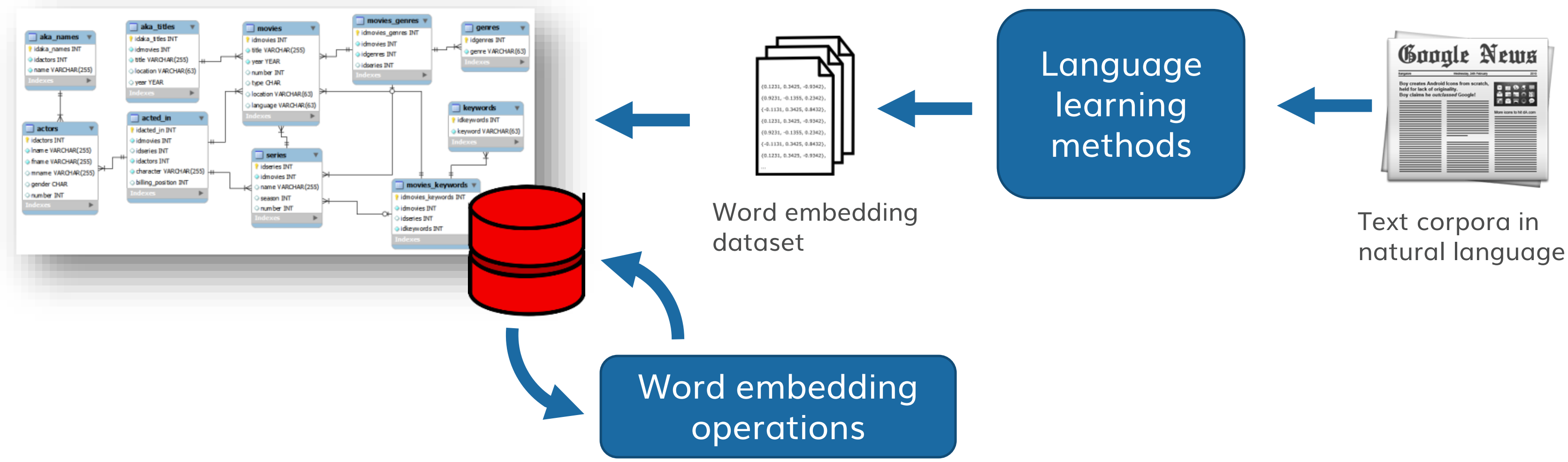
TECHNISCHE UNIVERSITÄT DRESDEN

Dresden Database Systems Group

Context Management in Word Embedding Database Systems

Considerations for Finding a Topic

Introduction



Introduction

Contribution of word embedding to database systems

- Use of external data sources of unstructured data (text in natural language)
- New operations for unstructured text values in the database
  - Analysing values
  - Extract new information from such values

```
SELECT m.title, t.word, t.squaredistance
FROM movies AS m, most_similar(m.title,
(SELECT title FROM movies)) AS t
```

Execution of most_similar operation

Results:
Inception | Shutter Island
…

Word-Embeddings

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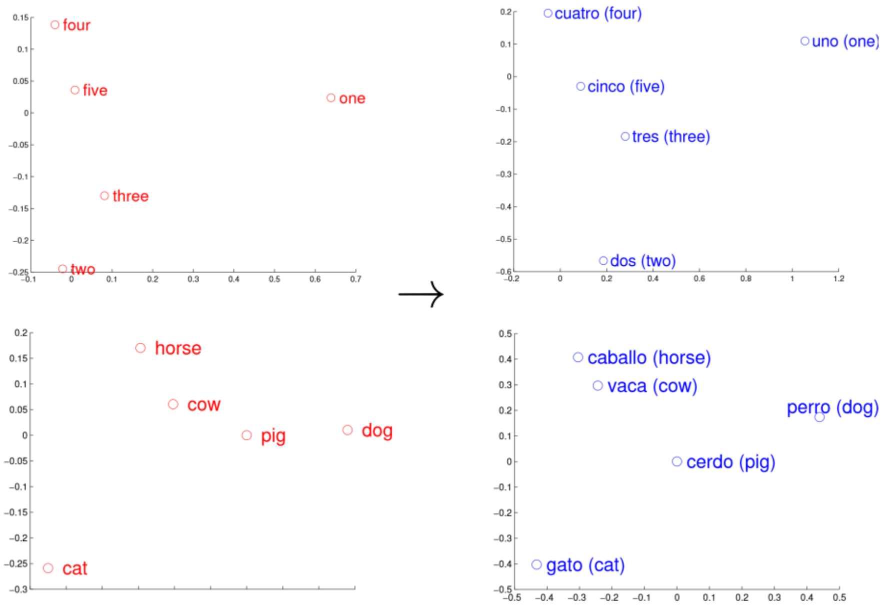
Word Embeddings

- Mapping: Tokens → Vectors
- Vectors modell semantic as well as syntactic relations between tokens.

→ Useful for NLP techniques (Sentiment Analysis, Maschine Translation, Information Retrieval, Word Clouds)

Properties

- Pretrained Word Embedding Datasets contain usually a few million vectors
- Dimensionality of the vectors: 200-300



Word Relations

Source: Mikolov, Tomas, Quoc V. Le, and Ilya Sutskever. "Exploiting similarities among languages for machine translation." *arXiv preprint arXiv:1309.4168* (2013).

Word-Embeddings: Operationen

Quantify Similarity

- Cosine similarity between vectors:

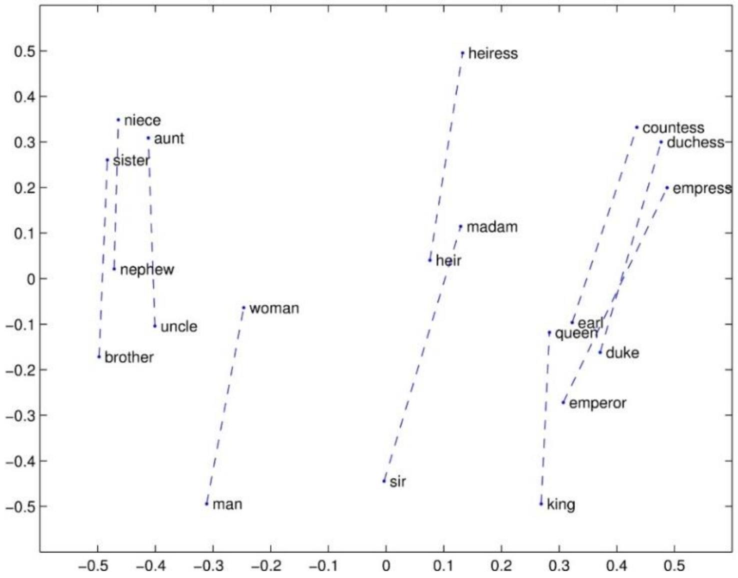
$$sim_{cos}(\boldsymbol{x},\boldsymbol{y}) = \frac{\boldsymbol{x}\cdot\boldsymbol{y}}{||\boldsymbol{x}||\cdot||\boldsymbol{y}||}$$

- Example: Top5('birch') → 'pine', 'birch trees', 'birches', 'tamarack', 'cedar'

Analogies

- Analogy Queries: $a\ - b\ \approx c - ?$
  e.g. man – woman ≈ king - ? → queen
- Pair-Direction: $\underset{d\,\epsilon V\setminus\{\boldsymbol{a},\boldsymbol{b},\boldsymbol{c}\}}{\arg\max}\ (sim_{cos}(\boldsymbol{a}-\boldsymbol{b},\boldsymbol{c}-\boldsymbol{d}))$

- 3CosAdd: $\underset{d\,\epsilon V\ \{\boldsymbol{a},\boldsymbol{b},\boldsymbol{c}\}}{\arg\max}\left(sim_{cos}(\boldsymbol{d},\boldsymbol{c}) - sim_{cos}(\boldsymbol{d},\boldsymbol{a})\right) + sim_{cos}(\boldsymbol{d},\boldsymbol{b})$
  $= \underset{d\,\epsilon V\ \{\boldsymbol{a},\boldsymbol{b},\boldsymbol{c}\}}{\arg\max}\ sim_{cos}(\boldsymbol{d},\boldsymbol{c}-\boldsymbol{a}+\boldsymbol{b})$



Relation Plot: man – woman
Source: https://nlp.stanford.edu/projects/glove/
Last access: 08.03.2018

System architecture

Fast woRd EmbedDings in Datatbase sYstem

Basis

- Postgres database system
  → Open source, Extensibility

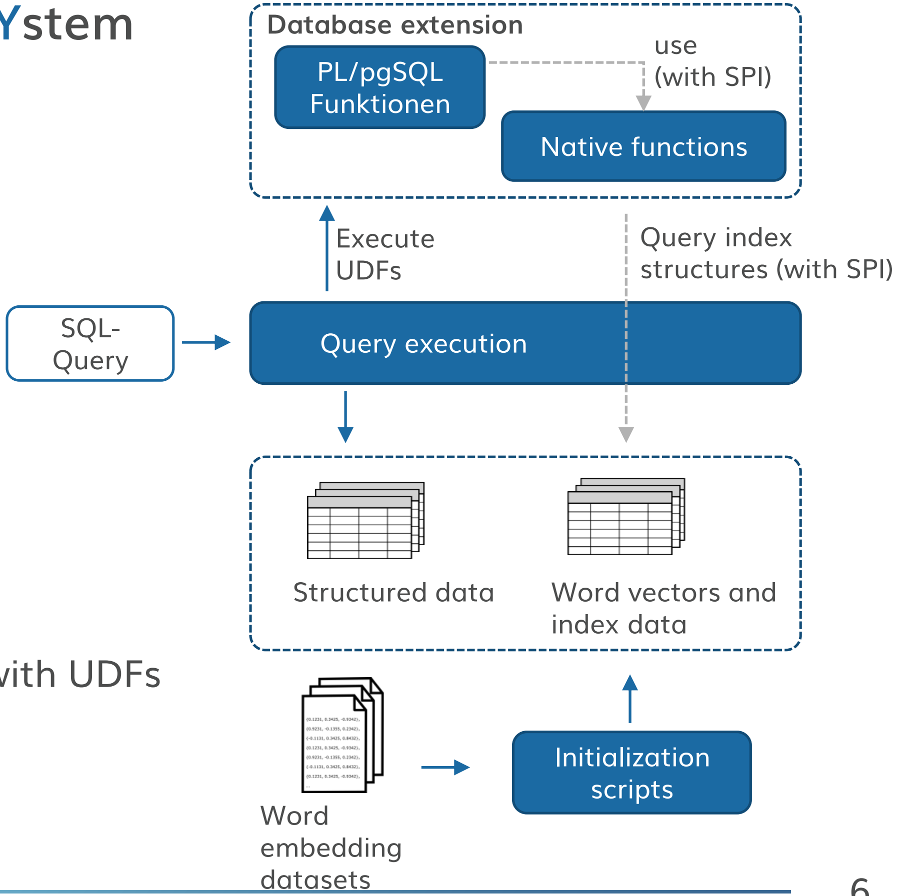
Word Embedding Operations

- implemented as User-Defined-Functions (UDFs)

→ Query optimization still active
→ Can be used in SQL queries
→ Search methods implemented in C
→ Interfaces implemented in PL/pgSQL

Index structures

- Stored in database relations
- Currently used index structure can be selected with UDFs while runtime



WE operations for database system

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Use cases

- Similarity Queries

```
SELECT keyword
FROM keywords
ORDER BY cosine_similarity('comedy', keyword)
```

→ comedy, sitcom, dramedy, comic, satire, …

- kNN Queries*

```
SELECT m.title, t.term, t.score
FROM movies AS kNN(m.title, 3) AS t
ORDER BY m.title ASC, t.score DESC
```

→ Godfather | {Scarface, Goodfellas, Untouchables}

- Analogy Queries

```
SELECT analogy_3cosadd(
'Godfather','Francis_Ford_Coppola', m.title)
FROM movies AS m
```

Incpeption → Christopher Nolan

- kNN_In Queries*

```
SELECT DISTINCT title FROM movies
WHERE keyword = ANY(
SELECT term
FROM kNN_in('historical fiction', 10,
ARRAY(SELECT keyword FROM movies))
```

→ Movies for keywords: historical, fiction, literary, fictionalized, novels

- Grouping*

```
SELECT term, groupterm
FROM grouping(SELECT title FROM movies),
'{Europe, America}')
```

→ Melancholia | Europe

→ Godfather | America

- Helper functions , e.g. to calculate centroids, …

* Function calls simplified

Product Quantization

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Idea

Reduce the computation time of the Euclidean square distance through an approximation by a sum of precomputed distances

$\rightarrow$ compact representation of vectors in index structure

$\rightarrow$ low computation time for distances

Preprocessing

Split vectors in m subvectors
$\rightarrow$ apply k-means on subvectors to obtain k centroids for every interval $\rightarrow$ quantizer $q_1, \dots, q_m$

Product-Quantization

1. Split vector in subvectors
2. Apply quantizers
   $\rightarrow$ Represent Product-Quantization as sequence
3. approximate squared distances by sums of precomputed squared distances $\mathrm{d}\left(u_j(\boldsymbol{x}), q_j\left(u_j(\boldsymbol{y})\right)\right)^2$

Query vector $\mathbf{x} = [x_1, \dots, x_n]$

Vector from index $\mathbf{y} = [y_1, \dots, y_n]$

Splitting into m subvectors of $\boldsymbol{y}$ with d dimensions $u_1(\boldsymbol{y}), \dots, u_m(\boldsymbol{y})$

Quantizer: assigns sub vector to on of the centroid of C_k $q : \mathbb{R}^d \rightarrow \{\boldsymbol{c}_1, \dots, \boldsymbol{c}_k\}$

Product quantization:

$$\underbrace{y_1, \dots y_d}_{u_1(\mathbf{y})}, \dots, \underbrace{y_{(n-d)+1}, \dots y_n}_{u_m(\mathbf{y})} \rightarrow q_1(u_1(\mathbf{y})), \dots, q_m(u_m(\mathbf{y}))$$

$\rightarrow$ Representation as sequence $Seq = \{1, \dots, |C_k|\}^m$

Approximated distance : $\hat{d}(\mathbf{x}, \mathbf{y}) = \sqrt{\sum_j d(u_j(\mathbf{x}), q_j(u_j(\mathbf{y})))^2}$

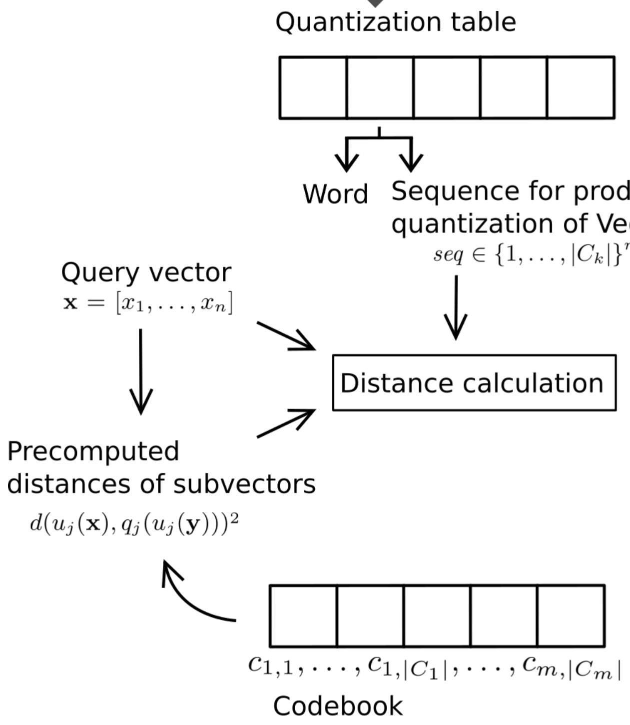
Product Quantization - Search

Index creation

- Use k-means to calculate centroids for quantizer $q_1, \dots, q_m$ and store them in a relation called "codebook"
- Calculate sequences for every vector and store them in a quantization table together with the corresponding token

Search

- Split query x vector into subvectors
- Precompute square distances $\mathrm{d}\left(u_j(\boldsymbol{x}), q_j\left(u_j(\boldsymbol{y})\right)\right)^2$ by using the codebook relation and the subvectors of x
- Determine the approximated kNN using the summation method to calculate distances for all sequences in the lookup table.



Product quantization search

IVFADC

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Idea:

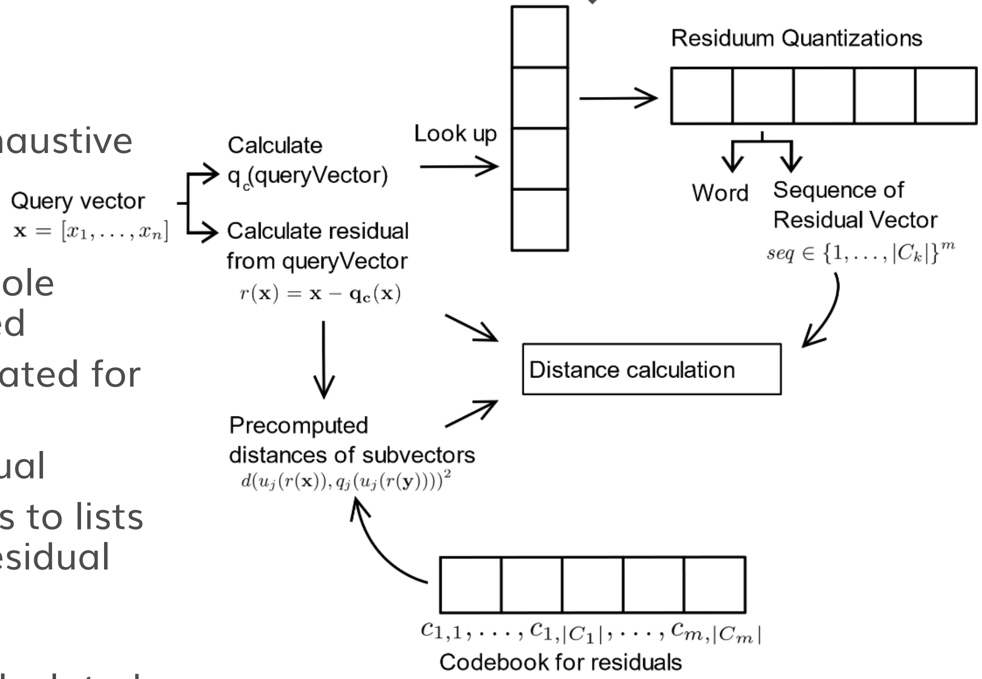
Accelerate computation by providing a non-exhaustive index with an inverted lookup

Preprocessing:

- A coarse quantizer q_c which quantize the whole vectors (considering all dimensions) is applied
- The residual vector $r(\boldsymbol{y}) = \boldsymbol{y} - q_c(\boldsymbol{y})$ is calculated for every vector
- Product quantization is applied on the residual
- A coarse lookup table is created which refers to lists of sequences of product quantizations for residual vectors of vectors with the same coarse quantization

Calculation: Approximated distances can be calculated by :

$$\hat{d}_r(\mathbf{x}, \mathbf{y}) = \sqrt{\sum_j d(u_j(r(\mathbf{x})), q_j(u_j(r(\mathbf{y}))))^2}$$



IVFADC search

Comparison: PQ-, IVFADC- and exact Search

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IVFADC Search

Very fast ≈ 300 times faster

Non-Exhaustive: Considers only a subset of the vectors in the index

Appropriated for:
- kNN queries
- 3CosAdd analogy queries
  $\max(\cos((v_1 - v_2 + v_3), ?))$

Inappropriate for:
- Computation of single similarity values
- Search queries with specific output set

PQ Search

Intermediate fast: ≈ 9 times faster

Exhaustive: Considers all vectors

Appropriated for:
- kNN-In queries
- 3CosAdd analogy queries on a specific output set
- Grouping queries

Inappropriate for:
- Computation of single similarity values
- Pair direction queries

Exact computation

slow (but no preprocessing)

Separate calculation of all similarity values (exact)

Appropriated for:
- Single similarity calculations
- Pair direction queries
- Search queries on a specific output set

Inappropriate for:
- Search queries on huge datasets

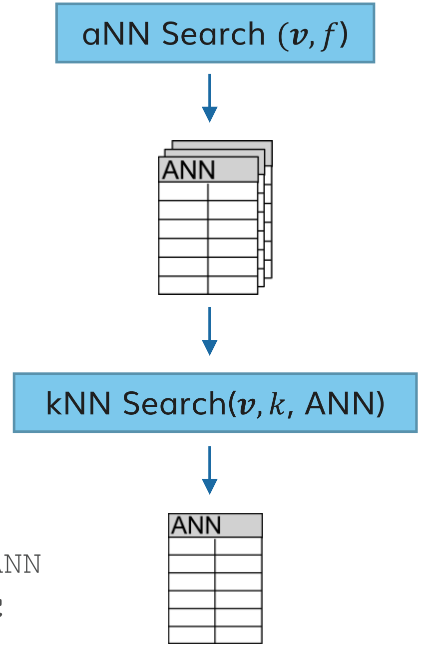
Post verification

Method

- Re-ranking of aNN results by exact kNN search
- Improve quality of results by retrieving more results f > k of nearest neighbors in the first run

  → Select best results with exact kNN Search
- Precision could be improved a lot

→ Especially useful for analogy queries



$\boldsymbol{v}$: Anfragevektor

f : Postverifikation-parameter

k : Anzahl gewünschter Ergebnisse

```sql
SELECT ANN.word
FROM k_nearest_neighbour_ivfadc('Godfather', 500) AS ANN
ORDER BY cosine_similarity('Godfather', ANN.word) DESC
FETCH FIRST 3 ROWS ONLY
```

Post verification process

Range Queries

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Problem Setting

- Many SQL queries trigger a lot of aNN queries at one time
- Retrieving index data from database with independend queries needs a lot of time
- Retrieval of the same index data (e.g. codebook) multiple times

Range Query Approach

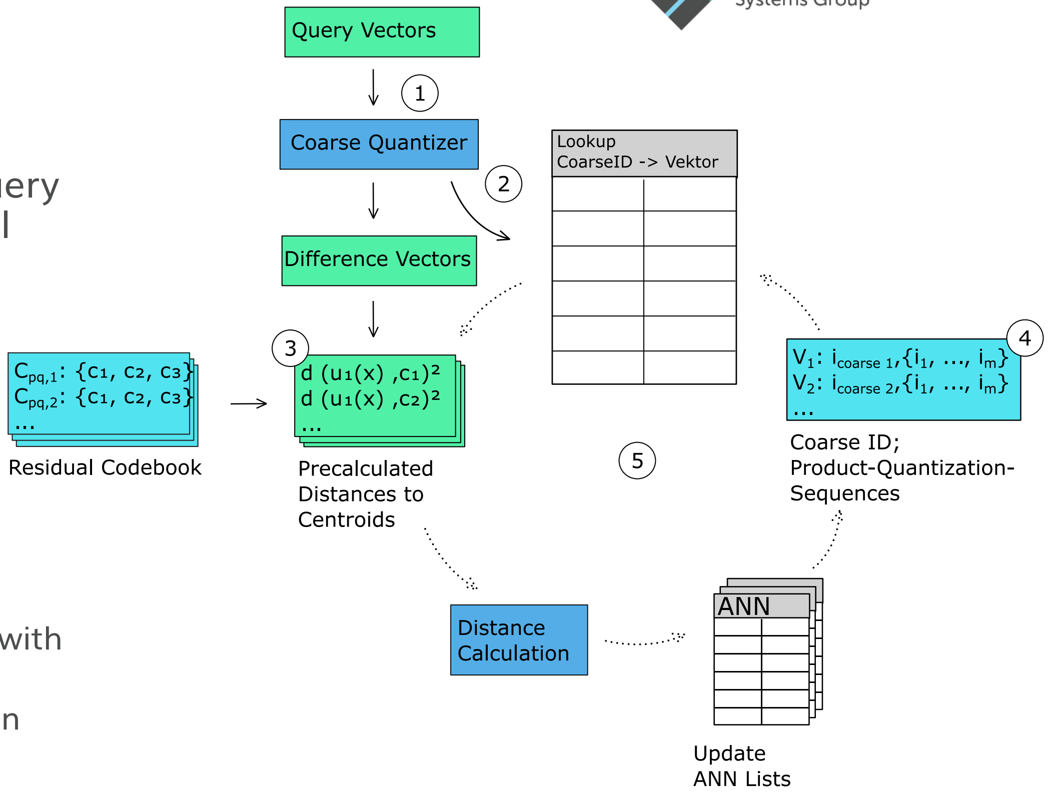
- Reduce retrieval time for aNN queries with batch-wise execution of queries
- UDF for range queries:

```
SELECT word
FROM k_nearest_neighbour_ivfadc_batch(ARRAY(SELECT title FROM movies), 3);
```

Range Queries

Algorithm

1. Determine coarse quantizations for query vectors and differentz vectors (residual vectors)
2. **Create lookup: coarse quantizations -> query vector**
3. Precalculate quadratic distances of subvectors
4. Retrieve IVFADC index entries (CoarseID, PQ-Sequenz von Residuum)
5. Iterative Processing of index entries:
    1. Retrieve residual vectors of query vectors with the same coarse id via lookup
    2. Caluclate approximated distances between residual vectors
    3. Update aNN for query vector



IVFADC batch search

Evaluation

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Evaluation Setup

- Search for 5 nearest neighbors
  - Calculation of response time and precision
  - Measurement for 100 Queries
    → Determine average values
- Dataset:
  - 3 million vectors
  - Dimensionality: 300
- Index parameter:
  - Length of PQ-sequences $m = 12$
  - Number of centroids for $q_1 \dots q_m$: 1024
  - Number of centroids for q_c : 1000
  - Results for post verification f : 1000
  - Size of batches : 100

Index	Response time	Precision
Exact search	8.79s	1.0
PQ search	1.06s	0.38
IVFADC	0.03s	0.35
PQ search (postverif.)	1.29s	0.87
IVFADC (postverif.)	0.26s	0.65
IVFADC (batch wise)	0.01s	0.35

Time and precision measurements

Current and Further Research

System Performance

Word2Bits

Source: Lam, M. (2018). Word2Bits - Quantized Word Vectors, 1–9. Retrieved from http://arxiv.org/abs/1803.05651

- Quantization of coordinate values in the training algorithm
- Allows compressed representation
- Act as a regularizer
- Study work: Lukas Stracke

$$Q_1(x) = \begin{cases} \frac{1}{3} & x \geq 0 \\ -\frac{1}{3} & x < 0 \end{cases}$$

Research Idea

- *Combine Word2Bits Approach with PQ- and IVFADC-search methods*
- *Finite number of possible centroids*

  $\rightarrow$ *Allows fast exact search*

System Performance

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LSH (Locality Sensitive Hashing)

- Hash functions mapping vectors which are nearby with high probability to the same bit sequence
- Index is obtained by applying multiple such locality sensitive hash functions on the vectors → Create lookup: hash value → vector
- Hash functions can be applied to the query vector → lookup vectors with same or similar hash values

$$h : \mathbb{R}^D \rightarrow \{0,1\}^k$$

$$LSH(\boldsymbol{v}) = h_1(\boldsymbol{v}), \ldots, h_l(\boldsymbol{v})$$

Research Idea

- Integration in relational database system
- Comparison with current aNN search methods
- Realization in bachelor theses: Carl Naumann

Demonstrator

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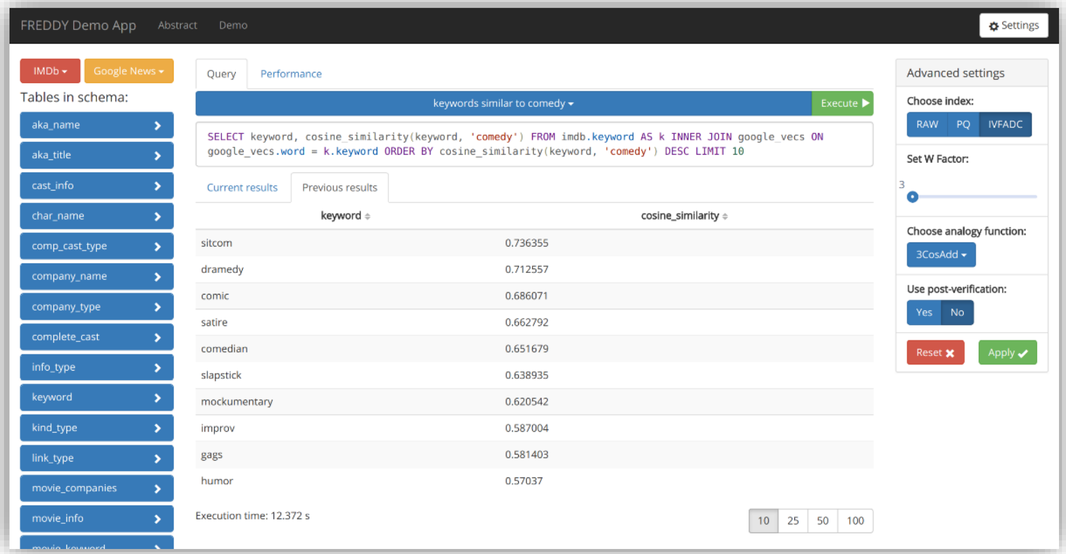
FREDDY Demo

- Web application as an interface for the WE-DBS
  → Currently only a command line interface
- Interactive Visualization of the performance and precision of the implemented search methods
- Submission for the CIKM 2018 (Deadline: 25.5.) (Demonstrator + Demo-Paper)
- Realization in Bachelor Theses: Zdravko Yanakiev

http://141.76.47.127:3000/



Context Advisor and Preprocessing

Problem Setting

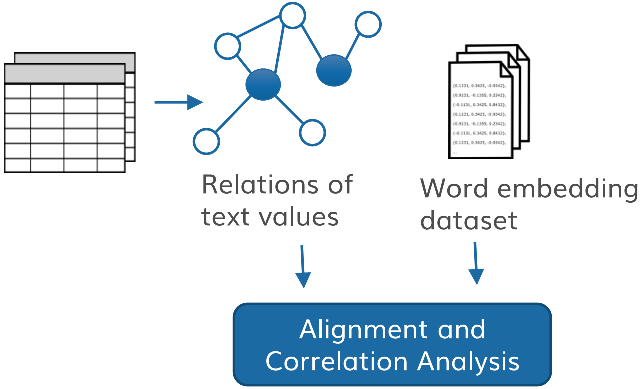
- Word vectors may refer to different entities as the tokens in the database
(e.g. apple: fruit vs. Apple Inc.)

  → Analyze context of the word vectors and database entities to make it possible to combine both information sources

Challenges

(1) Extract structured Information of text values in the DBS

- *Database does not contain explicit knowledge about the semantic of textual values*
→ Obtain semantic knowledge by observing the relations
- Column describes a context for the text values in it
→ Could be used to cope with polysemy of words
- Different text values can refer to the same instance (e.g. aliases, nicknames, etc.)



Context Advisor and Preprocessing

Challenges

(2) *Determine if entities are represented in the word embedding dataset*

- Observe how far structured knowledge is encoded in the word vectors
- Do relations encoded in the word vectors contradict with relations in the database?

(3) *Map Text Values to Word Vectors*

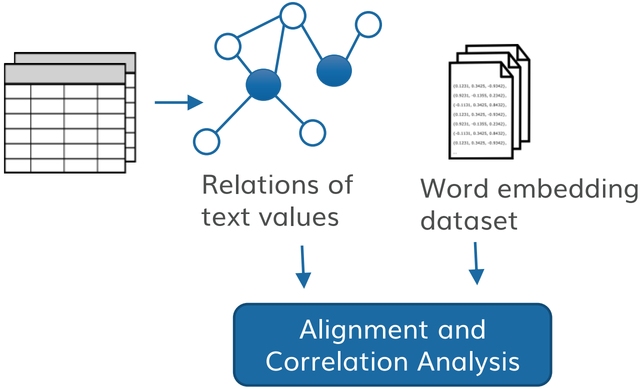
- Align structured knowledge in the database with the word vectors
- Decide which word embedding fits to the text value
- System can contain multiple word embedding datasets
  → Decide which word embedding dataset fits best

(4) *Result Set Interpretation for WE-DBS-Queries*

- kNN is not always meaningful (too small similarity values have low validity or at least could hardly be interpreted)
  → Quantify certainty of the truth of results

(5) *Word Embedding Imputation: Integrate Missing Entities in Word Embedding Dataset*

Vectorization of structured knowledge and align to word vectors



Related Work

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Sense2Vec: NER tagging before training

Trask, A., Michalak, P., & Liu, J. (2015). sense2vec - A Fast and Accurate Method for Word Sense Disambiguation In Neural Word Embeddings, 1–9. Retrieved from http://arxiv.org/abs/1511.06388

- Named Entity Recognition as preprocessing
  → Classes are annotated to named entities
- Instead of vector set for words vector set for senses

Apple has presented a new product in Chicago ...

Text corpora in natural language

NER Tool

Apple_ORG has presented a new product in Chicago_GPE ...

Text corpora where NE are tagged

Word2Vec

Apple_ORG: [0.343, -0.212, ...]
Apple_NOUN: [0.343, -0.212, ...]
...

Related Work

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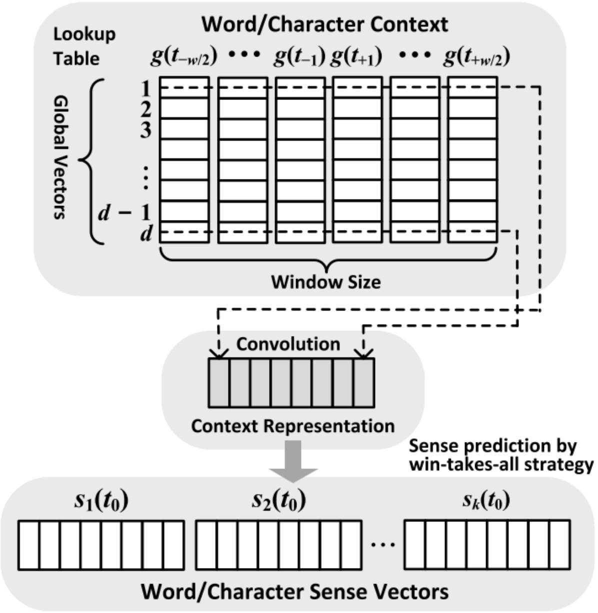
Context-Specific Multi-Prototype Word Embeddings

Zheng, X., Feng, J., Chen, Y., Peng, H., & Zhang, W. (n.d.). Learning Context-Specific Word/Character Embeddings, 3393–3399.

- Assumption: Different word senses occur in different contexts
- Idea: Convolutional Layer represents context
  → Trained to predict word sense from context representation
- Second Step: If context vector is dissimilar to sense vector
  → Create additional sense vectors for the respective words
  → Retrain the model with multiple sense vectors per token



Source: Zheng, X., Feng, J., Chen, Y., Peng, H., & Zhang, W. (n.d.). Learning Context-Specific Word/Character Embeddings, 3393–3399.

Related Work

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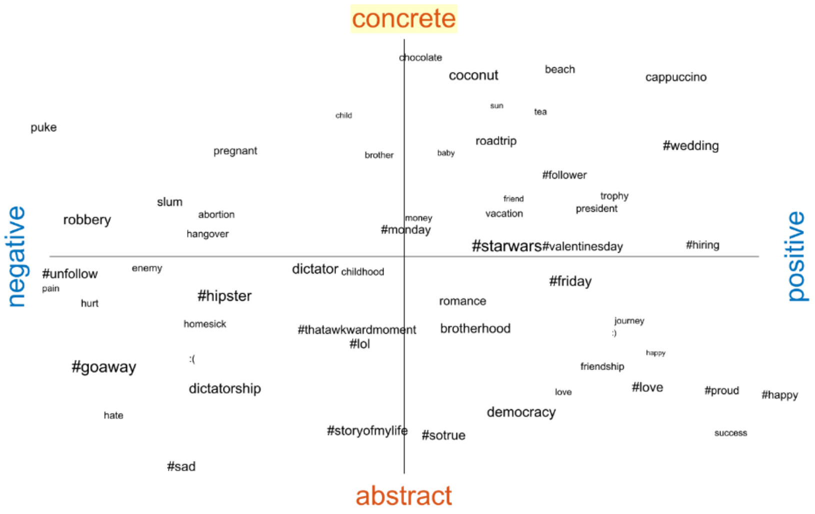
Densifer: Focus information for specific properties (sentiment, frequency, concreteness) in ultradense subspaces

Rothe, S., Ebert, S., & Schütze, H. (2016). Ultradense Word Embeddings by Orthogonal Transformation. Retrieved from http://arxiv.org/abs/1602.07572

- Training of Orthogonal Matrix $Q \in \mathbb{R}^{d \times d}$ for projecting Word Embedding $e_w \in \mathbb{R}^{d}$ in a vector space where specific dimensions (ultradense subspaces) represent specific properties of the token (e.g. sentiment, concreteness)
- Subspace $u_w \in \mathbb{R}^{d^*}$ can be obtained by multiplication with an Identity Matrix $P \in \mathbb{R}^{d^* \times d}$ specific for the property:

$$u_w = PQe_w$$



Source: Rothe, S., Ebert, S., & Schütze, H. (2016). Ultradense Word Embeddings by Orthogonal Transformation. Retrieved from http://arxiv.org/abs/1602.07572

Related Work

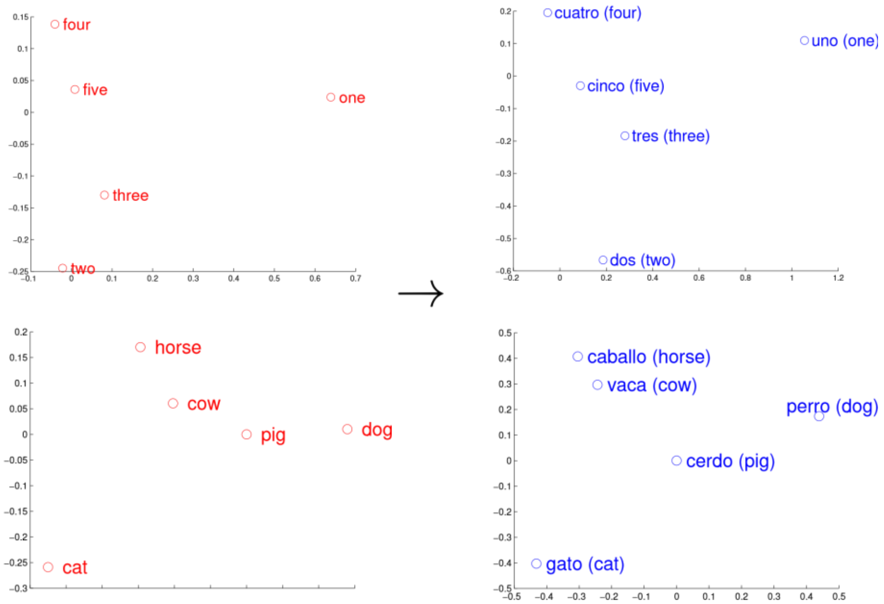
Translation Matrix

Mikolov, T., View, M., Le, Q. V, View, M., Sutskever, I., & View, M. (n.d.). Exploiting Similarities among Languages for Machine Translation.

- Training of Translation Matrix W for Transformation of Embeddings from one vector space to another

$$\min_{W} \sum_{i=1}^{n} \|W x_i - z_i\|^2$$

- Training Data: small dictionary of token pairs (x_i, z_i)
- Training with Stochastical Gradient Decent



Source: Mikolov, Tomas, Quoc V. Le, and Ilya Sutskever. "Exploiting similarities among languages for machine translation." *arXiv preprint arXiv:1309.4168* (2013).

Related Work

Joint Embeddings (for Knowledge Graph Completion)

Wang, Z., Zhang, J., Feng, J., & Chen, Z. (2014). Knowledge Graph and Text Jointly Embedding. Emnlp

- Joint Model - Embeddings for nodes in knowledge graphs and tokens in texts
- Knowledge Graph Nodes:
  - Minimze: $||\boldsymbol{h} + \boldsymbol{r} - \boldsymbol{t}||$ for a fact $(\boldsymbol{h}, \boldsymbol{r}, \boldsymbol{t})$ in the Graph (Edge)
- Text Model:
  - Similar to Word2Vec SkipGram Model (Trained to predict probability of co-occurrence)
- 3 Likelihood consists of three terms:
  - Knowledge Model L_K
  - Text Model L_T
  - Alignment L_T: Nodes with the same label as named entities should have similar vectors as the according tokens
- Training: Maximization of $L_k + L_T + L_A$

Related Work

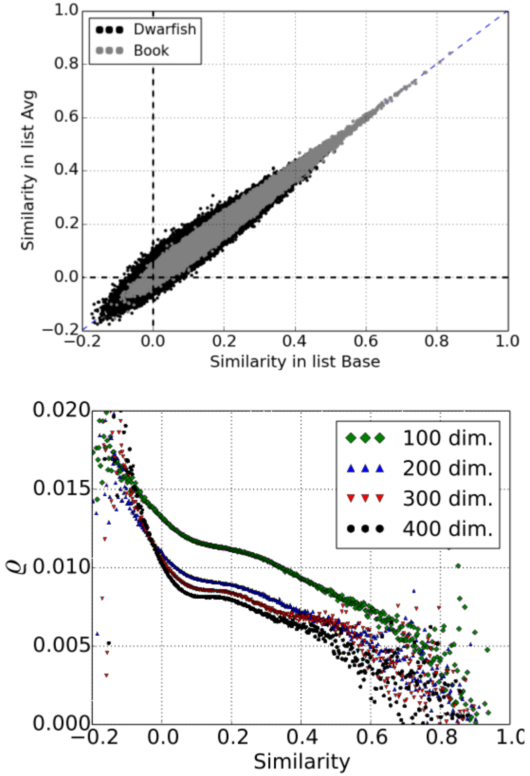
Uncertainty of word vector similarity

Rekabsaz, N., Lupu, M., & Hanbury, A. (2016). Uncertainty in Neural Network Word Embedding: Exploration of Threshold for Similarity. https://doi.org/10.1007/978-3-319-56608-5_31

- Measured the distribution of Similarity values
- Determine uncertainty ϱ of similarity values by training a model two times on the same text corpora with different model initialization

→ Low similarity values are more uncertain

→ For specific tasks usability of word vectors could be improved by thresholds for similarity values



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Complexity of the WE-Queries

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Multiple Datasets:

- Word embedding operations can be executed on different WE datasets
- Word embedding datasets could be combined
- (Not all entities in a column have an corresponding instance in the word embedding dataset)

Multiple Parameters:

- Different queries have different demands in terms of
  - Precision of Search Operations itself
  - Execution Time of the Operations
  - Certainty of similarity values

Index structures

- Multiple index structures for one dataset (different types and different parameters)
- Change over time (It is possible to add entities during runtime)

Complexity of the WE-Queries

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Deal with the Complexity

- Huge number of User Defined Functions:

  At the moment 86 additional UDFs (, and there will be more …)
  But: Only 5 basic operations
- At the moment two options:
  1) Cope with complexity – Operations with a lot of parameters
  2) Transfer configuration to separate functions – define configuration global

     Problems:
     - Non-transparent: same query returns different results (with different configuration)
     - Inflexible: multiple operations in one query share the same configuration
- Possible Solution:
  - Objects storing for database entries how they could be examined by word embedding operations
  - In specific contexts where an entity is used it might play different roles