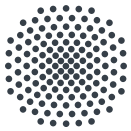

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The LSCD Benchmark: A testbed for diachronic word meaning tasks

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Introduction

- Lexical Semantic Change Detection (Schlechtweg, 2023)
  - goal: automate the analysis of changes in word meanings over time
    (1) *Der zweyte Theil vom Bauernrechte ist schon lange aus der **Presse**;*
    'The second part of Farmers' Rights already left the **press**;'
    (2) *Alle Freiheiten suspendirt! die persönliche Freiheit wie die der **Presse**!*
    'All freedoms suspended! the personal freedom as well as the one of the **press**!'
- **heterogeneity** and **modularity** in models, datasets and tasks

→ create one repository[1] standardizing model component combinations, dataset preprocessing and evaluation

[1] `https://github.com/ChangeIsKey/LSCDBenchmark`

Human Measurement of Lexical Semantic Change

A	1824	and taking a knife from her pocket, she opened a vein in her little **arm**,
B	1842	And those who remained at home had been heavily taxed to pay for the **arms**, ammunition;
C	1860	and though he saw her within reach of his **arm**, yet the light of her eyes seemed as far off
		...
D	1953	overlooking an **arm** of the sea which, at low tide, was a black and stinking mud-flat
E	1975	twelve miles of coastline lies in the southwest on the Gulf of Aqaba, an **arm** of the Red Sea.
F	1985	when the disembodied **arm** of the Statue of Liberty jets spectacularly out of the

Table 1: Sample of diachronic corpus.

Word Use Pairs

(A) [. . .] and taking a knife from her pocket, she opened a vein in her little **arm**, and dipping a feather in the blood, wrote something on a piece of white cloth, which was spread before her.

(D) It stood behind a high brick wall, its back windows overlooking an **arm** of the sea which, at low tide, was a black and stinking mud-flat [. . .]

Semantic Proximity Scale

4: Identical
3: Closely Related
2: Distantly Related
1: Unrelated

Table 2: DURel relatedness scale.

Graph representation

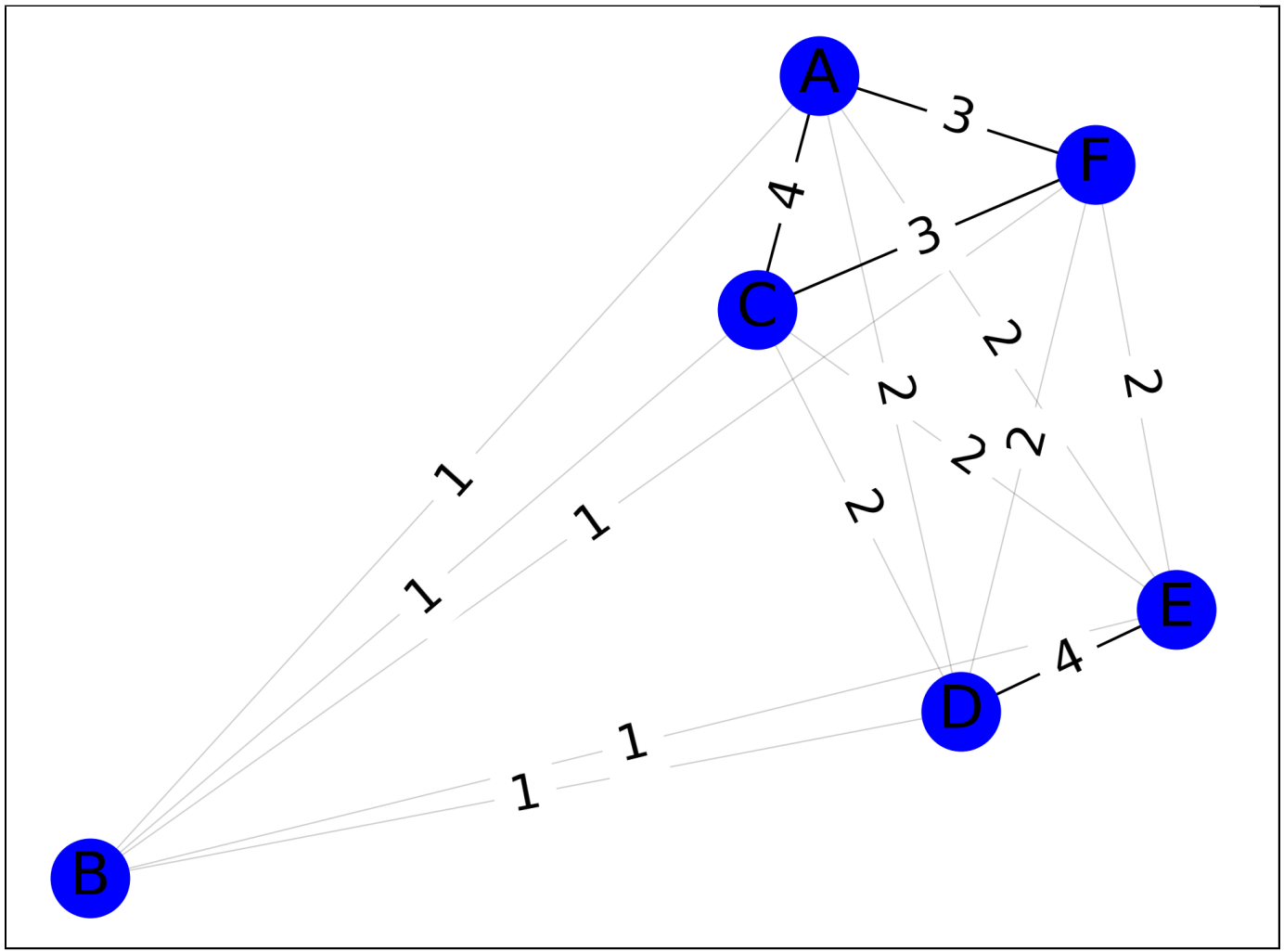


Figure 1: Word Usage Graph of English *arm*.

Clustering

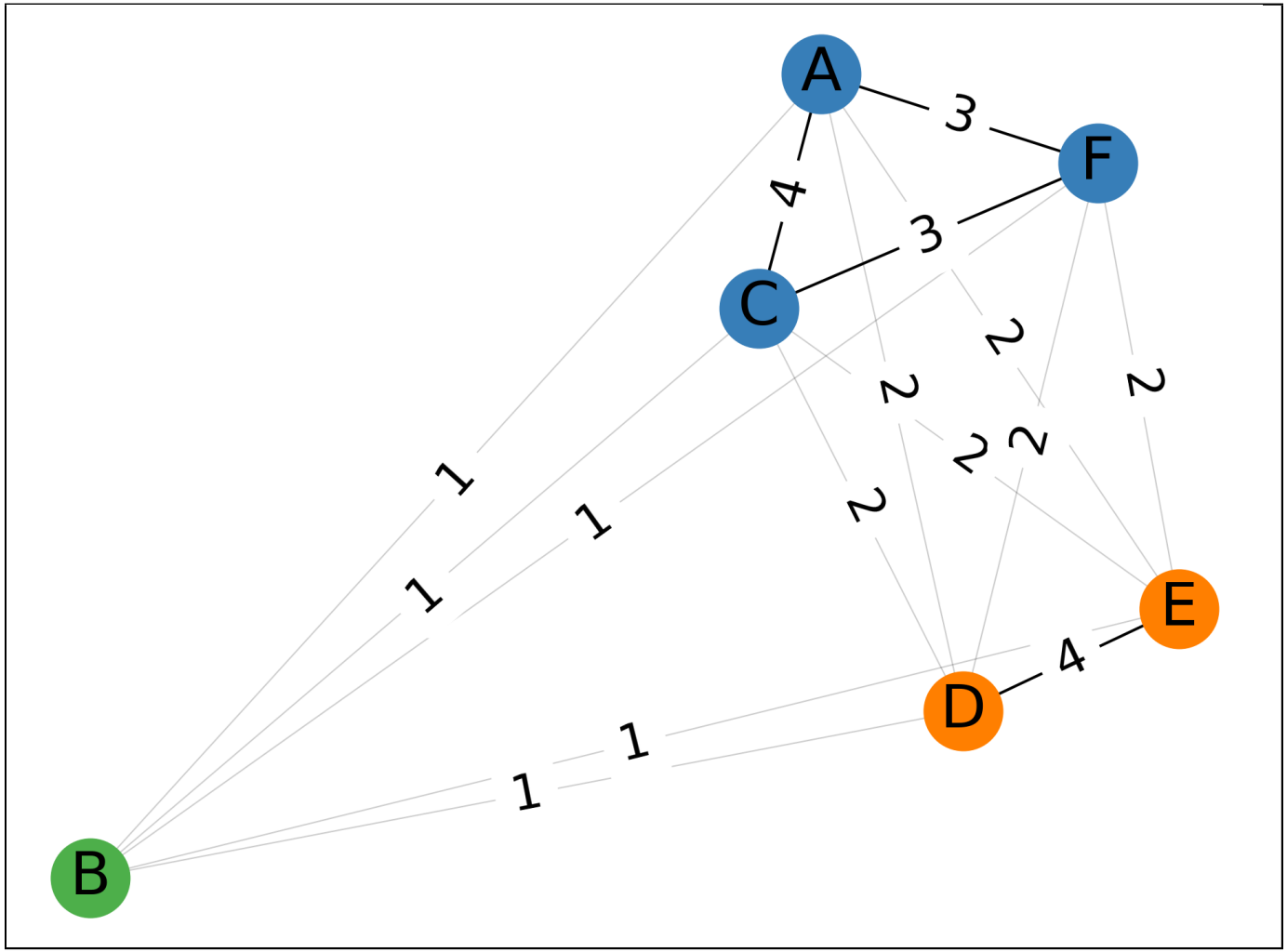
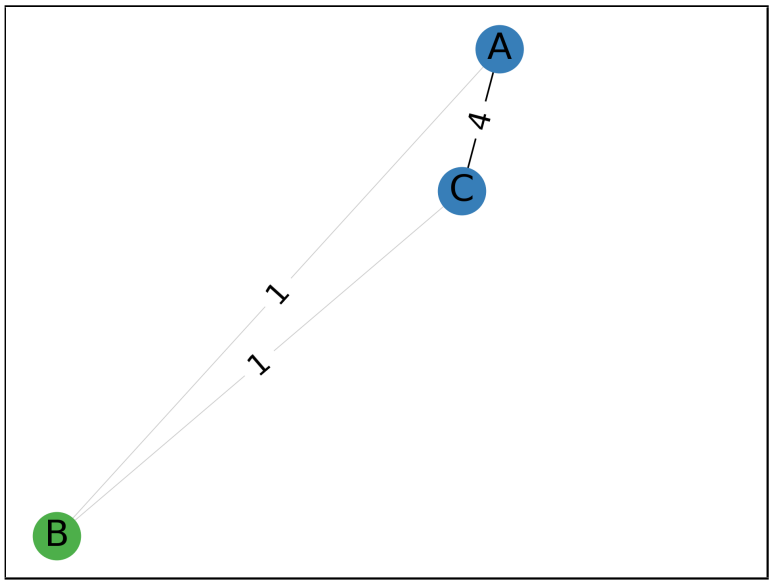
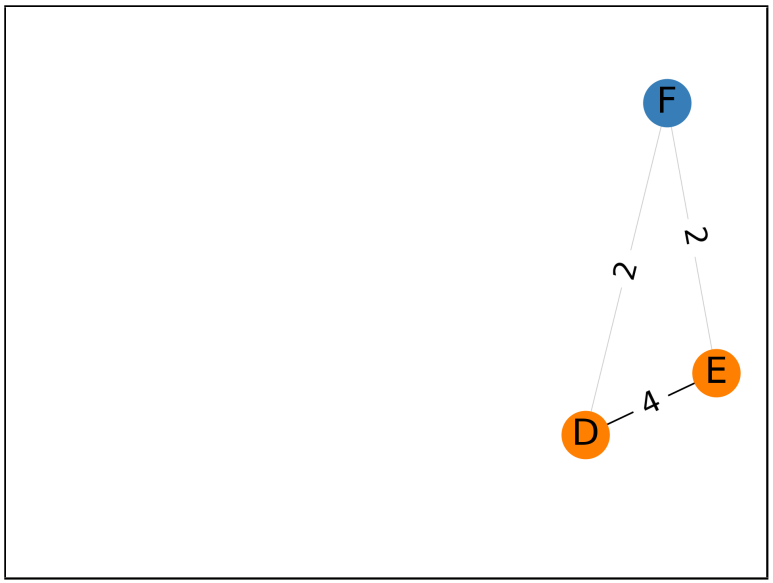


Figure 2: Word Usage Graph of English *arm*. $D = (3, 2, 1)$.

Lexical Semantic Change



$t_1,\ D_1 = (2,0,1)$



$t_2,\ D_2 = (1,2,0)$

Change Scores

- **binary change** (loss and gain of senses)
- **graded change** (changes in sense probabilities)

Example: Swedish *ledning*[2]

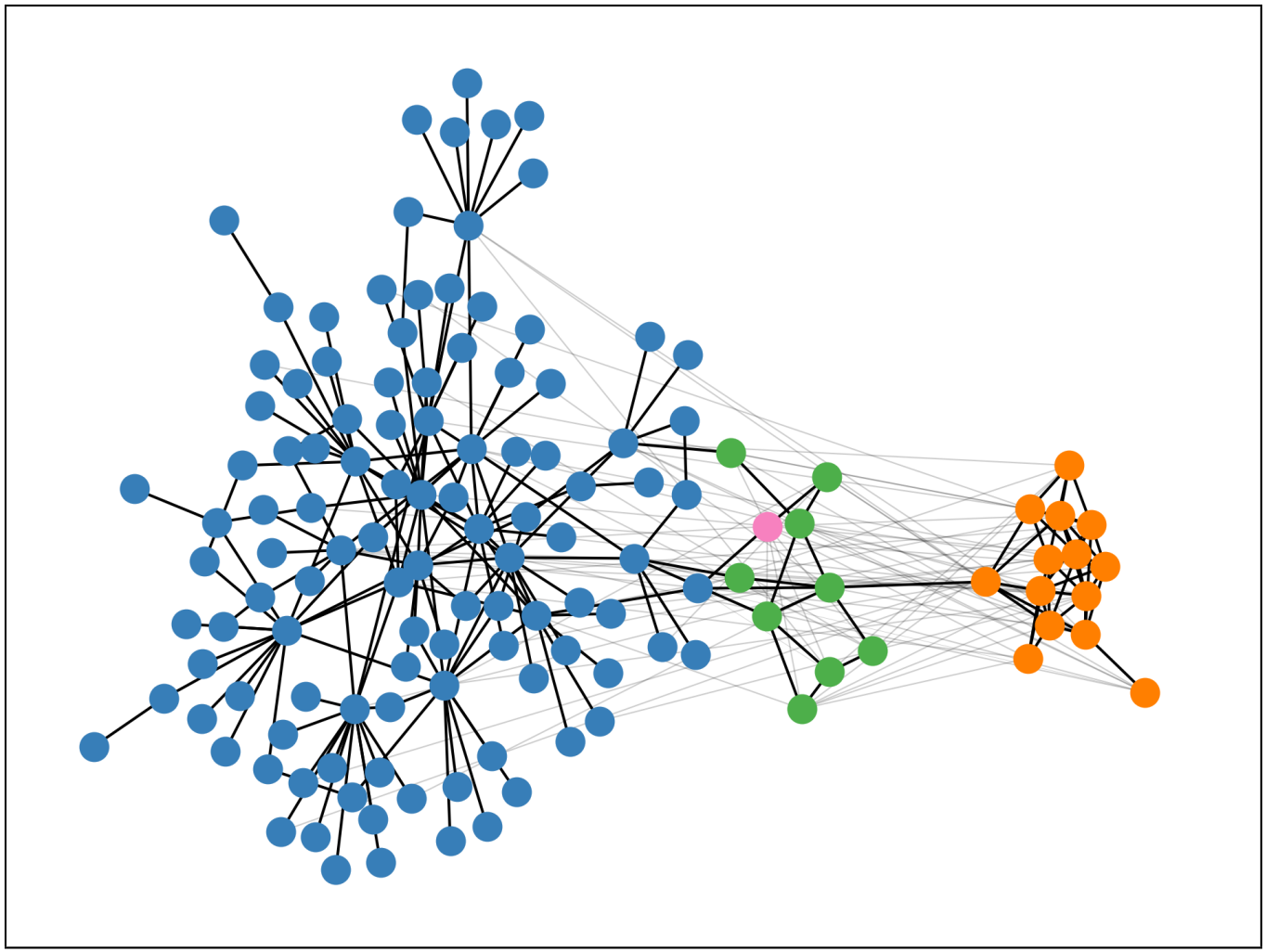


Figure 4: WUG of Swedish *ledning*.

[2]Datasets available at `https://www.ims.uni-stuttgart.de/data/wugs`

Example: Swedish *ledning*

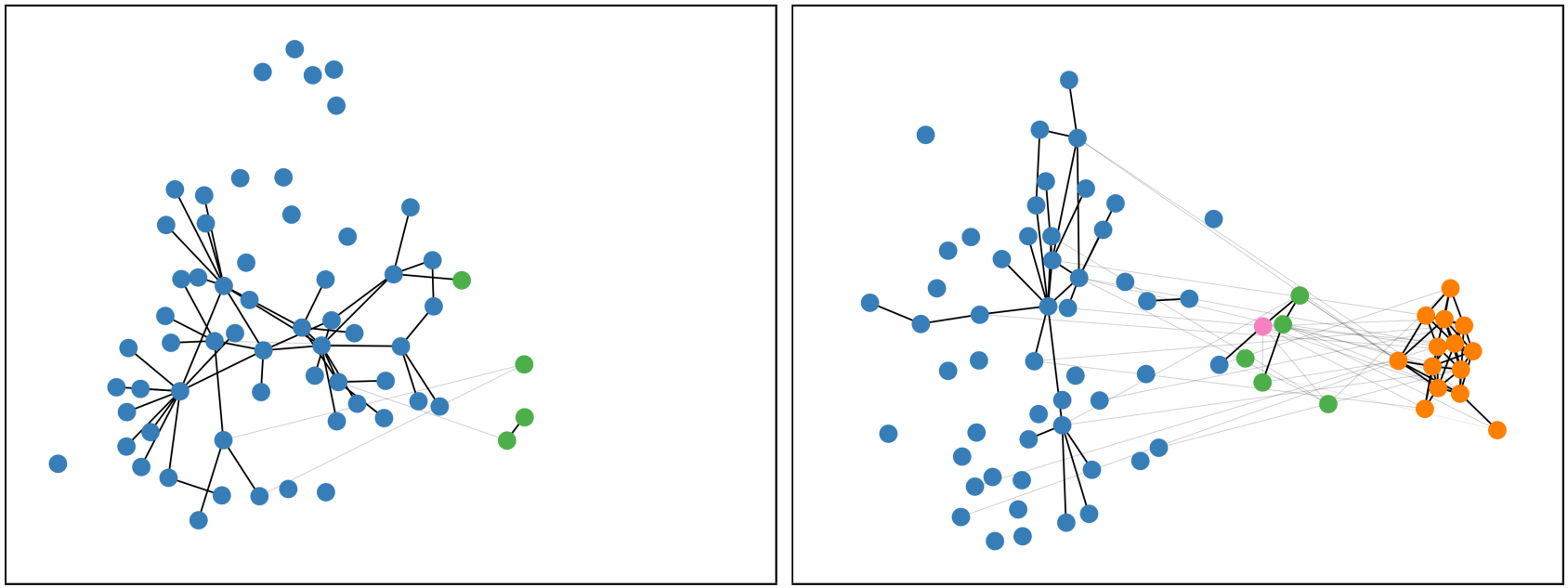


Figure 5: WUGs of Swedish *ledning*: subgraphs for 1st time period G_1 (left) and 2nd time period G_2 (right). $D_1 = (58, 0, 4, 0)$, $D_2 = (52, 14, 5, 1)$, $B(w) = 1$ and $G(w) = 0.34$.

Example: German *Eintagsfliege*

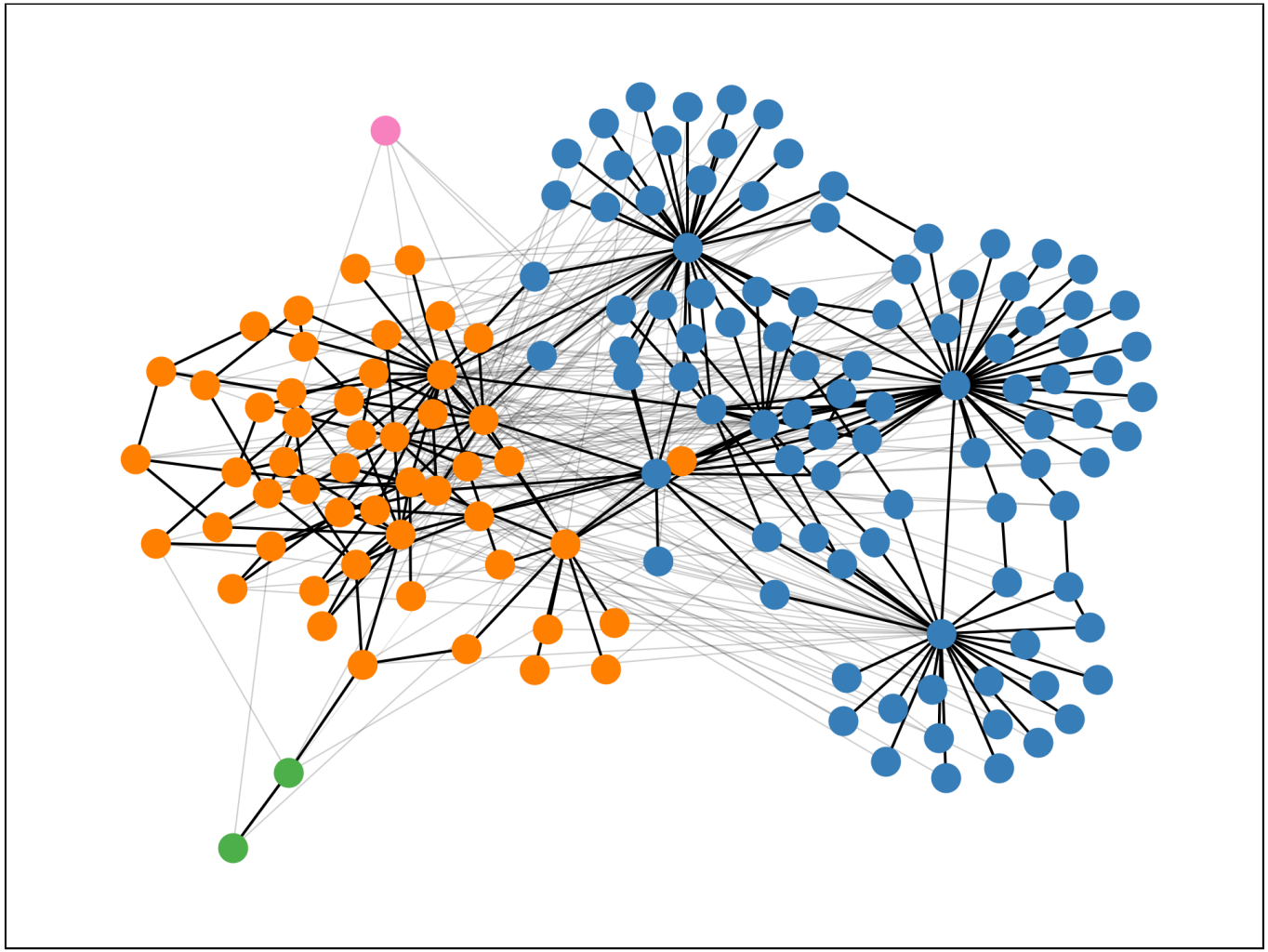


Figure 6: WUG of German *Eintagsfliege*.

Example: German *Eintagsfliege*

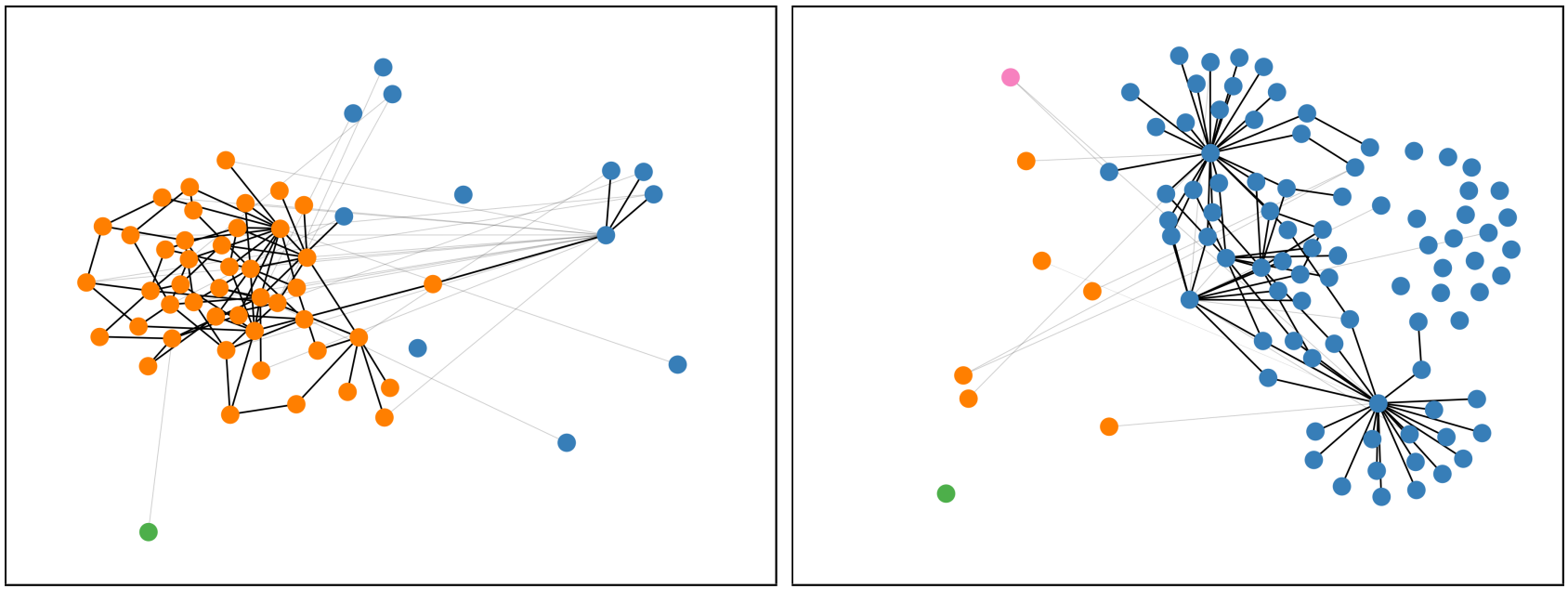


Figure 7: WUG of German *Eintagsfliege*: subgraphs for 1st time period G_1 (left) and 2nd time period G_2 (right). $D_1 = (12, 45, 0, 1)$, $D_2 = (85, 6, 1, 1)$, $B(w) = 0$ and $G(w) = 0.66$.

Summary of Annotation Steps

1. semantic proximity labeling
2. clustering
3. change measurement

Summary of Annotation Steps with Tasks

1. semantic proximity labeling ↔ **Word-in-Context Task**
2. clustering ↔ **Word Sense Induction**
3. change measurement ↔ **Lexical Semantic Change Detection** (including previous tasks)

Computational Measurement of Lexical Semantic Change

- Typical (token-based) Model is composed by
  1. semantic proximity model (e.g. similarity between contextualized embeddings)
  2. clustering method (optional)
  3. change measure

The LSCD Benchmark

- exploit **modularity**
- guarantee **reproducibility** through standardization of data preprocessing and task evaluation
- simplify model **application**

Usage Example

```
python main.py \
  dataset=dwug_de_210 \
  dataset/split=dev \
  dataset/preprocessing=raw \
  task/lscd_graded@task.model=apd_compare_all \
  task/wic@task.model.wic=contextual_embedder \
  task/wic/metric@task.model.wic.similarity_metric=cosine \
  task.model.wic.ckpt=bert-base-german-cased \
  task=lscd_graded \
  evaluation=change_graded
```

Proof of Concept

- test two model alternatives on a common dataset (DWUG DE) under comparable conditions

Full graph representation

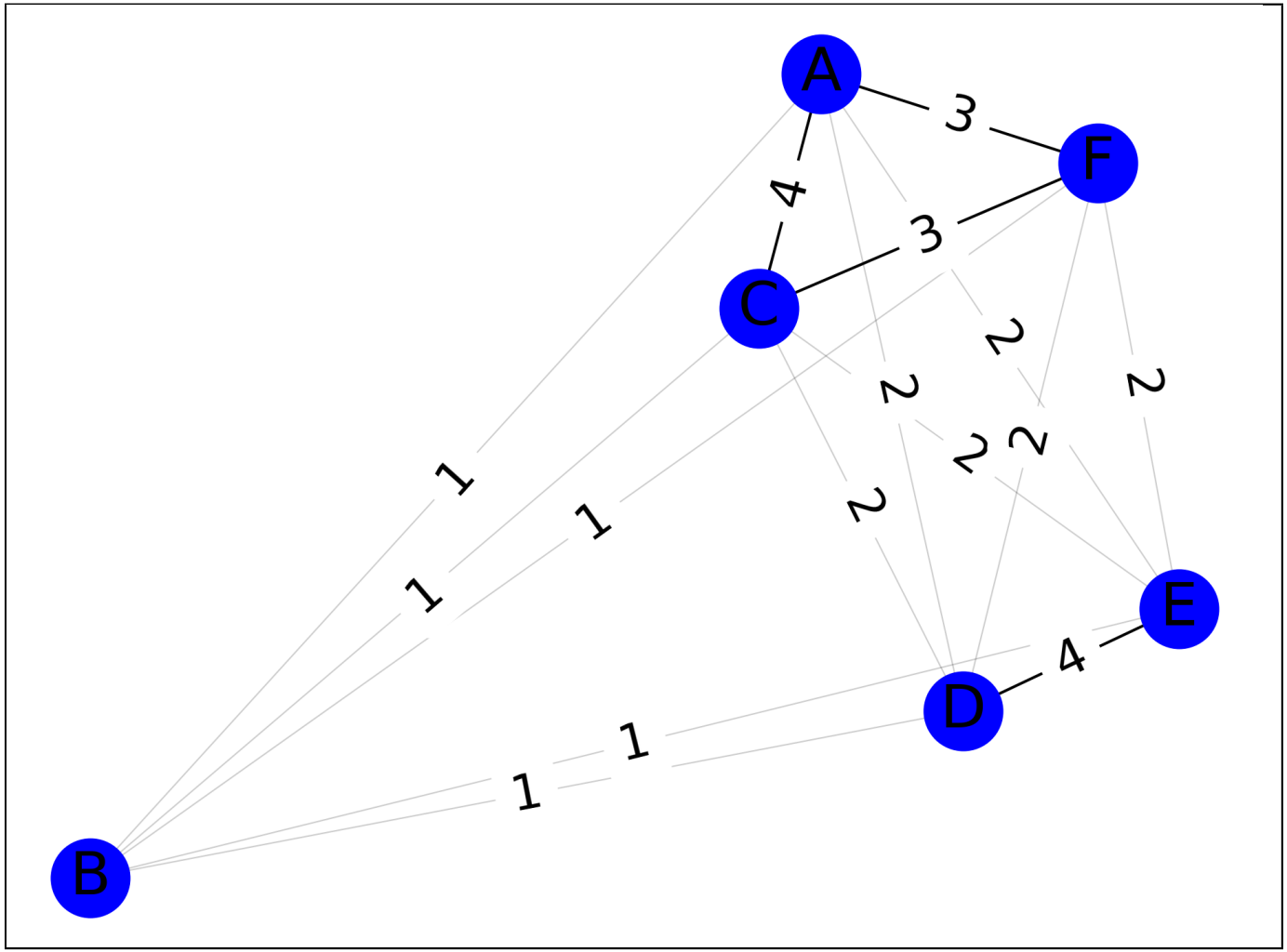
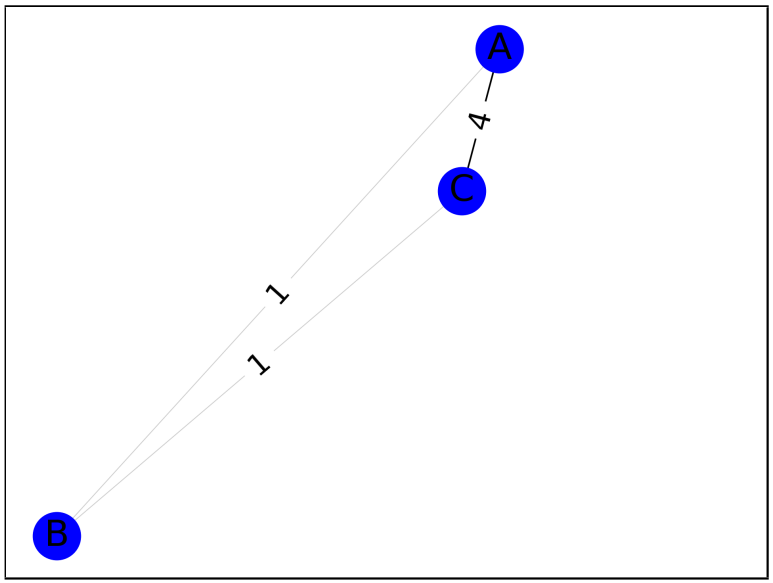
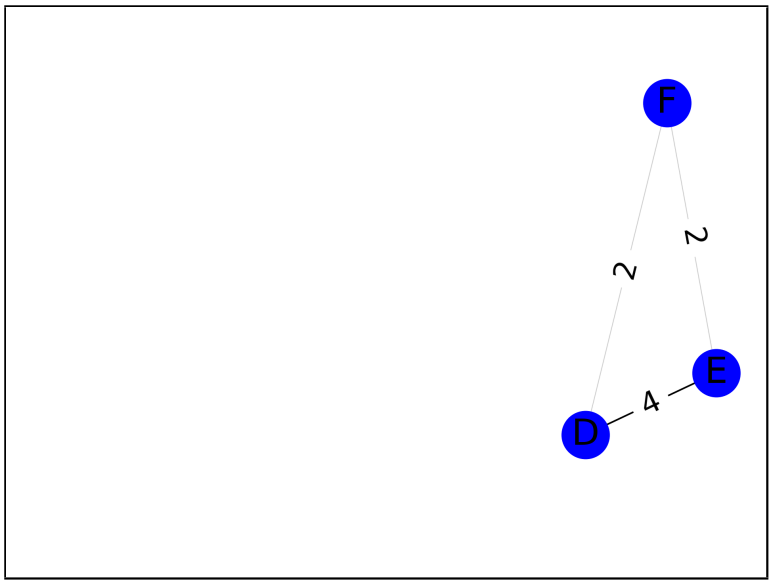


Figure 8: Word Usage Graph of English *arm*.

Time-wise subgraphs (EARLIER and LATER)



t_1 (EARLIER)



t_2 (LATER)

COMPARE subgraph

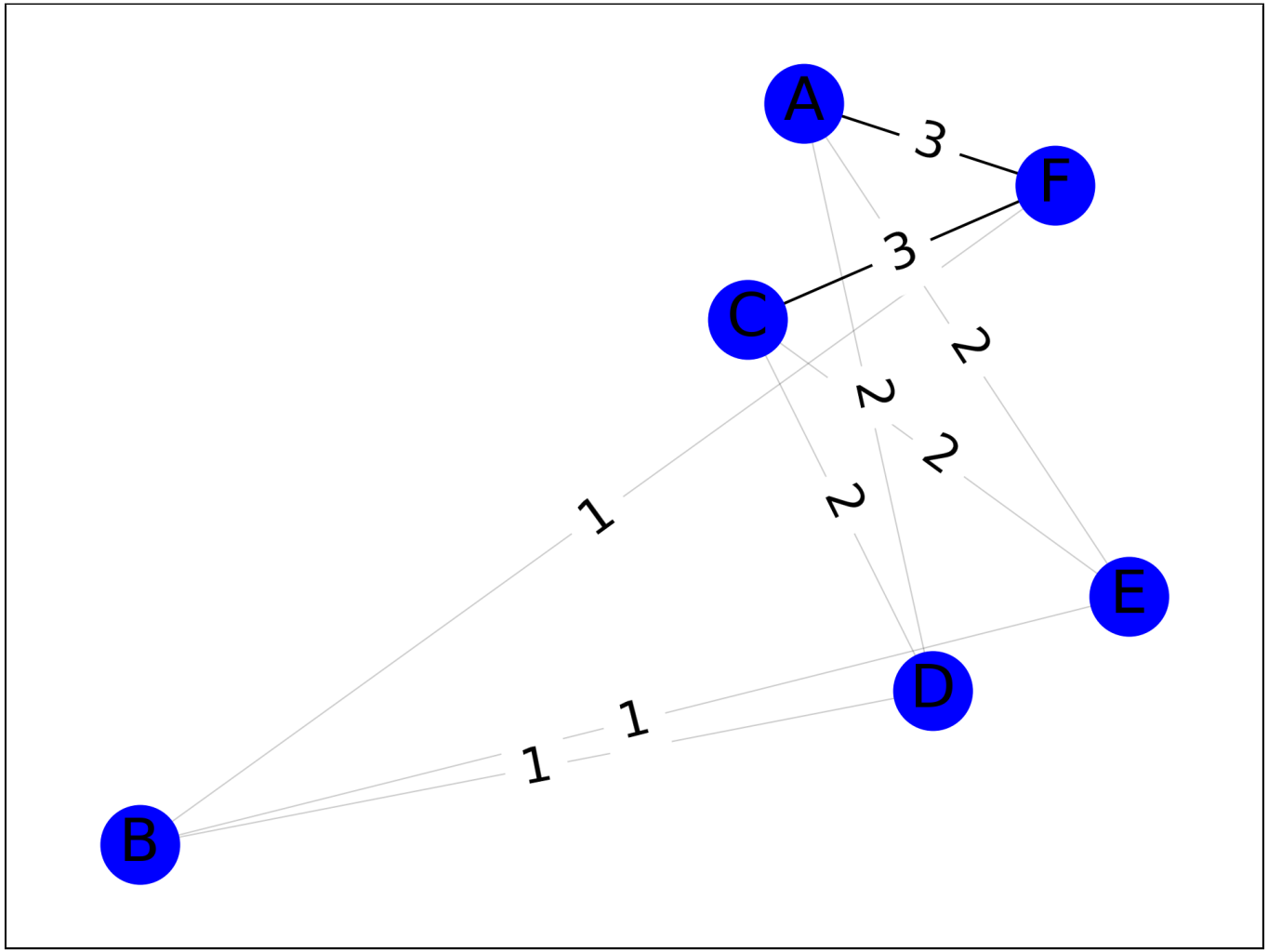


Figure 10: COMPARE subgraph of English *arm*.

Common graded change models

- **Average Pairwise Distance** (APD): estimates the edge weights from COMPARE graph and takes their mean: $G(w) = mean(COMPARE)$ (e.g. Kutuzov & Giulianelli, 2020)
- **DiaSense**: normalizes APD by weights from full graph: $G(w) = mean(COMPARE) - mean(FULL)$ (Beck, 2020)

Benchmark command APD

```
python main.py \
  dataset=dwug_de_210 \
  dataset/split=dev \
  dataset/preprocessing=toklem \
  task/lscd_graded@task.model=apd_compare_sampled \
  task/wic@task.model.wic=contextual_embedder \
  task/wic/metric@task.model.wic.similarity_metric=cosine \
  task.model.wic.ckpt=bert-base-german-cased \
  task=lscd_graded \
  evaluation=change_graded
```

Benchmark command DiaSense

```
python main.py \
  dataset=dwug_de_210 \
  dataset/split=dev \
  dataset/preprocessing=toklem \
  task/lscd_graded@task.model=diasense_sampled \
  task/wic@task.model.wic=contextual_embedder \
  task/wic/metric@task.model.wic.similarity_metric=cosine \
  task.model.wic.ckpt=bert-base-german-cased \
  task=lscd_graded \
  evaluation=change_graded
```

Result

Model	Run 1	Run 2	Run 3
APD	.63	.61	.63
DiaSense	**.64**	.55	.61

Table 3: Performance of model alternatives under comparable conditions on DWUG DE.

Upcoming

- Are current results for SOTA models reproducible on cleaned data?
- Can we find better measures for graded change than APD?
- Can clustering on optimized WiC models improve results on binary change?
- How do current models for binary change perform in scenarios where correlation is low with graded change?
- How do current models for graded change perform in high-polysemy scenarios?
- How do model hyper-parameters generalize between data sets?

References I

Beck, C. (2020). DiaSense at SemEval-2020 Task 1: Modeling sense change via pre-trained BERT embeddings. In *Proceedings of the 14th international workshop on semantic evaluation.* Barcelona, Spain: Association for Computational Linguistics.

Kutuzov, A., & Giulianelli, M. (2020). UiO-UvA at SemEval-2020 Task 1: Contextualised Embeddings for Lexical Semantic Change Detection. In *Proceedings of the 14th international workshop on semantic evaluation.* Barcelona, Spain: Association for Computational Linguistics.

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