The Alan Turing Institute

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Mining the UK Web Archive for Semantic Change Detection

RANLP
03 Sept '19
Varna, Bulgaria

INTRODUCTION

- **Semantic Change:** Identify words whose lexical semantics have changed over time (tweet, follow, blackberry, etc.)
- **Importance**: historical/social studies, NLP tasks

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- **Importance**: historical/social studies, NLP tasks

- **Challenges**: (a) lack of labelled datasets
  (b) short-term Semantic Change Detection
  (c) evaluation

CONTRIBUTIONS

- **Data**: Labelled dataset of word vectors during 2000–2013
- **Approach**: Variant of Procrustes Alignment trained on an extremely small number of "stable" words
- **Evaluation**: Rank-based approach

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BACKGROUND

- **Early work:**
  - comparison of frequency & co-occurrence patterns between words across time [Sagi et al., 2009; Cook & Stevenson, 2010; Gulordava & Baroni, 2011]
- **Current approaches:**
  - Learn word representations over different time intervals & compute shift [Kim et al., 2014; Hamilton et al., 2016; Del Tredici et al., 2018]
  - Diachronic word embeddings [Bamler and Mandt, 2017; Rosenfeld and Erk, 2018; Yao et al., 2018; Rudolph and Blei, 2018]

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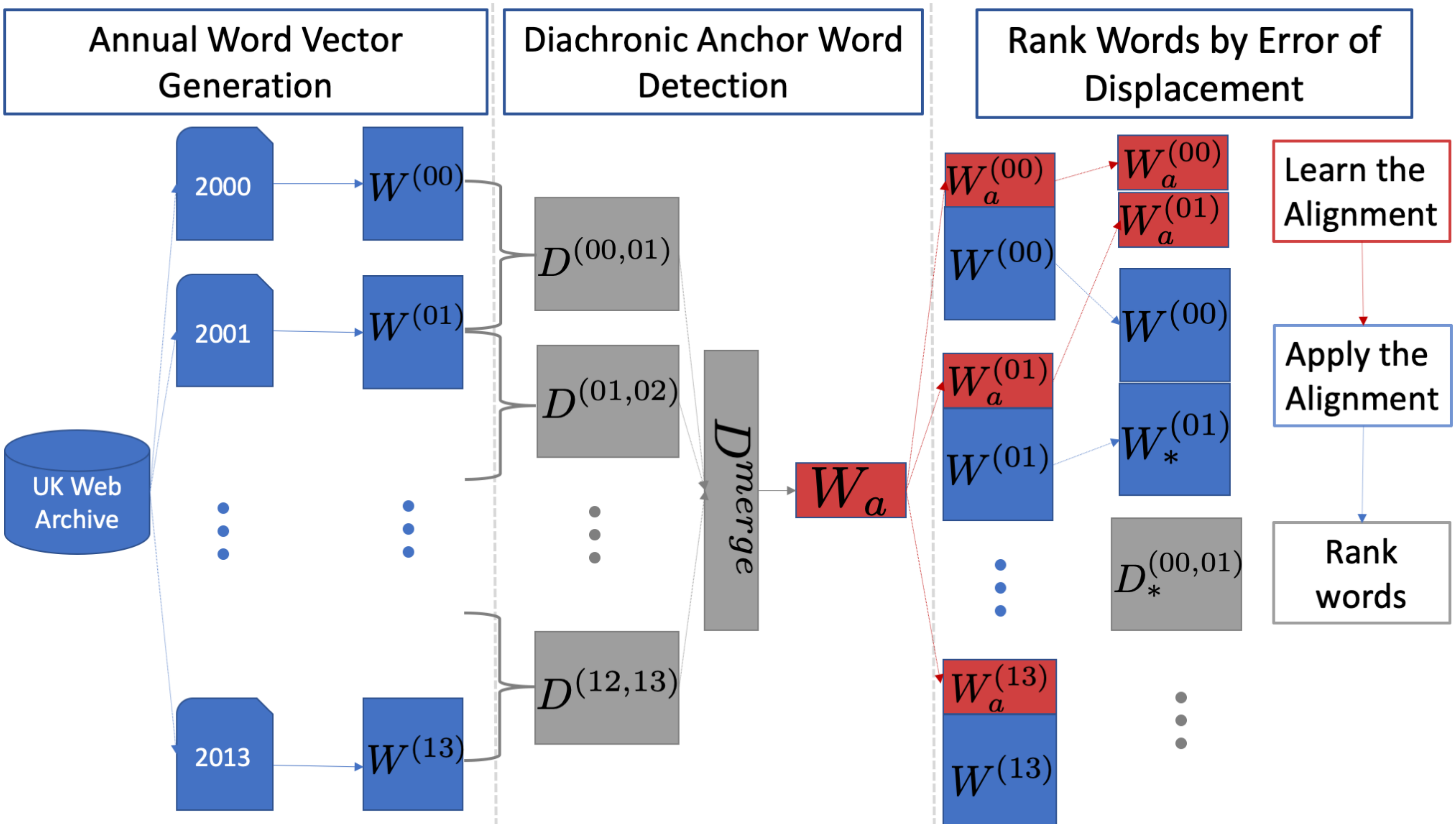
Solutions:

- initialise word vectors at *t+1* based on the word vectors at *t* [Kim et al., 2014]
- Orthogonal Procrustes [Schönemann,1966]: map the word vectors of *the whole vocabulary* at *t* to their corresponding ones at *t+1* [Hamilton et al., 2016]

Problem: trying to align *all* words can be noisy (those that have changed meaning?)

APPROACH: OVERVIEW



APPROACH: DETAILS

- We want to find:

$$R = \underset{\Omega;\Omega^T\Omega=I}{\operatorname{argmin}} \left\| W^{(t)}\Omega - W^{(t+1)} \right\|_F$$

- Solved as:

$$R = UV^T$$, where

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- **Anchors:** *k* words with lowest displacement error between *[t, t+1]*
- **Diachronic Anchors:** *k* words with lowest avg displacement error across time
- **Core idea:** learn a new alignment based *strictly* on (diachronic) anchors

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DATASET

- **Word Vectors**:
  - *UK Web Domain Dataset 1996-2013* (>20TB) [Basile & McGillivray, 2018]
  - Annual word2vec representations [Mikolov et al., 2013] during 2000–2013

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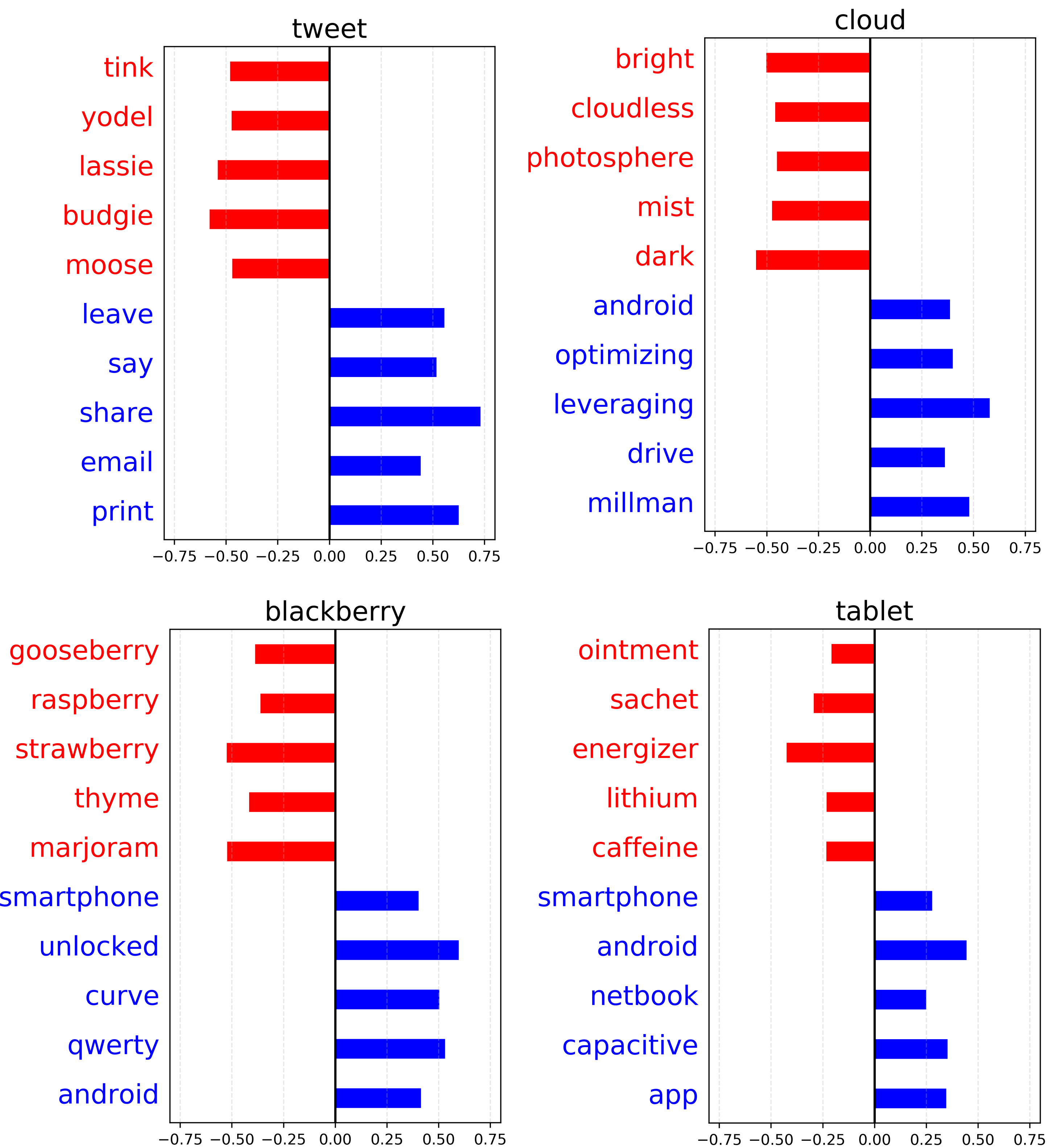
- **Intersected Dataset**:
  - 47,886 word vectors per year (2000-13)
  - 65 words with known semantic shift

EMPIRICAL INSIGHTS



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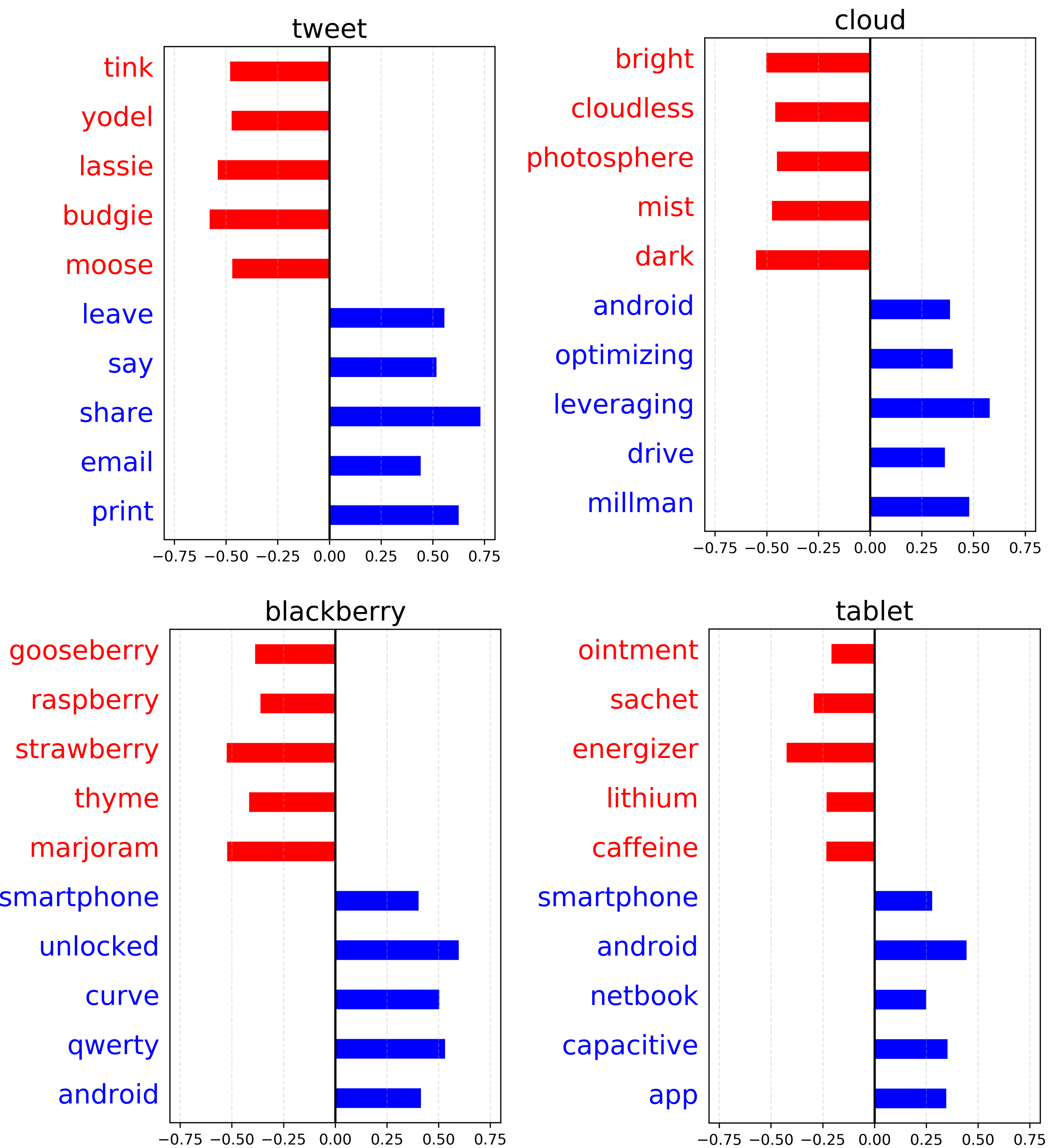

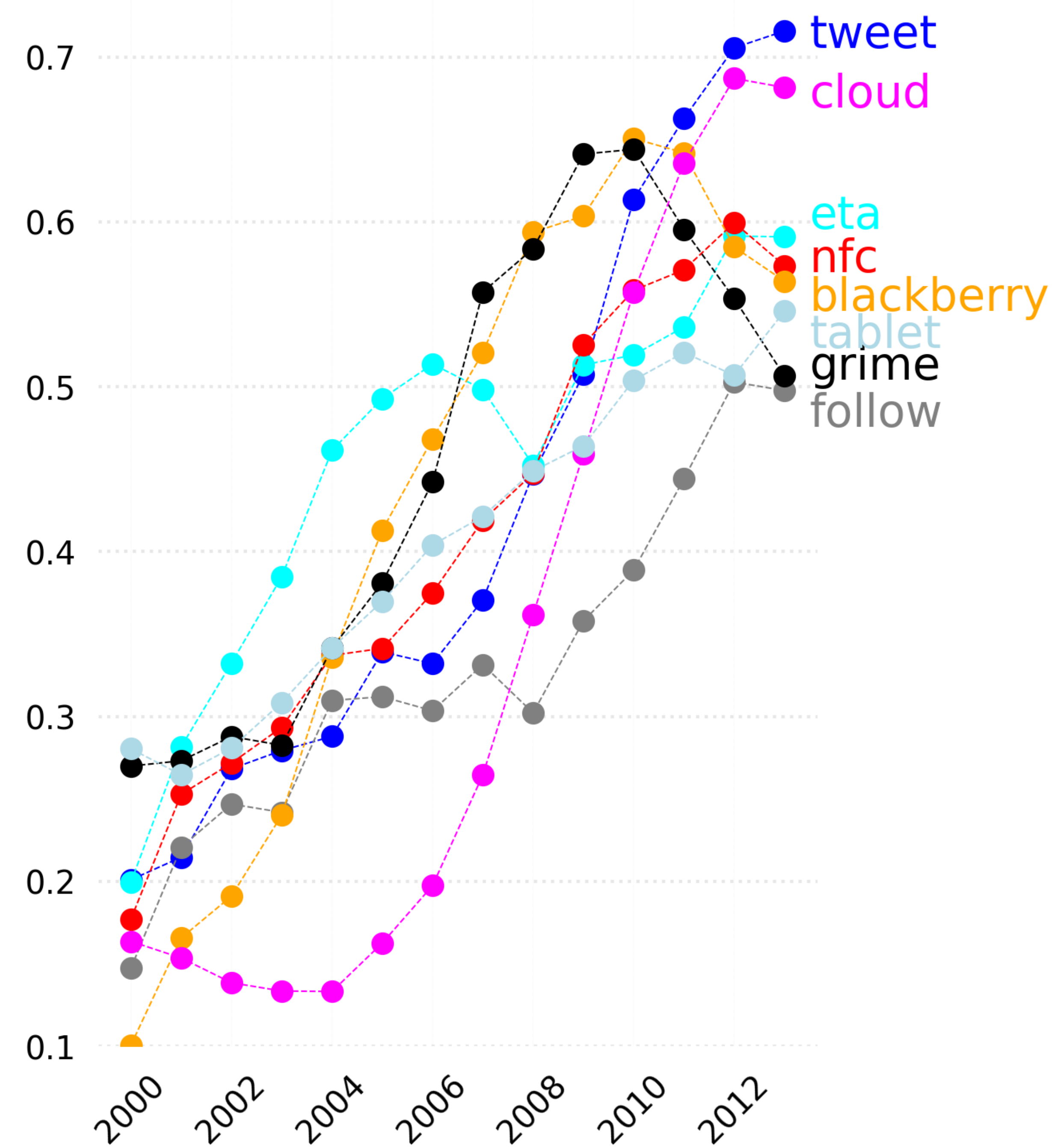

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EXPERIMENTS

- **Experiment 1:** train/eval split | eval set size: {10%, …, 50%} | 40 runs
- **Experiment 2:** single run (whole dataset)

- **Models:**
  - PROCR_90: alignment based on train set (Experiment 1)
  - PROCR_100: alignment using all words
  - PROCR_k: alignment based on anchor words
  - PROCR_kt: alignment based on diachronic anchor words

- **Evaluation:** rank (%) of a semantically shifted word based on displacement error (*μ-rank*)

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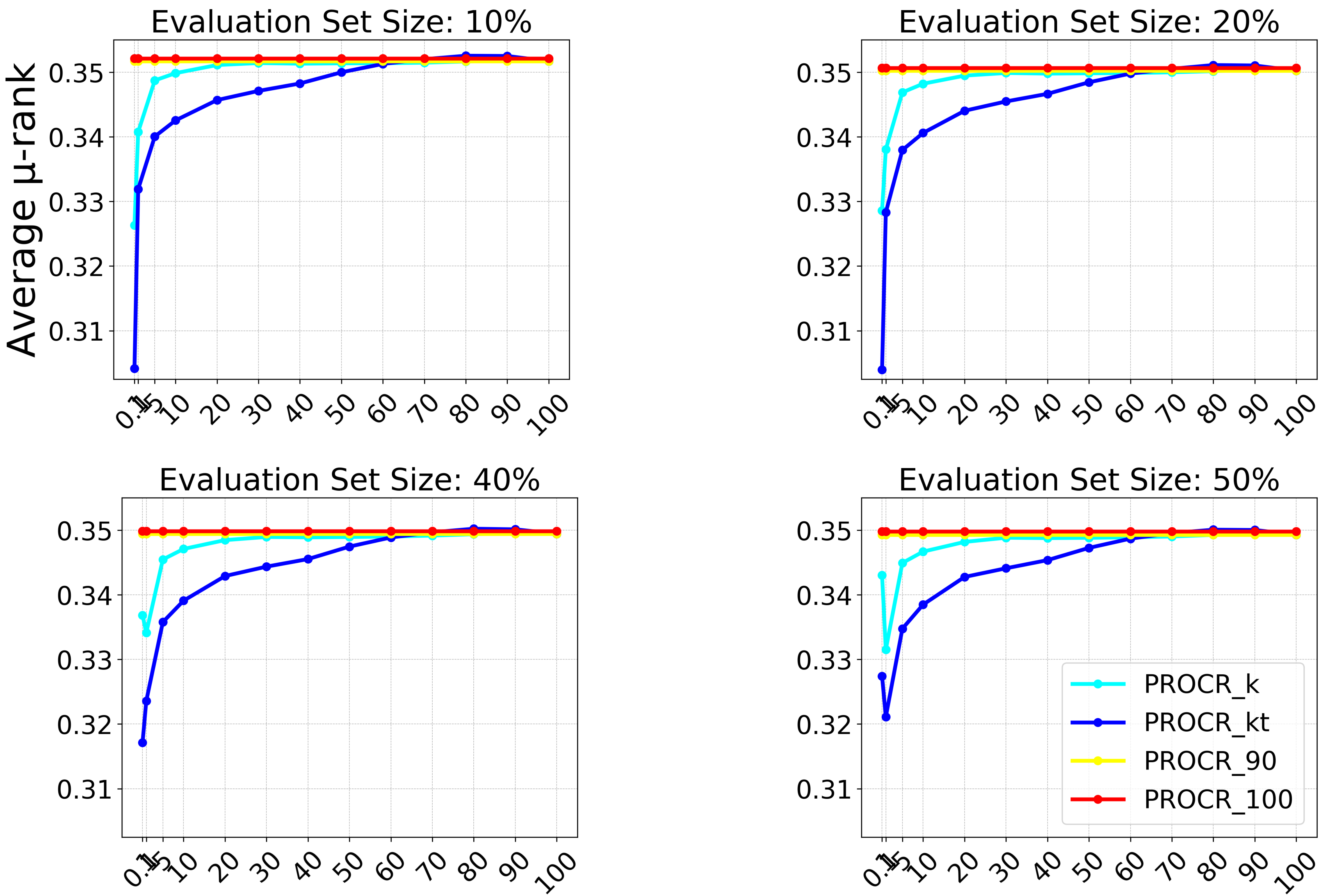
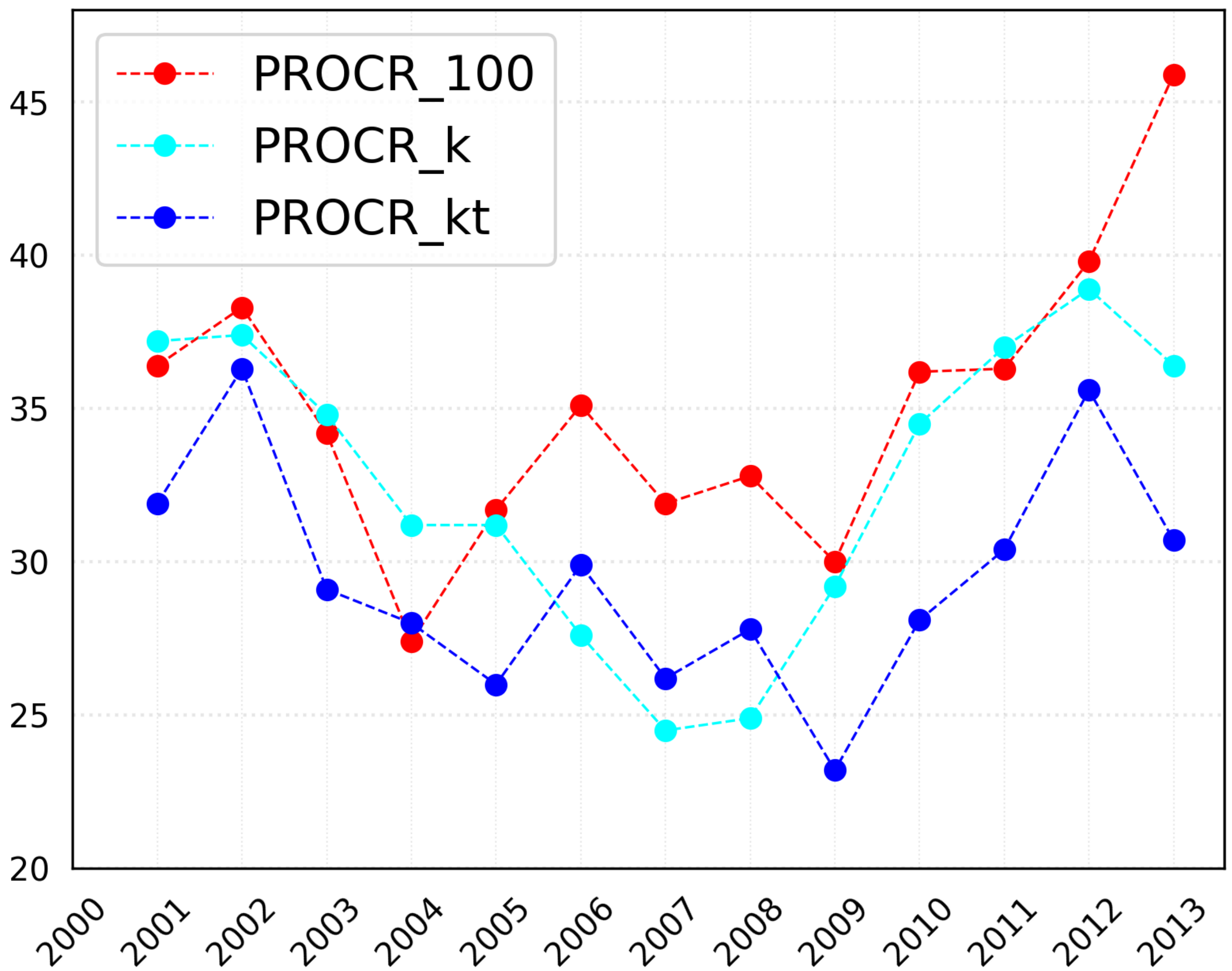
RESULTS: EXPERIMENT 1



RESULTS: EXPERIMENT 2

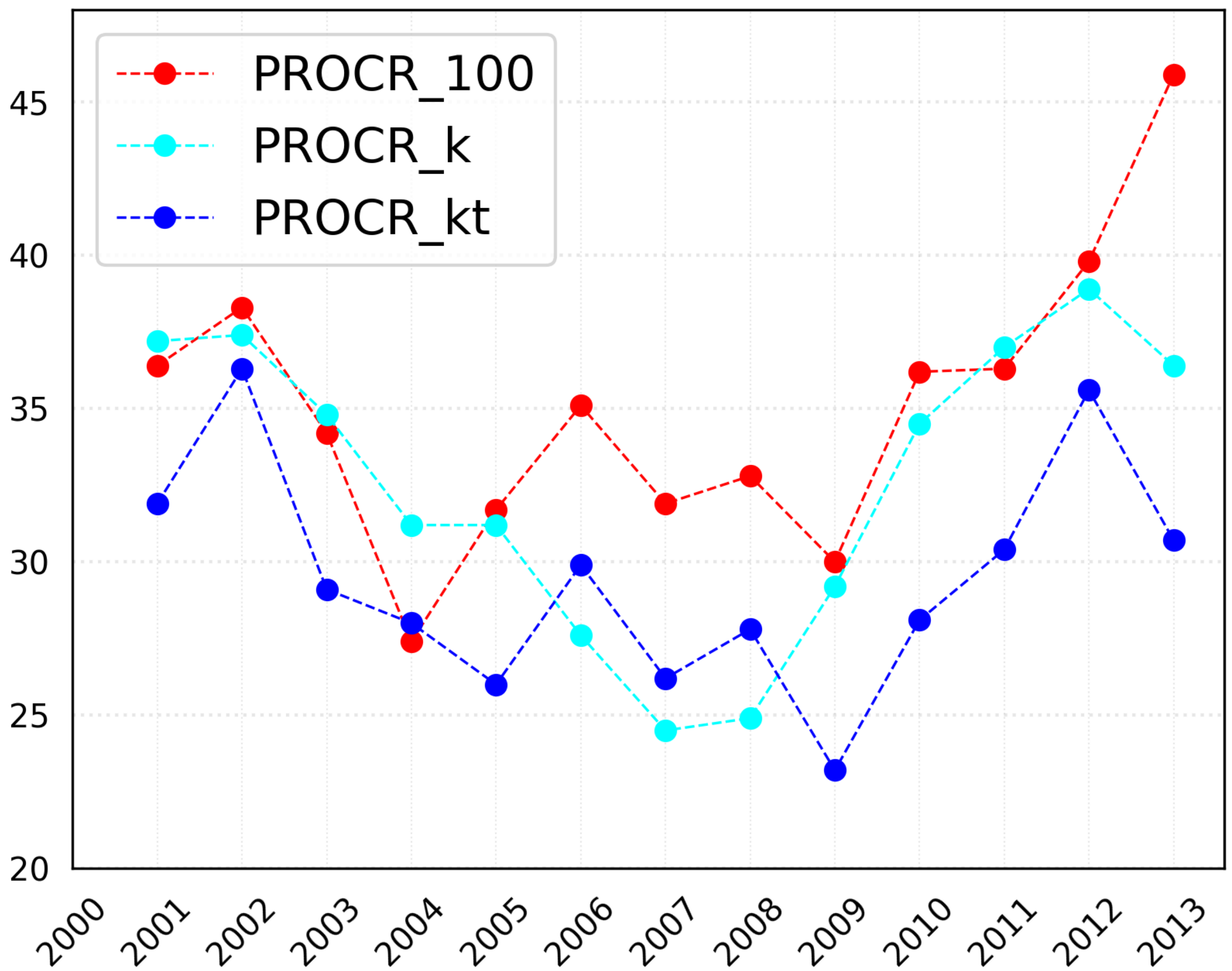


PROCR_100: 35.08±4.71

PROCR_k: 32.68±4.93

PROCR_kt: 29.48±3.67

RESULTS: EXPERIMENT 2



PROCR_100: 35.08±4.71

PROCR_k: 32.68±4.93

PROCR_kt: 29.48±3.67

***Anchor* vs *Diachronic Anchor* words:**

- #Diachronic Anchor words: 48 (i.e., top-0.1%)
- #Anchor words: 434 (from an overall possible of 631)
- Only 16% of anchor are diachronic anchor words (noise)

Diachronic Anchor words: more robust short-term alignments

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CONCLUSION & FUTURE WORK

- **Summary**:
  - New labelled dataset for Semantic Change Detection
  - Rank-based task & evaluation
  - Procrustes Alignment based on a few diachronically stable words
- **Future Work**:
  - Generalised Procrustes Alignment [Gower, 1975]
  - Temporal Modelling (Temporal Clustering, Changepoint Detection)

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THANK YOU!

Any
Questions?

Dataset: https://github.com/adtsakal/Semantic_Change

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