Sequential Modelling in Vector Space

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Embed Discrete Objects in Vector Space

Two examples

- **Word embedding**
- User/item embedding

Learn implicit features that could be adaptively updated during training

Word Embedding

- **Prediction-based method [1,2]**
  - e.g., using neural networks to predict central/neighboring words

- **Count-based method [3]**
  - e.g., decompose PPMI matrices

[1] Bengio et.al. A Neural Probabilistic Language Model. JMLR 2003

[2] Mikolov et.al. Efficient Estimation of Word Representations in Vector Space. NIPS 2013.

[3] Pennington et.al. GloVe: Global Vectors for Word Representation. EMNLP 2014

Sequential aspects to model

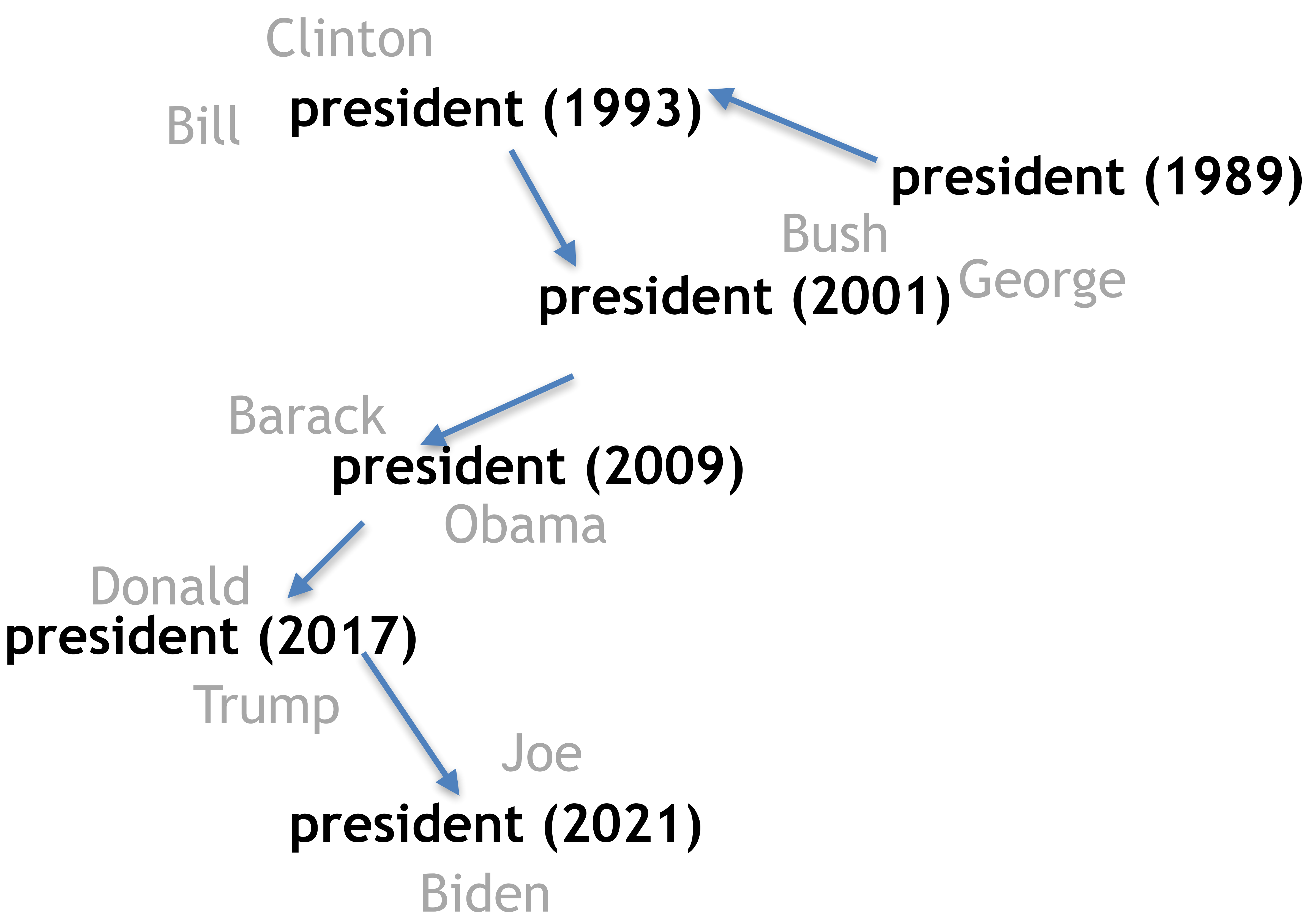
- Position
  - Encode word order in neural networks (e.g., Transformer [1]) [2]

- Temporal Evolution
  - Individual words may change their meaning over time
  - Existing solutions, e.g., Dynamic Word Embeddings

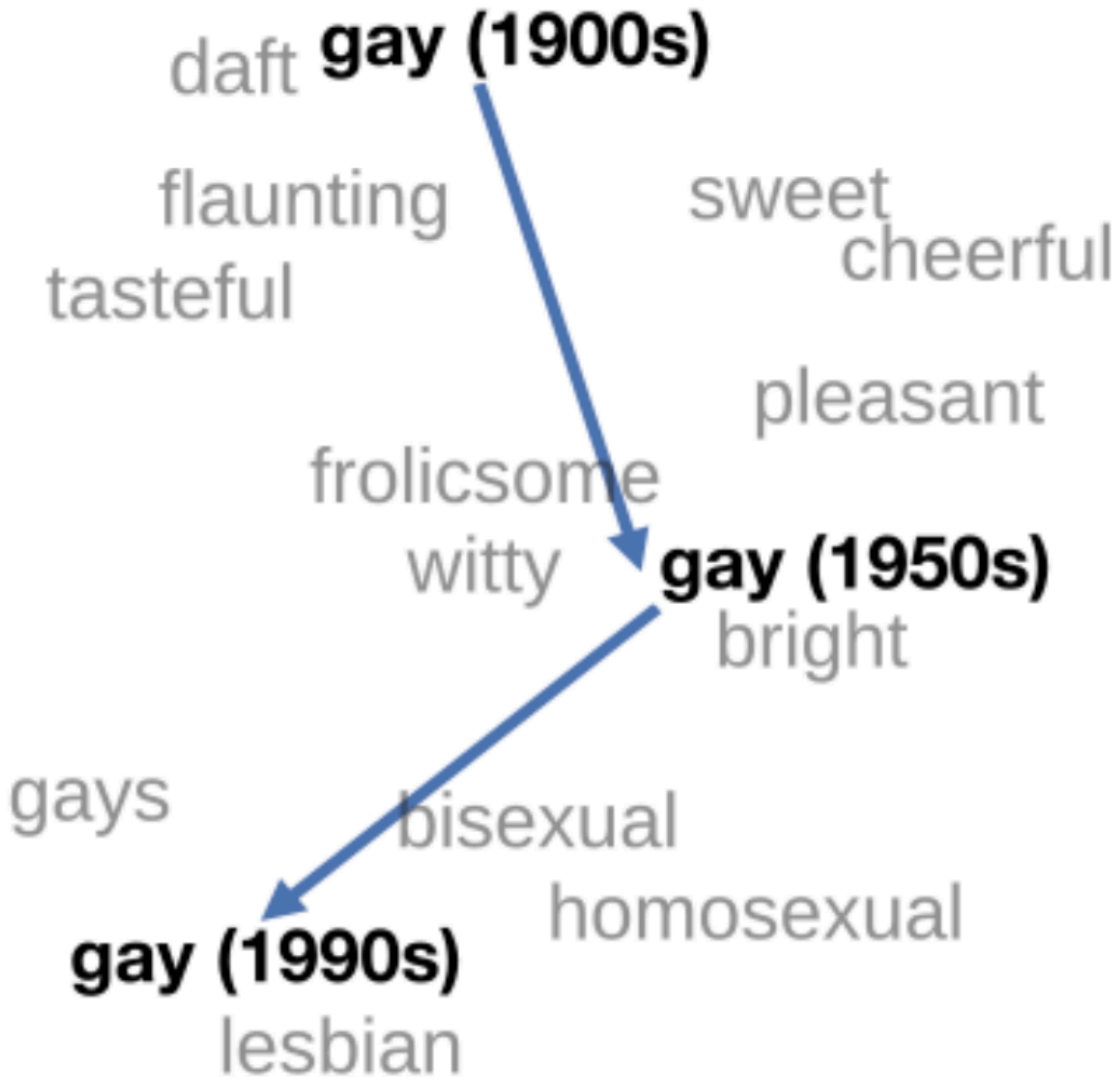
[1] Vaswani et.al. Attention is all you need, NIPS 2017

[2] Benyou Wang et.al. Encoding word order in complex embeddings

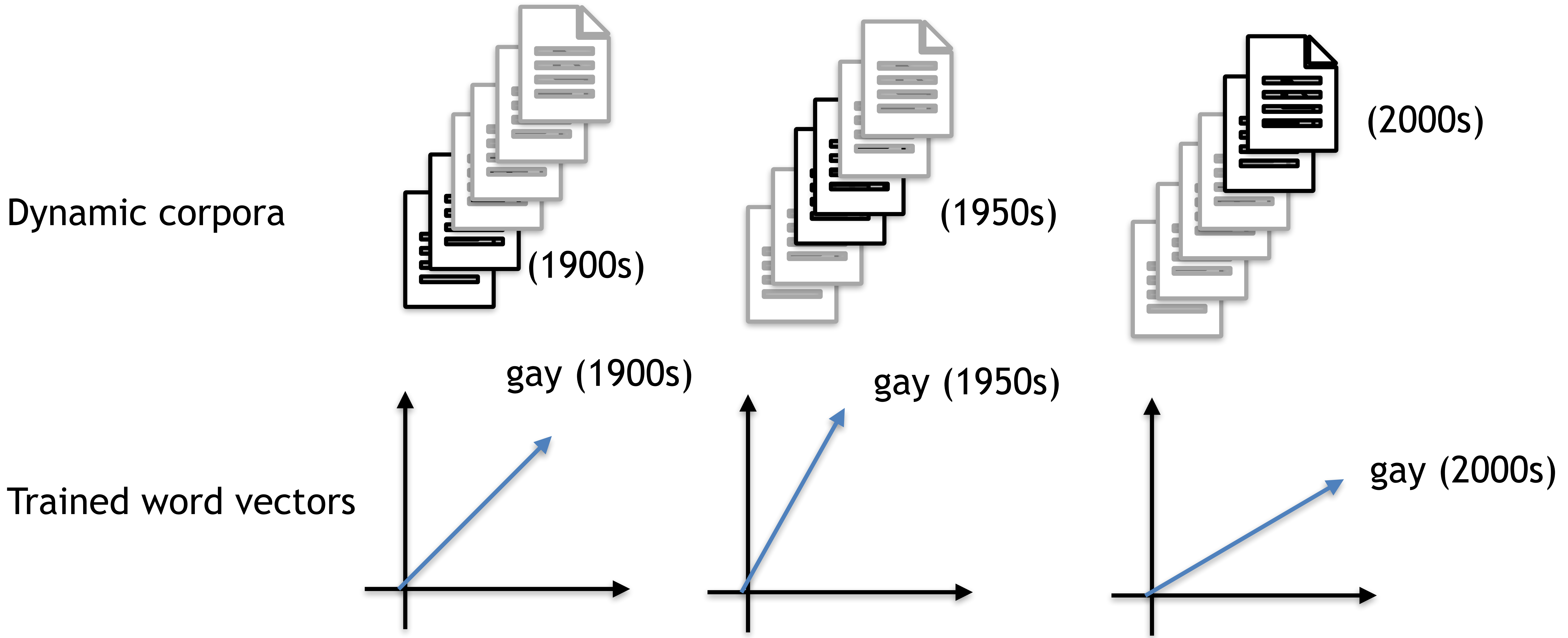
Example 1: short-term evolution



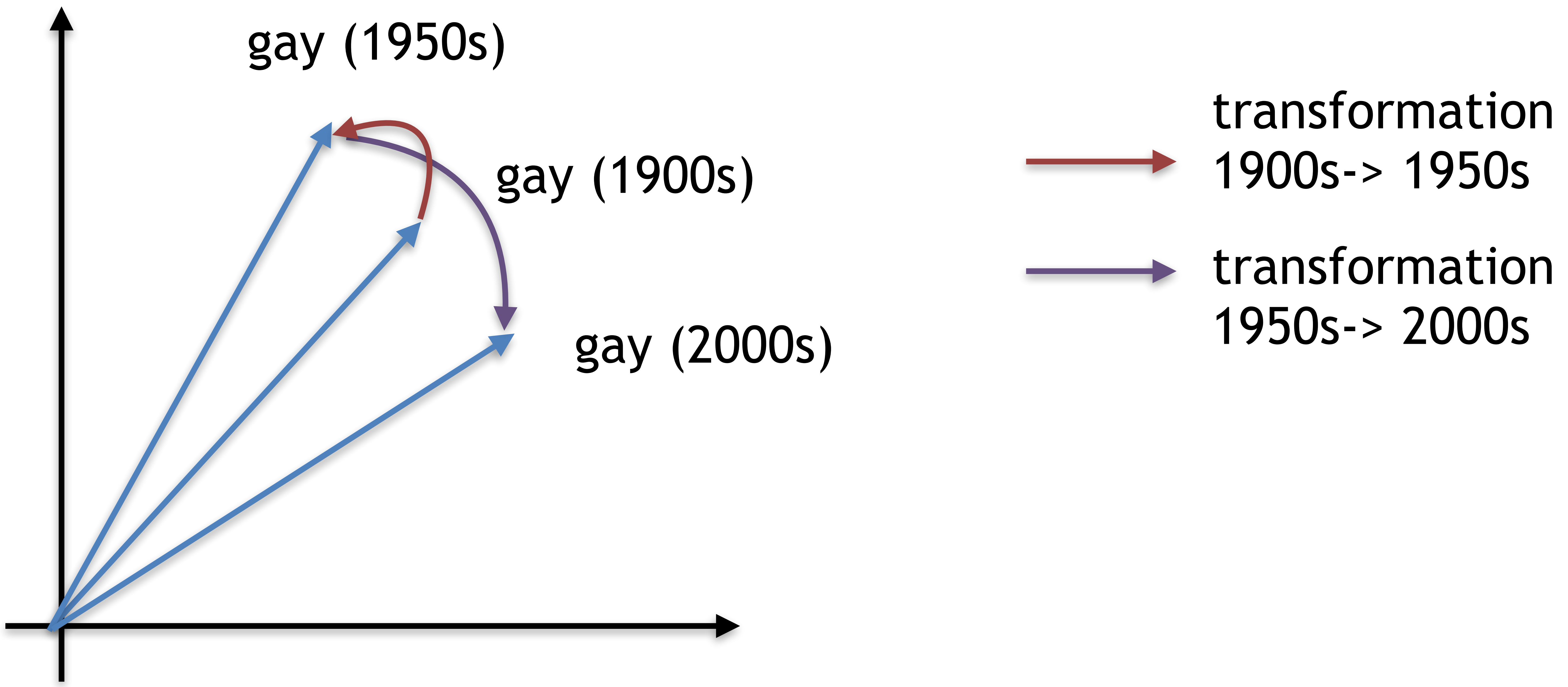
Example 2: long-term evolution



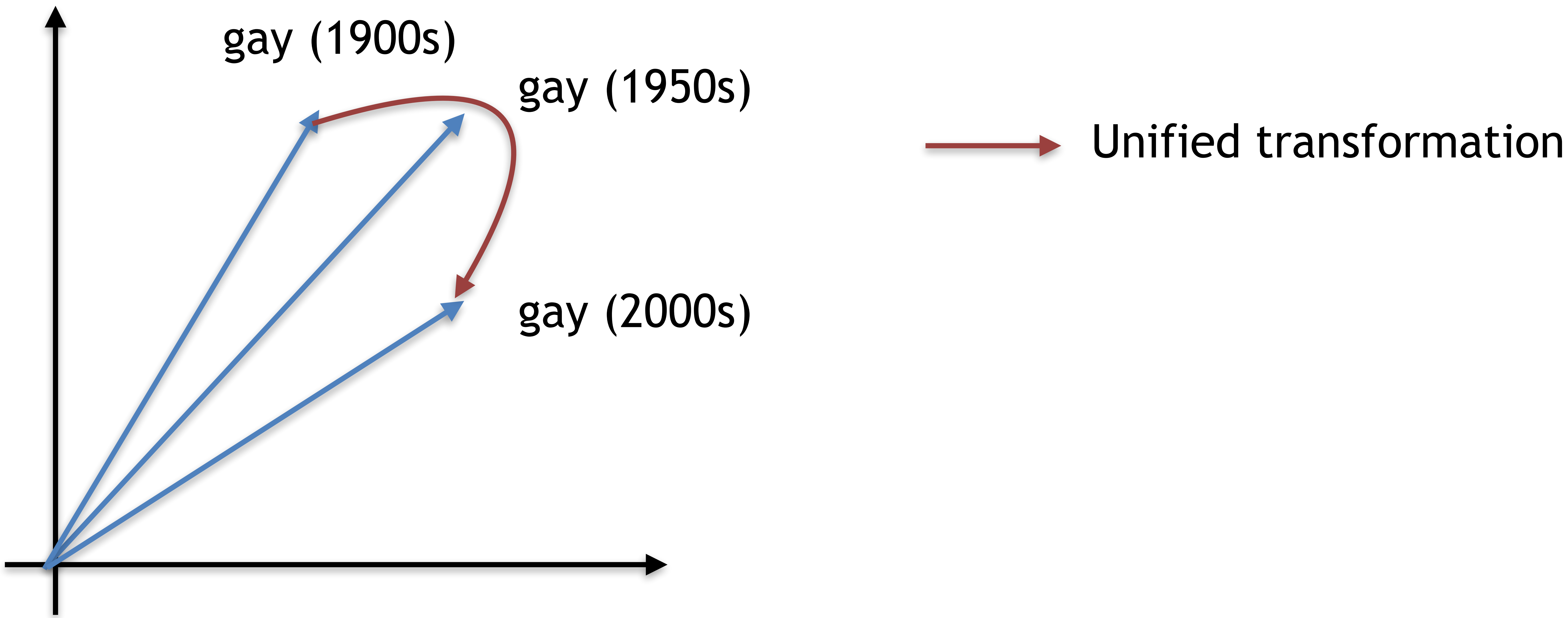
Train and Align Paradigm



Previous one-hop assumption



Our approach

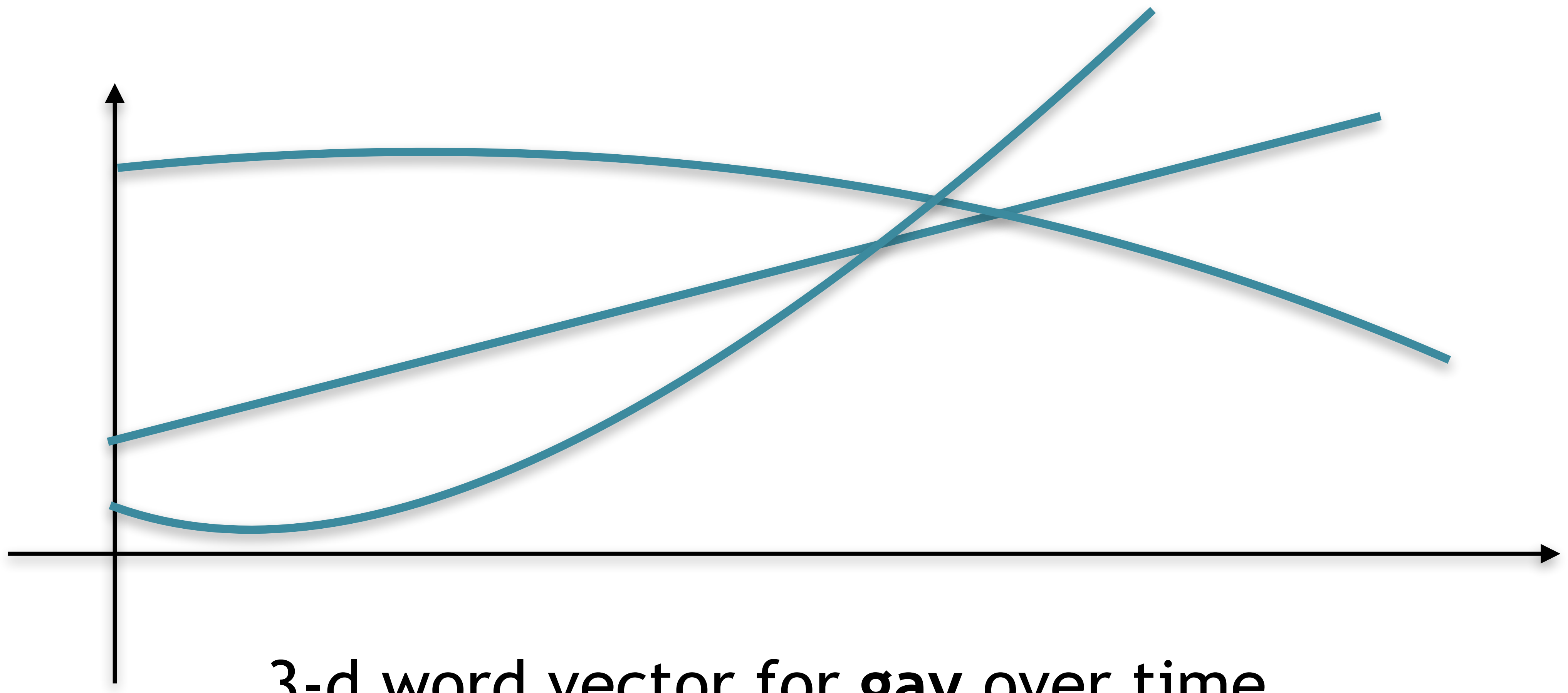


Modeling Word as Functions

Treating time as a continuous variable [4] induces a new formalization (Word2Fun)

$$f:(N) \rightarrow G\{g; g: N \rightarrow R^k\}$$

Word index   Time index



3-d word vector for **gay** over time

<u>Question:</u> ***Which functions should we use?***

[4] Alex Rosenfeld, Katrin Erk. Deep Neural Models of Semantic Shift. NAACL 2018

Approximation of Word Meaning Evolution

Here we define a **temporal word embedding**

$$f(\cdot\,,\cdot\,) : (\mathbb{N}, \mathbb{R}) \rightarrow \mathbb{R}^D$$

that maps a word w_i in time t as a N-dimensional vector $f(i, t) \in \mathbb{R}^D$. $f_i(t)$ is a function over t.

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We also define a static word embedding for alignment, also called a compass [1].

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[1] Valerio Di Carlo et.al. Training Temporal Word Embeddings with a Compass. AAAI 2019

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A dot product between them should approximate their PPMI over time.

$$f_i(t)g(j)^T \propto PPMI_{i,j}(t)$$

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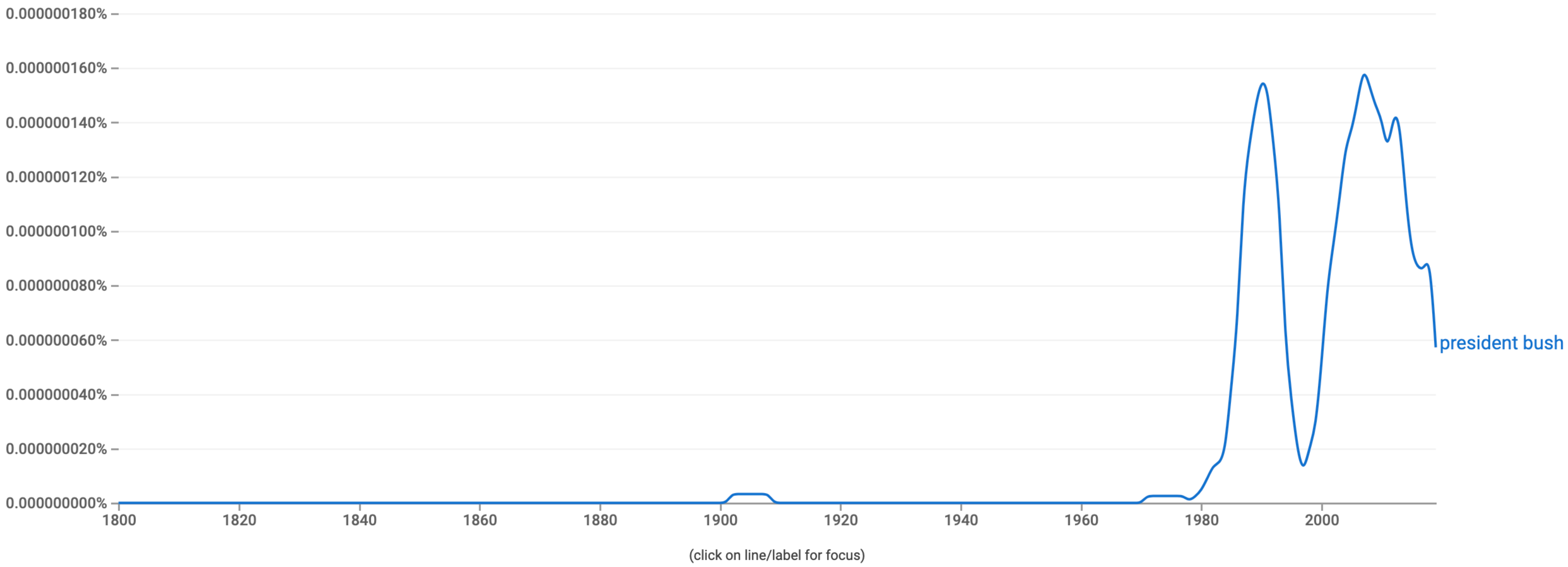
Between-word relatedness over Time



evolving relatedness between “**president**” and “**bush**” may be *highly-nonlinear*

The result is from https://books.google.com/ngrams

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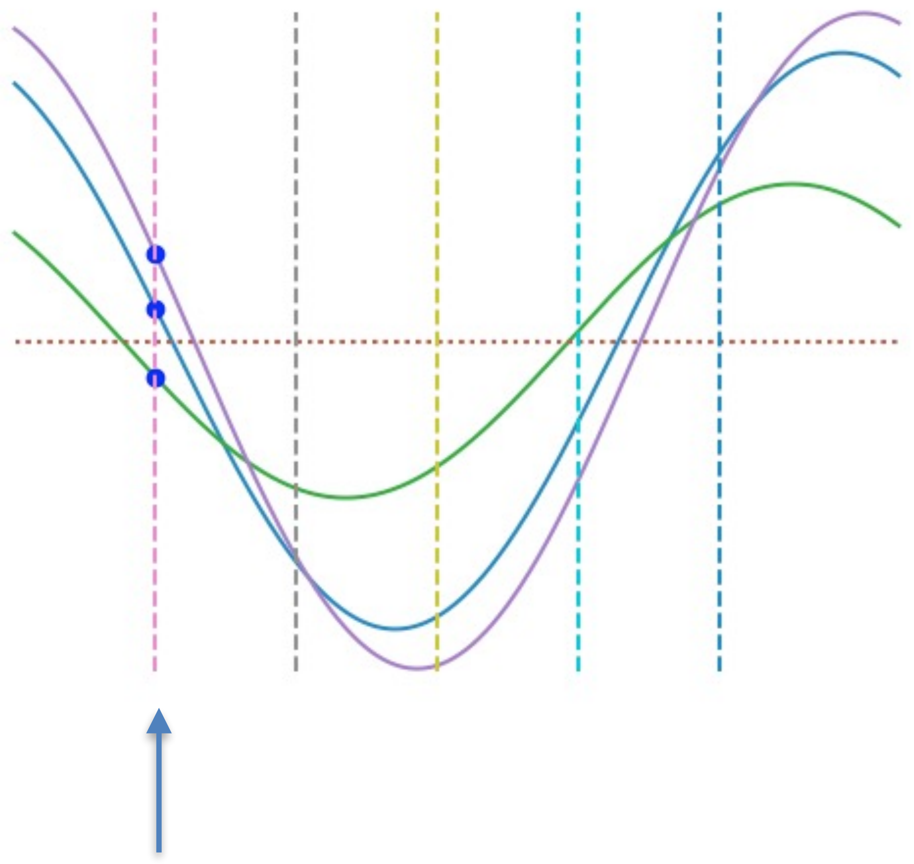
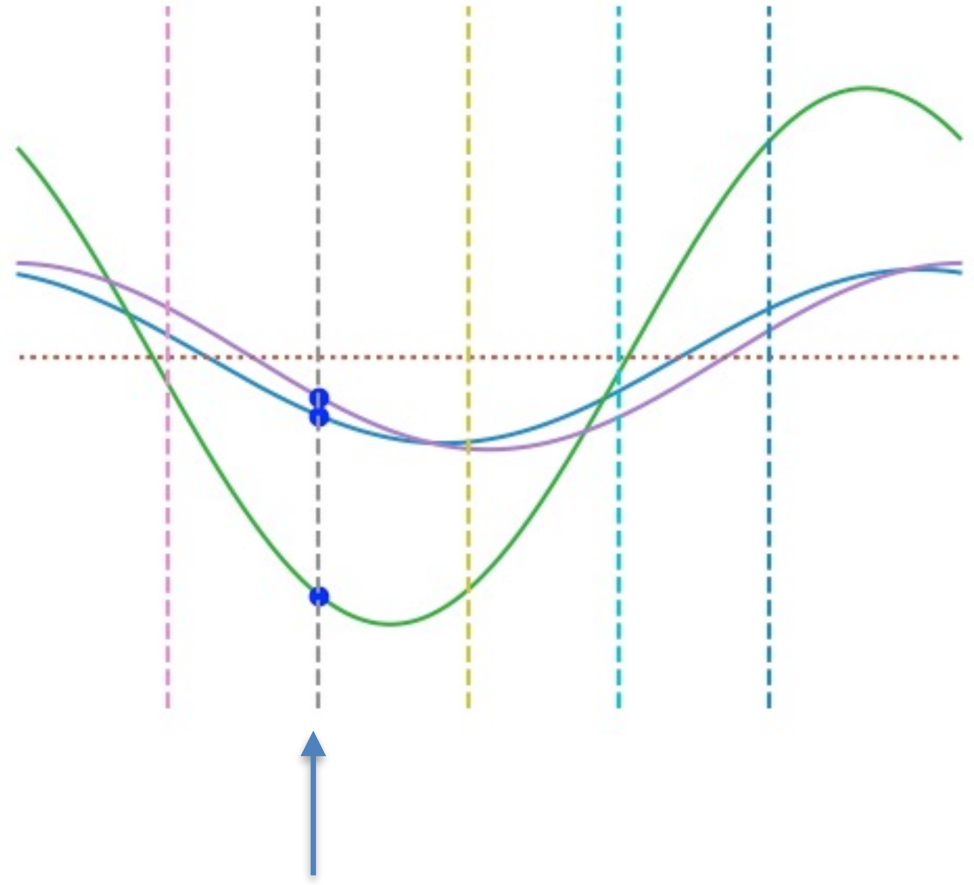
When $f_i(t)$ is formalised as a **sinusoidal** function. $f(i, t)g(j)^T$ is proved to **approximate any continuous functions** thanks to the **Weierstrass Approximation theorem**.

[1] Valerio Di Carlo et.al. Training Temporal Word Embeddings with a Compass. AAAI 2019

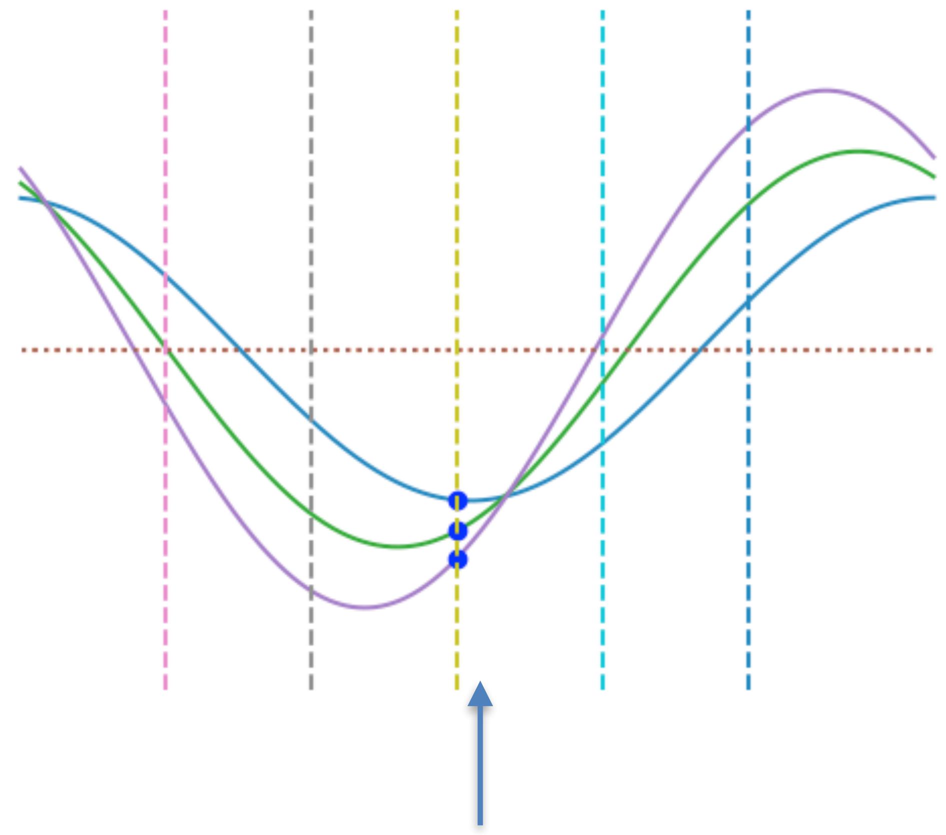
Word2Fun (examples)



gay in 1910s



cheerful in 1920s



homosexual in 1930s

Experimental Evaluation

Table 3: Experimental results of Time-aware word clustering.

Method	10 Clusters		15 Clusters		20 Clusters	
	NMI	F_β	NMI	F_β	NMI	F_β
Global/static word vector [16]	0.6736	0.6163	0.6867	0.7147	0.6713	0.7214
Transformed Word2Vec [14]	0.5175	0.4584	0.5221	0.5072	0.5130	0.5373
Aligned Word2Vec [9]	0.6580	0.6530	0.6618	0.7115	0.6386	0.7187
Dynamic Word2Vec [26]	0.7175	0.6949	0.7162	0.7515	0.6906	0.7585
Compass aligned Word2Vec [6]	0.5191	0.3750	0.5062	0.4051	0.5077	0.4331
Word2Fun linear	0.1676	0.1813	0.2826	0.3035	0.2473	0.2932
Word2Fun I (Time2Fun)	0.1703	0.1783	0.2691	0.2680	0.2842	0.2649
Word2Fun II	**0.7281**	**0.7147**	**0.7181**	0.7645	**0.7012**	0.7616
Word2Fun III	0.7233	0.7080	0.7086	**0.7701**	0.6980	**0.7630**
Word2Fun IV	0.7111	0.6913	0.7023	0.7451	0.6823	0.7602

Time-aware word clustering

Table 4: Experimental results of temporal analogy in *test1*

Method	MRR	P@1	P@3	P@5	P@10
Global/static Word2Vec [16]	0.3560	0.2664	0.4210	0.4774	0.5612
Transformed Word2Vec [14]	0.0920	0.0500	0.1168	0.1482	0.1910
Aligned Word2Vec [9]	0.1582	0.1066	0.1814	0.2241	0.2953
Dynamic Word2Vec [26]	0.4222	0.3306	0.4854	0.5488	0.6191
Compass aligned Word2Vec [6]	**0.481**	**0.404**	**0.534**	0.582	0.636
Word2Fun linear	0.3016	0.2649	0.3255	0.3426	0.3630
Word2Fun I (Time2Fun)	0.3735	0.2646	0.4300	0.4955	0.5874
Word2Fun II	0.4061	0.2756	0.4916	0.5614	0.6434
Word2Fun III	0.4354	0.3076	0.5330	**0.5837**	**0.6647**
Word2Fun IV	0.4208	0.2954	0.5076	0.5715	0.6470

Temporal analogy test1

Table 5: Experimental results of temporal analogy in *test2*

Method	MRR	P@1	P@3	P@5	P@10
Global/static Word2Vec [16]	0.0472	0.0000	0.0787	0.0787	0.2022
Transformed Word2Vec [14]	0.0664	0.0404	0.0764	0.0989	0.1438
Aligned Word2Vec [9]	0.0500	0.0225	0.0517	0.0787	0.1416
Dynamic Word2Vec [26]	0.1444	0.0764	0.1596	0.2202	0.3820
Compass Aligned Word Embedding [6]	0.1361	0.0749	0.1918	0.2904	0.3918
Word2Fun linear	0.0425	0.0137	0.0384	0.0630	0.1014
Word2Fun I (Time2Fun)	0.0992	0.0000	0.1315	0.1726	0.2849
Word2Fun II	0.1194	0.0358	0.1075	0.2219	0.3863
Word2Fun III	**0.1824**	**0.0795**	**0.1973**	**0.2932**	**0.4164**
Word2Fun IV	0.1536	0.0548	0.1562	0.2411	0.3918

Temporal analogy test2

Table 6: Semantic change detection. Baselines in the first group are implemented by this work.

models	Pearson	Spearman
Global/static Word2Vec [16]	nan	nan
Transformed Word2Vec [14]	0.0727	0.0865
Aligned Word2Vec [9]	0.3333	0.3083
Dynamic Word2Vec [26]	0.2727	0.2877
Compass aligned word embedding [6]	0.3199	0.2567
Word2Fun linear	-0.1200	-0.0790
Word2Fun I (Time2Fun)	0.3925	0.4550
Word2Fun II	0.4478	**0.5038**
Word2Fun III	**0.5355**	0.4057
Word2Fun IV	0.4483	0.3578
multilingual BERT [20] (SemEval-2020 1st)	-	0.436
ensemble between aligned Word2Vec and BERT [18] (SemEval-2020 2nd)	-	0.422

Semantic change detection

Case study

word	1900s	1920s	1940s	1960s	1980s	2000s
frolicsome	**0.5230**	0.3574	0.2802	0.1511	0.1649	0.1992
playful	0.4094	0.3757	**0.4268**	0.3298	0.2425	0.2839
debonair	0.3840	0.4705	**0.5523**	0.4597	0.2243	0.3547
activists	0.2319	0.2430	0.0892	0.2894	**0.4698**	0.4072
homosexuality	-0.1435	-0.0274	0.1209	0.2605	0.3242	**0.3727**

Word similarity to “gay” over time

Acknowledgments

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