Time-Aware and Corpus-Specific Entity Relatedness

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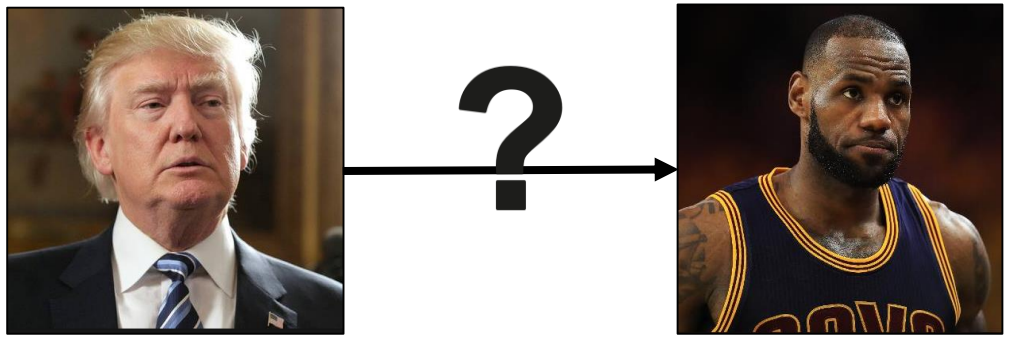
Introduction

- Entity Relatedness
  - Determining the degree of relatedness between two entities

- Useful in a variety of applications
  - IR
  - Search Recommendations
  - Entity Linking



- Approaches:
  - Structural similarity in graphs
  - Using lexical characteristics
  - Wikipedia-based entity distributions and embeddings

Introduction

- Temporality of entity context
  - Entity popularity often changes across time [Fang et al. 2014]
  - Entity recommendations are time-dependent [Zhang et al. 2016] [Tran et al. 2017]
  - Exploiting different KB versions can advance entity relatedness [Prangnawarat and Hayes, 2017]

- What about the **corpus-context?**

Introduction

- What about the **corpus-context?**

- Example:
  - Input entity: 2014 FIFA World Cup
  - Related entities:

German news articles	Greek news articles
Germany national football team	Greece national football team
Argentina national football team	Costa Rica national football team
Mario Götze	Sokratis Papastathopoulos

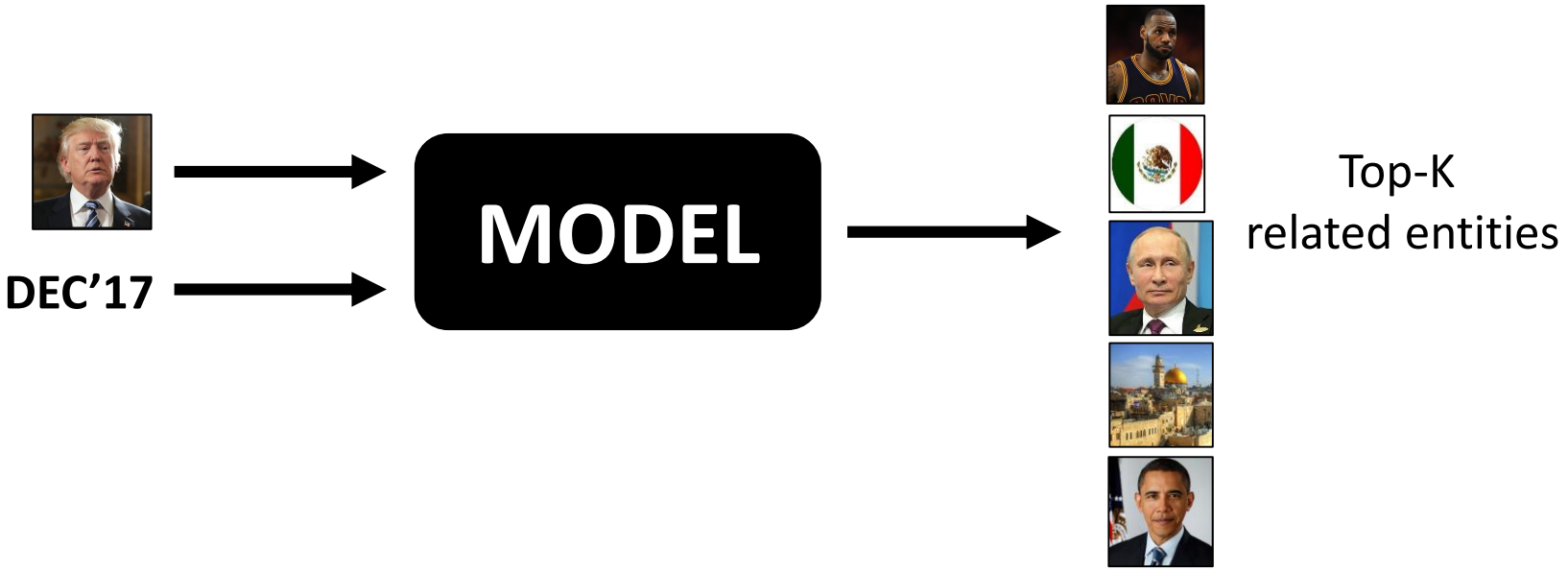
Approach overview

- Entity relatedness depends on both:
  - Time-context
  - Corpus-context

- Method:
  - Train time- and corpus-specific word embeddings (using Word2Vec)
    - Not using general-purpose corpora like Wikipedia!
  - Exploit entity annotations for transforming word embeddings to entity embeddings
  - Relax the time boundaries (optionally)

Problem Modeling

- Corpus of documents D covering a time period T
  - E.g., German sport articles of 2015
- Entities E mentioned in the documents (persons, locations, events, …)
  - Extracted using an entity linking system
  - Each entity is associated with a unique URI in a KB

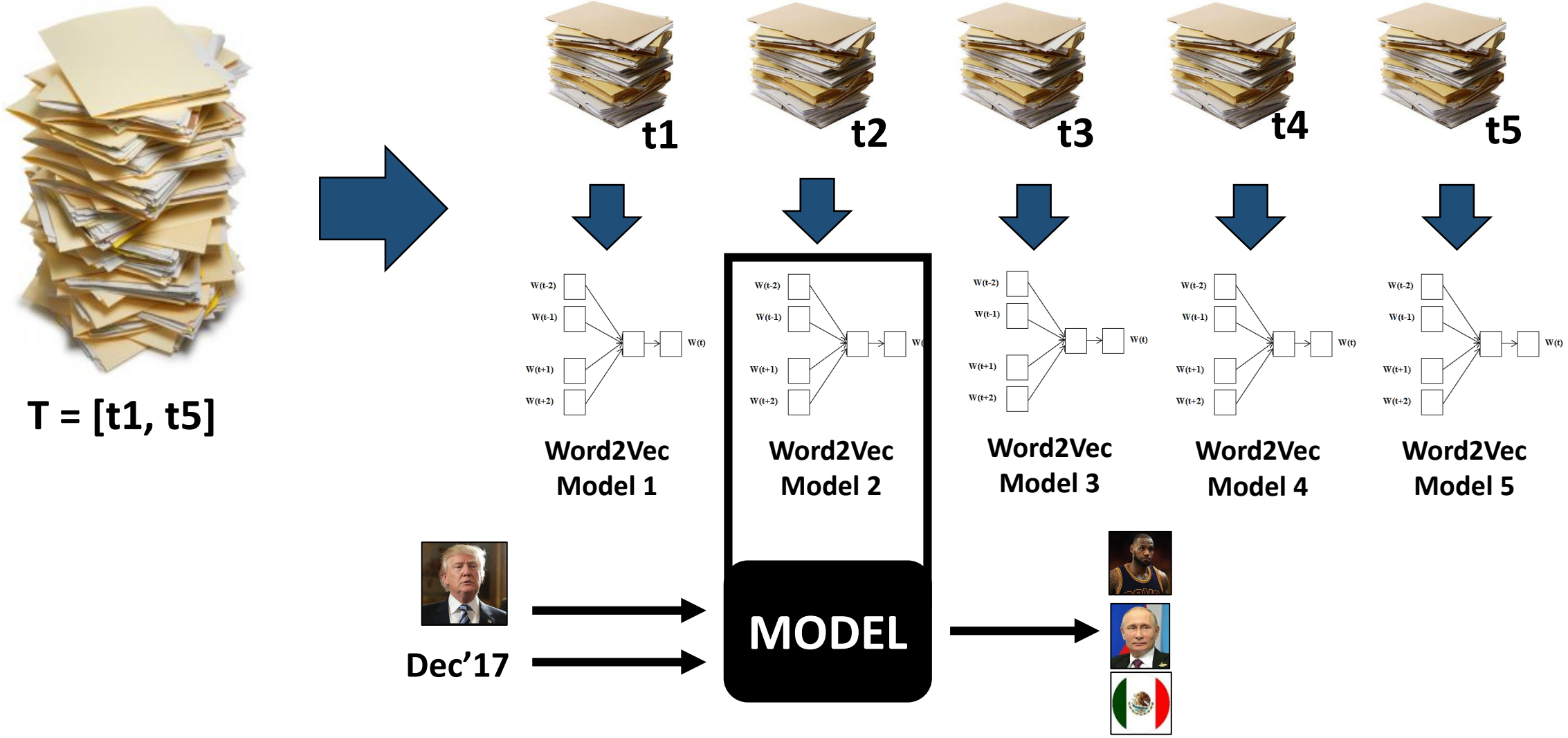


Problem Modeling

- Modeling: ranking problem

1. Generate a list of candidate entities
   - Exploiting Wikipedia links, DBpedia, and entity co-occurrences in the corpus [Zhang et al. 2016]
2. **Rank the candidate entities based on their relevance to the query entities**

Time-Aware Word Vector Similarity



Time-Aware Word Vector Similarity

T = [t1, t5]

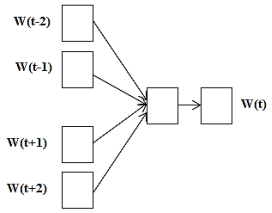
t1

t2

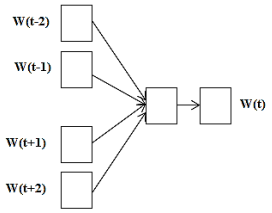
t3

t4

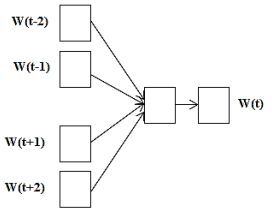
t5



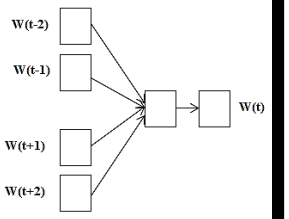
Word2Vec Model 1



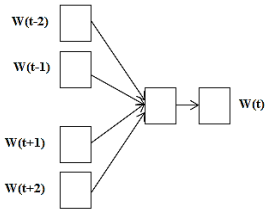
Word2Vec Model 2



Word2Vec Model 3



Word2Vec Model 4



Word2Vec Model 5

Feb'18

MODEL

Making the embeddings entity-aware

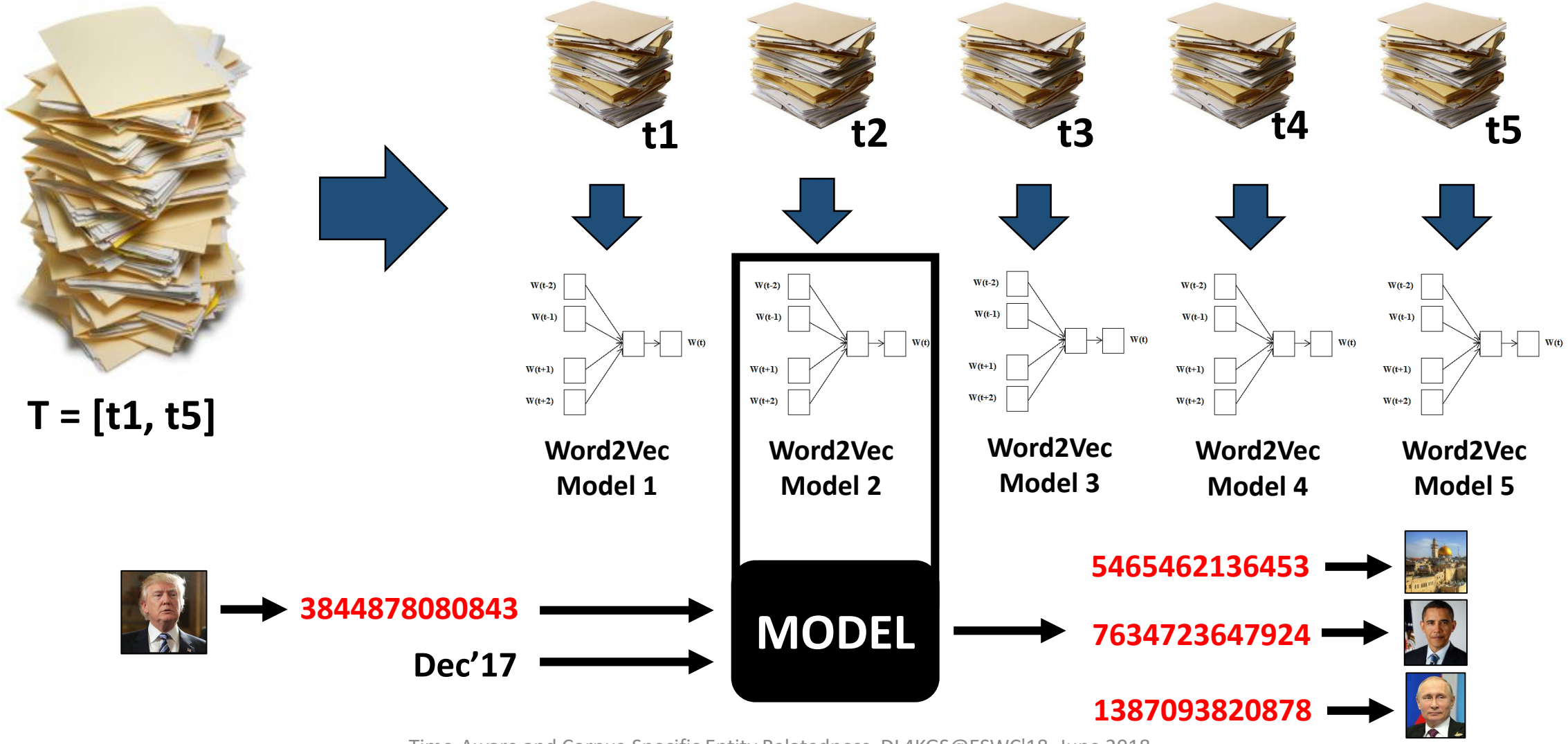
- Limitations of word embeddings:
  - Handling of multi-word entity names, e.g. “United Nations”
  - Same entity name may refer to different entities, e.g. “Kobe”

- Solution: exploit entity annotations
  - Each entity mention in a document is associated with a unique URI in a KB
- Replace entity mentions with unique IDs
  - As done in [Mikolov et al. 2013] for phrases
- Train Word2Vec models on the modified corpora
- Use entity IDs for computing entity relatedness

3844878080843 was elected president in a surprise victory over 8798729506352 nominee 1365985456623.

MAPPINGS:
3844878080843 → https://en.wikipedia.org/wiki/**Donald_Trump**
8798729506352 → https://en.wikipedia.org/wiki/**Democratic_Party_(United_States)**
1365985456623 → https://en.wikipedia.org/wiki/**Hillary_Clinton**

Making the embeddings entity-aware

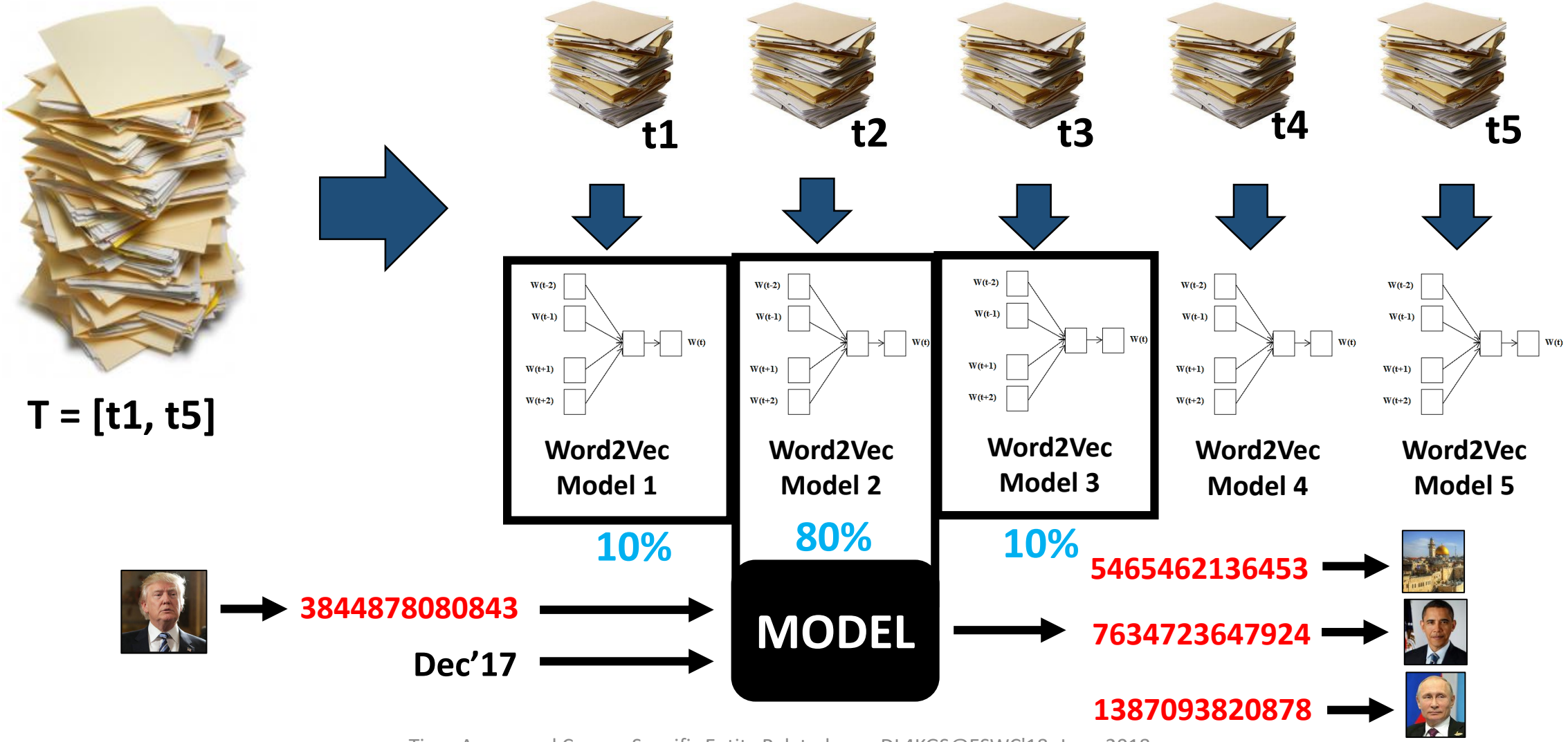


Relaxing the time boundaries

- Problem
  - Entity embeddings built on specific time periods (e.g., November 2017)
    - An important event related to the query entity may happened very close to the boundaries of the query time period
    - The query entity may correspond to an event spanning a longer time period
- Two entities might be highly related some time before or after the query time period!

- Consider the Word2Vec models before & after the model of the query time period
  - But with smaller weight
- This can increase the ranking of an important candidate entity that co-occurs frequently with a query entity some time before of after the query time period
  - But can also decrease the ranking of an entity co-occurring with the query entity during the query time period

Relaxing the time boundaries



Evaluation

- Objective:
  - Evaluate the effectiveness of the proposed approach
  - Compare it with similar but time and entity agnostic models

- Dataset and Ground Truth:
  - Provided in [Zhang et al. 2016]
  - Different task: Time-aware **entity recommendation** (for keyword queries)
  - Candidate entities and relevance judgements for 22 keyword queries (July 2014 – January 2015)
    - Each query corresponds to a particular date range (month)
  - Adapted for our problem (time-aware **entity relatedness**)
    - Keyword query → query entities
    - Remove query entities from list of candidate entities
  - Example: “Tour de France Nibali” (07/2014)
    - Query entities: {Wikipedia:Tour_de_France, Wikipedia:Vincenzo_Nibali}

Evaluation

- Setup
  - 7 CBOW models (one per month)
    - Using default Word2Vec setting (300 dimensions, 5 words window size, 5 min word count)
  - Compare our approach on ranking the candidate entities with two baselines:
    - 1) entity-agnostic, time agnostic
    - 2) entity-agnostic, time-aware

Evaluation

- Results

nDCG@k	Time+Entity Agnostic	Entity Agnostic	Time+Entity Aware
k=5	0.3210	0.3653	**0.4999** ‡
k=10	0.3748	0.4113 ‡	**0.5402** ‡
k=20	0.4546	0.4971 ‡	**0.6115** ‡
k=30	0.5092	0.5704 ‡	**0.6562** ‡

Evaluation

- Relaxing the time boundaries

nDCG@k	$w_1 = 1.0$	$w_1 = 0.9$	$w_1 = 0.8$	$w_1 = 0.7$	$w_1 = 0.6$
k=5	0.4999	**0.5017**	0.4990	0.4933	0.4890
k=10	**0.5402**	0.5332	0.5358	0.5296	0.5291
k=20	**0.6115**	0.6039	0.5971	0.5932	0.5893
k=30	**0.6562**	0.6517	0.6451	0.6403	0.6371

- Examples of positive impact
  - “2014 FIFA World Cup” (July 2014): nDCG@5 increases from 0.45 to 0.51 (w1=0.8)
  - “Tim Cook” (October 2014): nDCG@5 increases from 0.58 to 0.62 (w1=0.8)

Conclusion

- Flexible model for entity relatedness
  - Considers the underlying corpus
  - Time- and Entity-aware
  - Outperforms similar but time and entity agnostic models

- Future work
  - Support of arbitrary time intervals (join results of several models)
  - Identify cases where time boundaries relaxation should be applied
  - Extensive evaluation using a variety of corpora (of different contexts and time periods)

Thank you

Comments / Questions?

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ALEXANDRIA Project
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