experiments

- Individual game × method results → see paper.
- Can use CPD to detect change in keyword/hashtag usage:
  - More labour intensive (need to specify k/w, #tag);
  - Does not work as well as tracking sentiment → see paper.
- Bin size impacts performance (see paper):
  - Large bin ⇒ short, smooth time series;
  - Small bin ⇒ long, noisy time series;
  - **bcp** better w. large, others with short bins.
- Computational time varies with CPD algo:



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Conclusion

- We develop a new framework for detecting change in social media;
  - Change in traffic, Sentiment, topic, etc.
- Works *online*, not retrospective;
  - Can detect changes as they occur (no waiting / re-running).
- Able to detect changes related to $\sim$ half reference events;

Extensions:

- Detect topic change using (online) topic models (tba);
- Re-architecture and extend R package for **ocpd** (ongoing);
- Extend to more data distribution (long-tailed / bursty);
- Optimization to improve computational cost; . . .

NRC is hiring researchers in applied Machine Learning: https://bit.ly/2wlWiuc

The end

Thank you.

Questions?