

Simulation and mining of social networks in a pandemic context

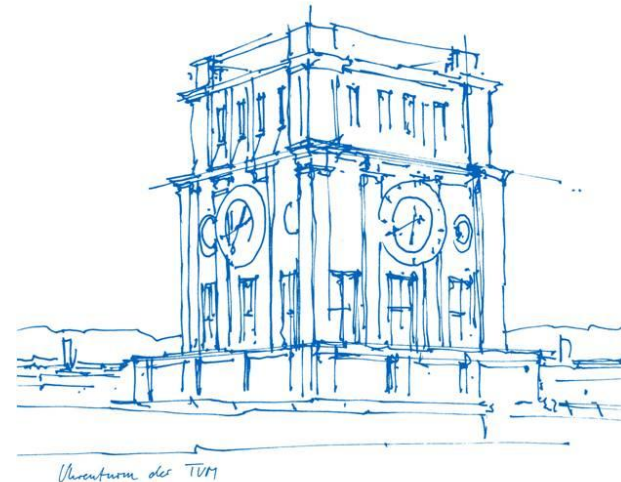
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Technische Universität München

Faculty of Informatics

Chair of Social Computing

Garching, 19.04.2021



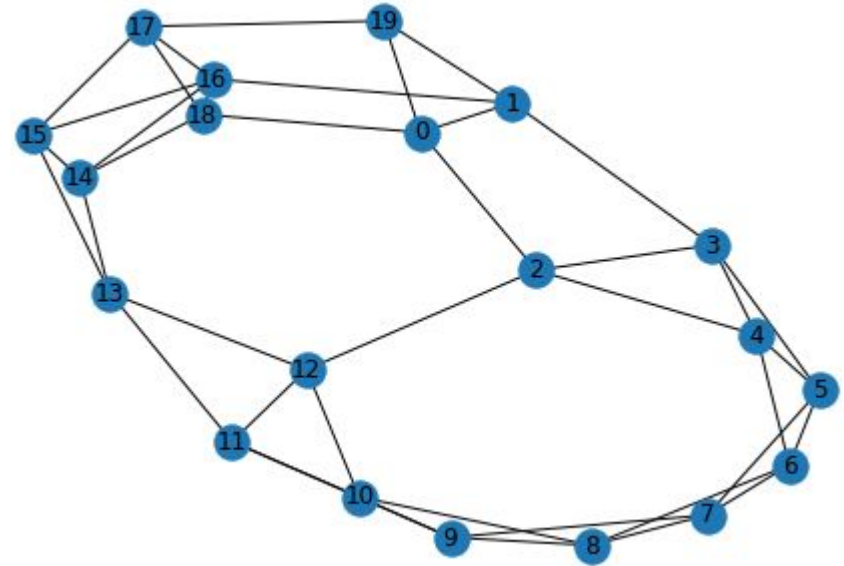
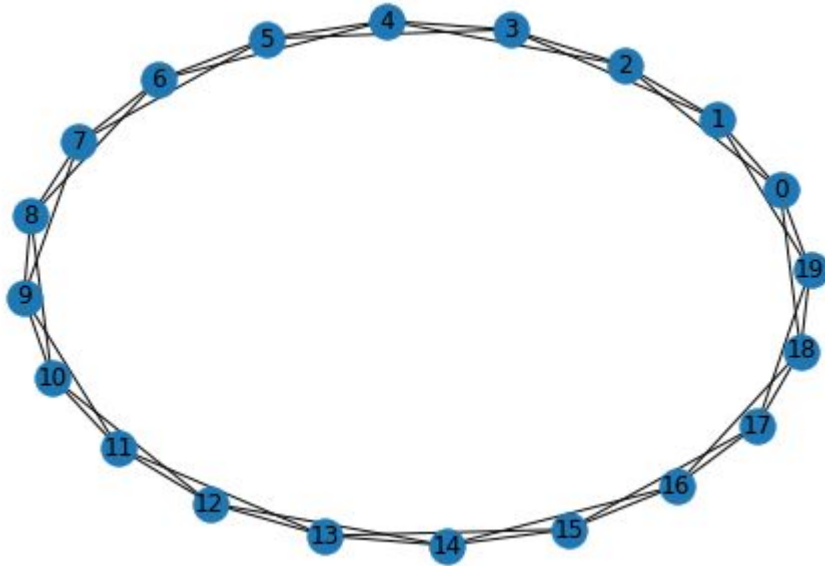
Outline

- Generation of long-term social network
- Individual risk prediction
- Action-based risk prediction

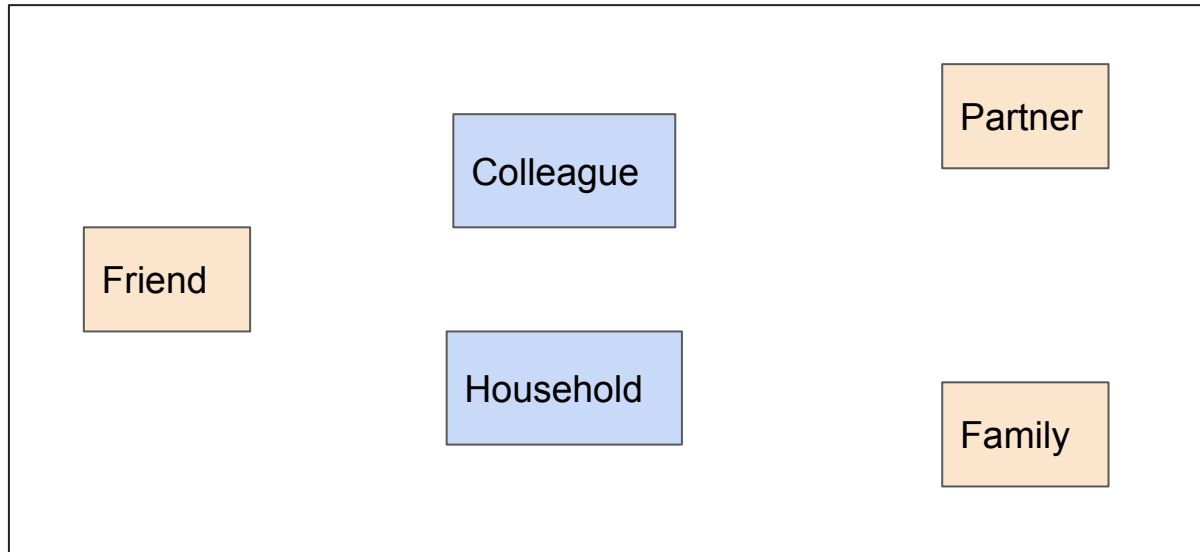
Objective

- Generate a real-world graph
- Model long-term relationships
- Store work and home facility

Watts-Strogatz model



Edge types

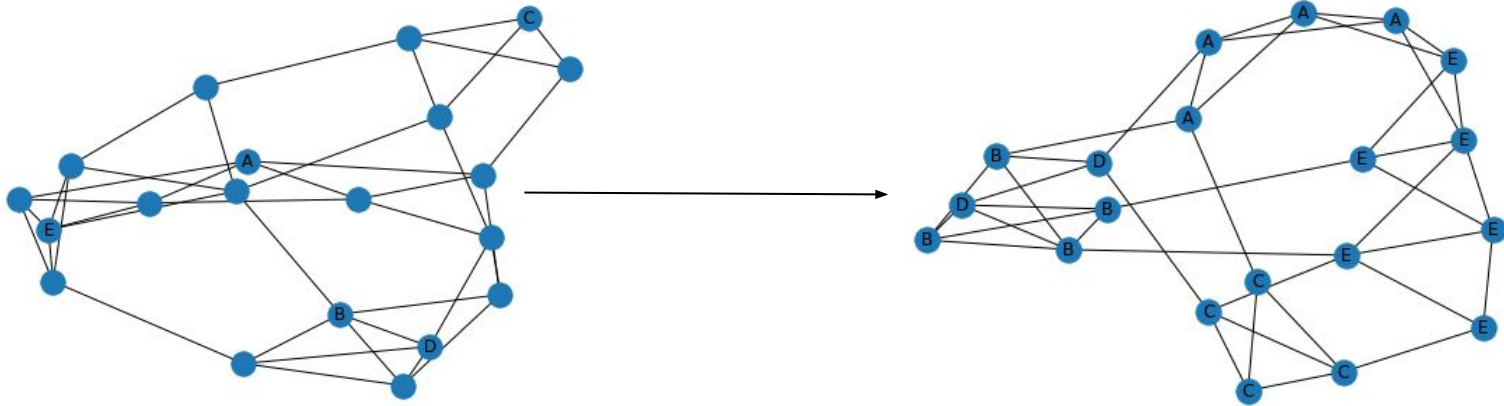


Based on node
attributes

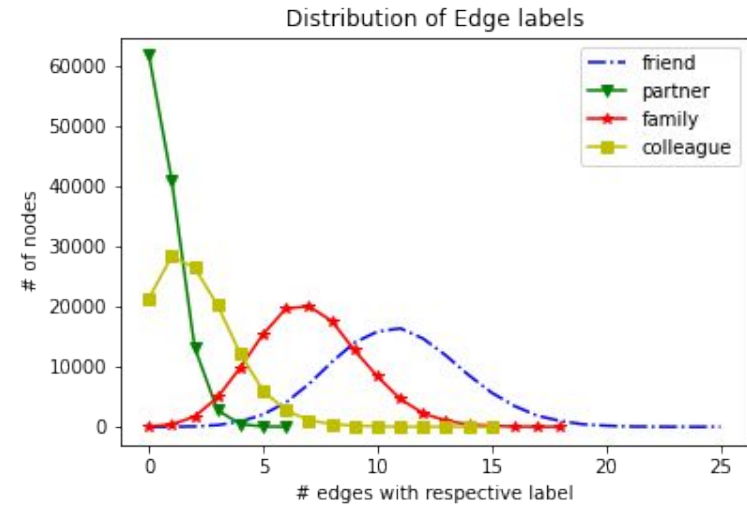
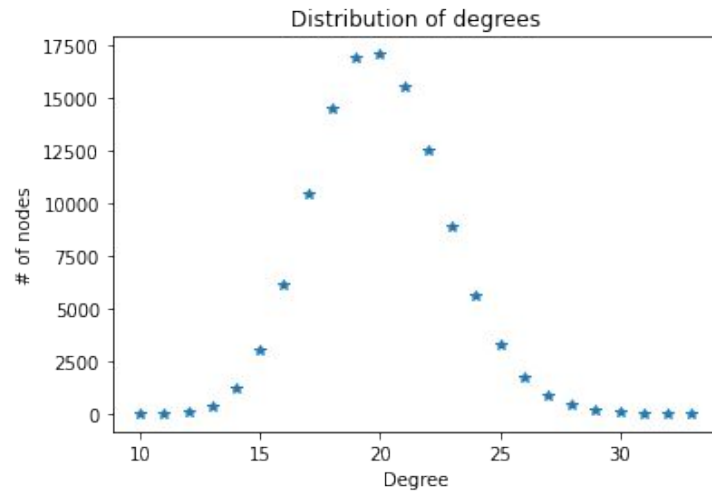
Random assignment

Node classification [1]

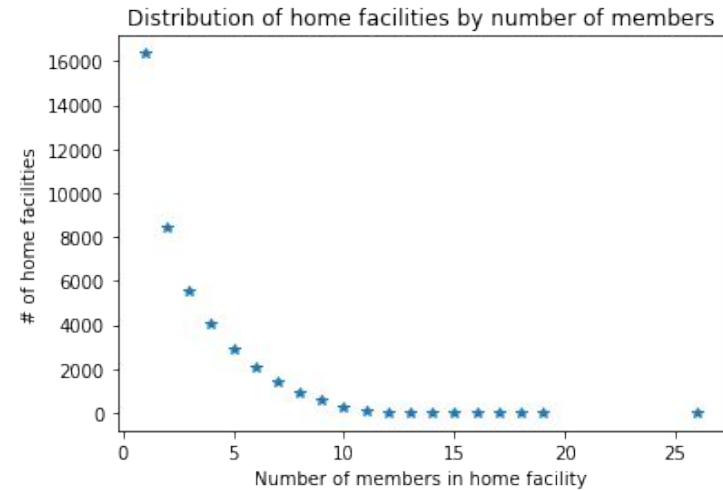
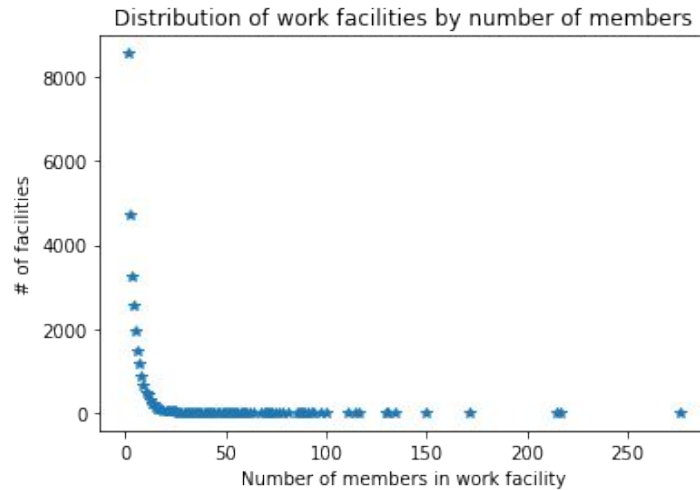
- Assign given facility to a random node
- Propagate attribute: Close nodes should have similar attributes



Results



Results



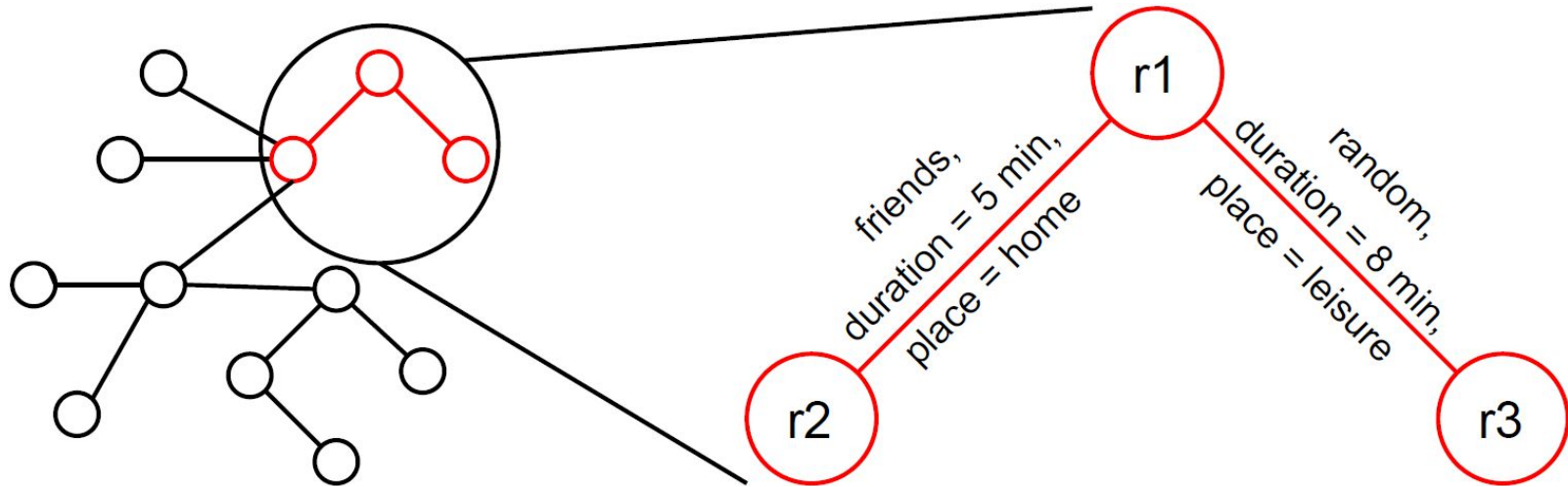
Outline

- Generation of long-term social network
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Objective: Extend the German Corona Warn app

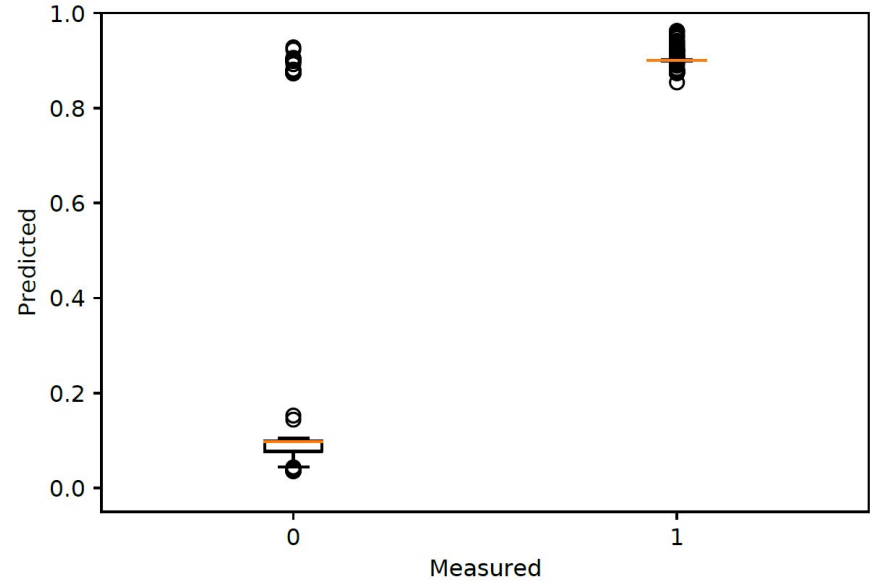
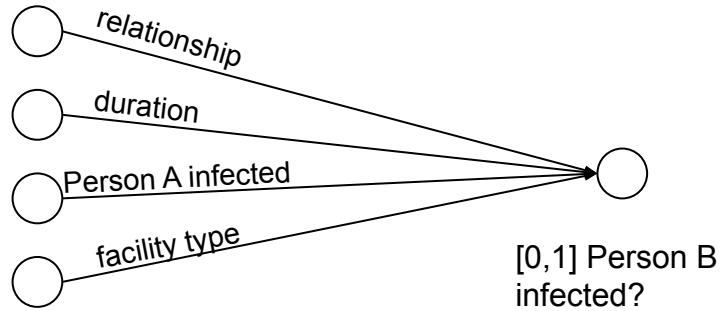
- Encounter-based live prediction
- Continuous instead of binary risk

Encounter network



Encounter risk with regression

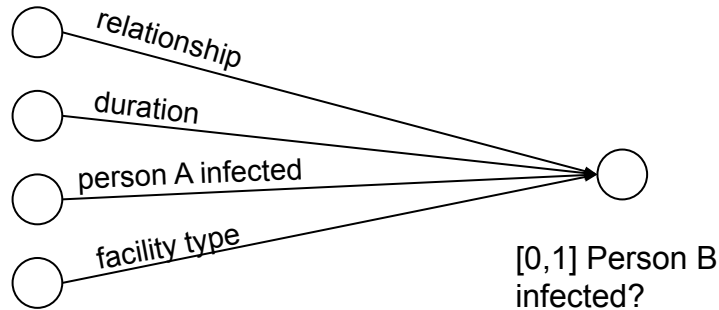
Person A meets Person B:



MAE: 0.12

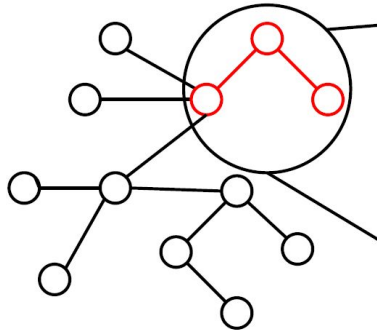
Discussion: Important features

Person A meets Person B:



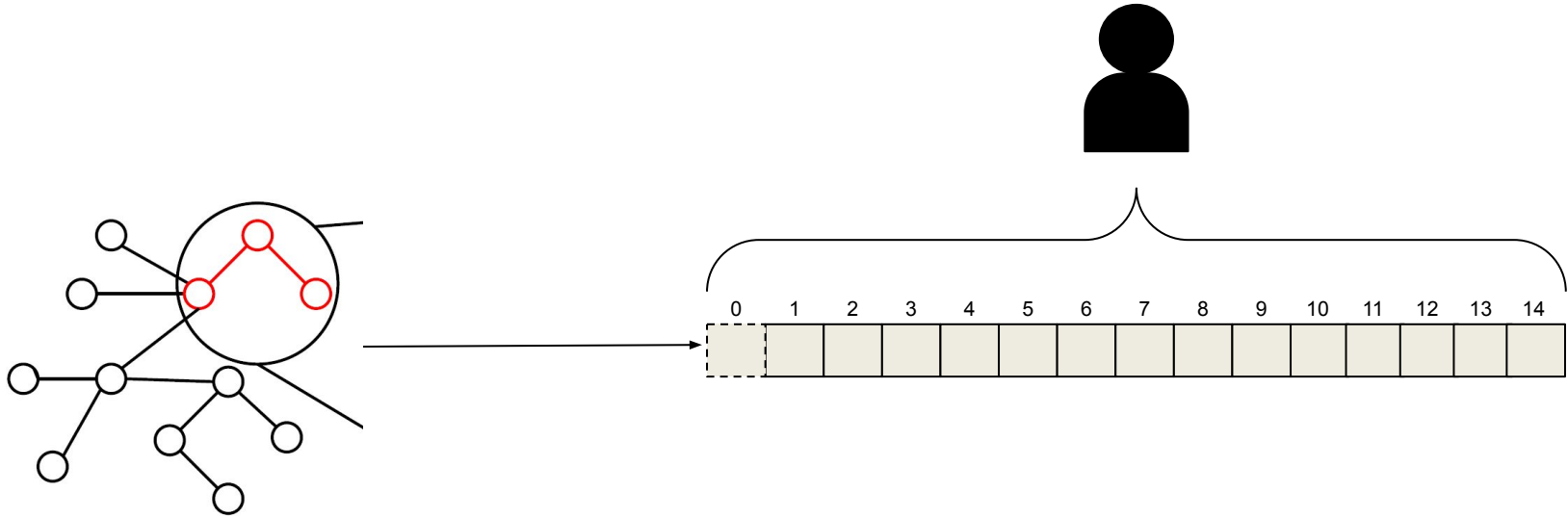
Feature left out	Mean absolute error
None	0.12
relationship	0.12
encountered person's infect risk	0.35
facility type	0.12
duration	0.12
all except person's infect risk	0.13

Predicting the daily risk

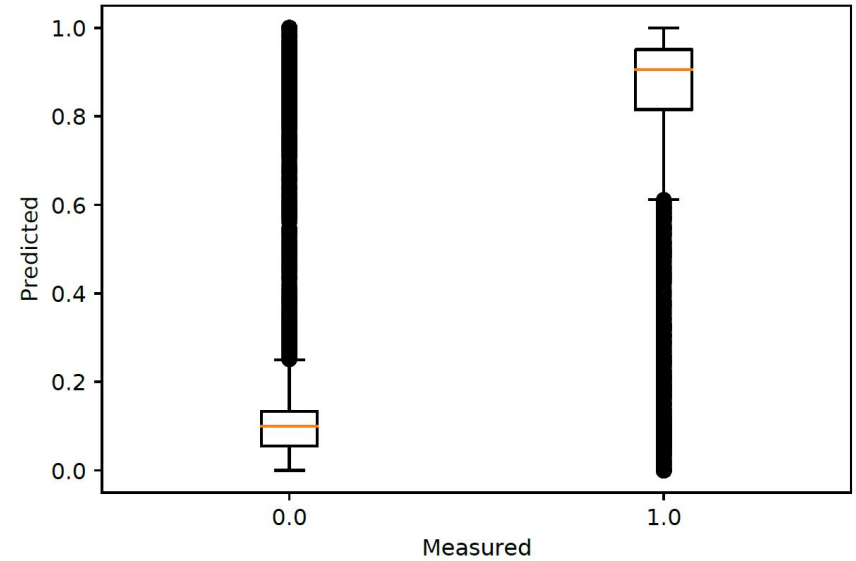
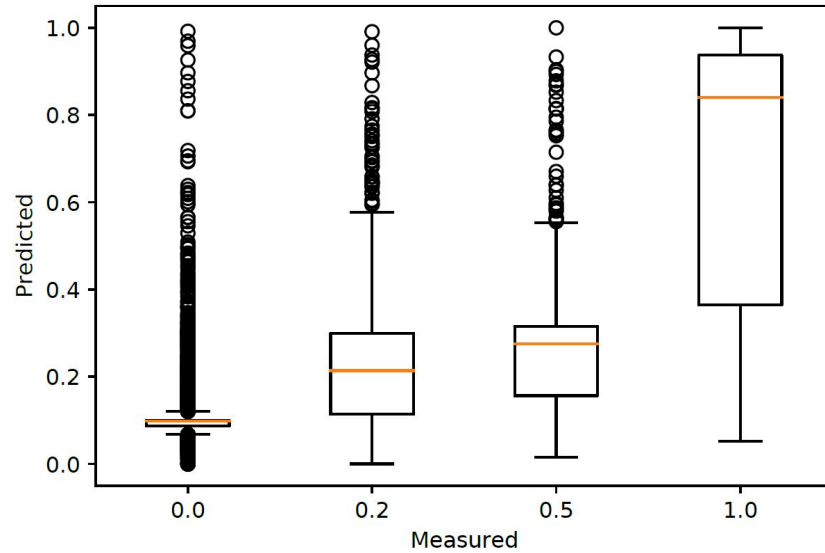


$$r_p = \max \left(1, \sum_{i=1}^n w_i \right)$$

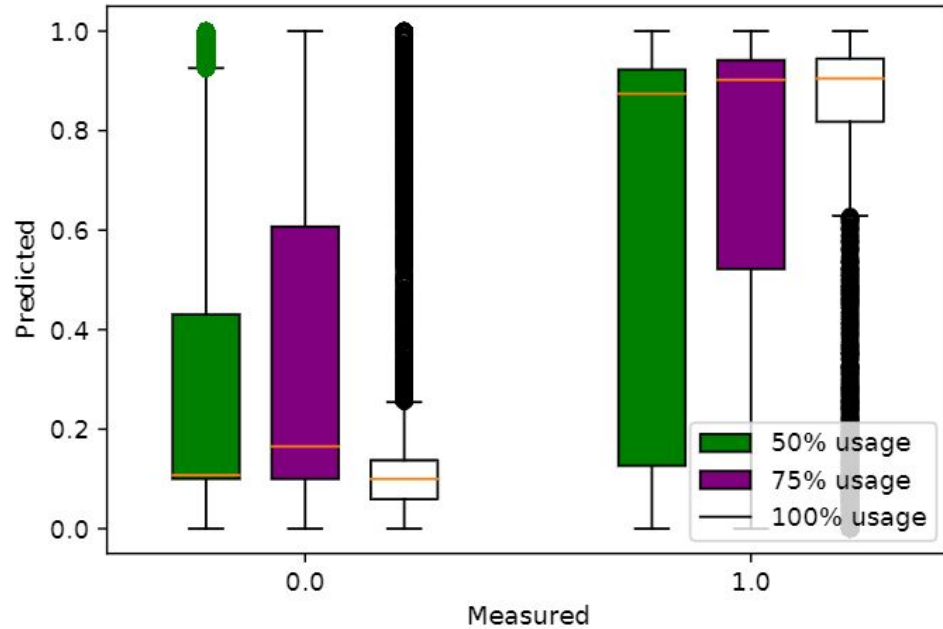
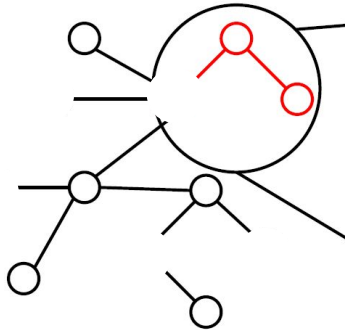
14 day risk aggregation



Results



Discussion: App usage in population



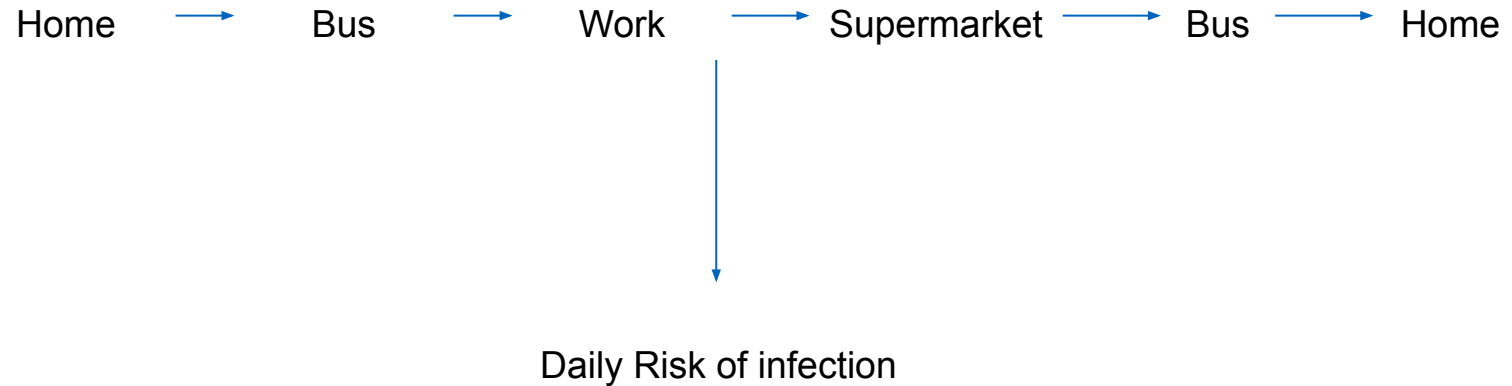
Outline

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Daily “sentence”

Home → Bus → Work → Supermarket → Bus → Home

Daily “sentence”



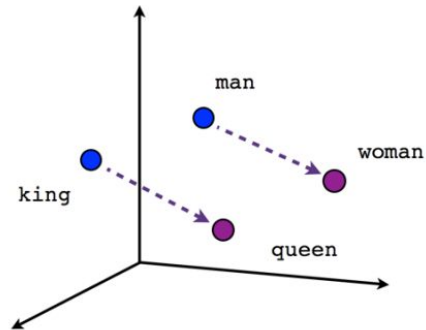
Actions

Each action has

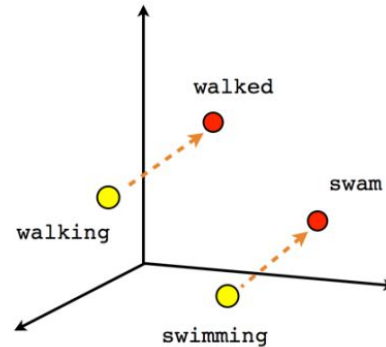
- A start time
- A group size
- A duration
- A facility (location)

Enter high dimensional space

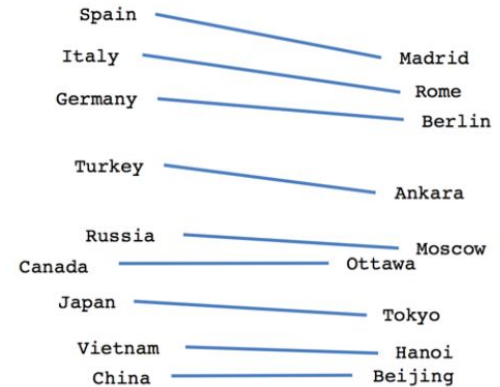
Map actions to an embedding space



Male-Female



Verb tense



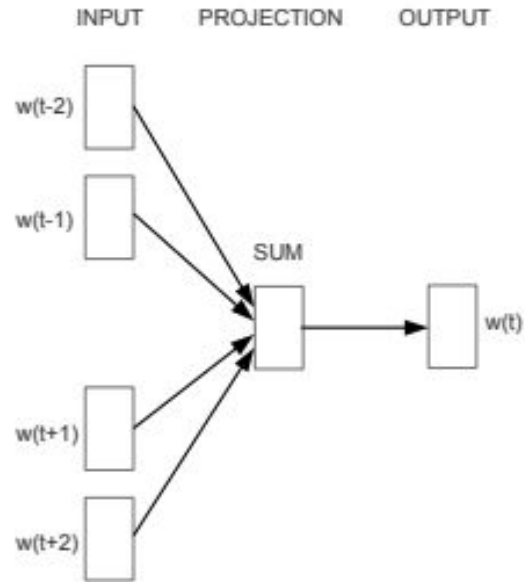
Country-Capital

Enter high dimensional space

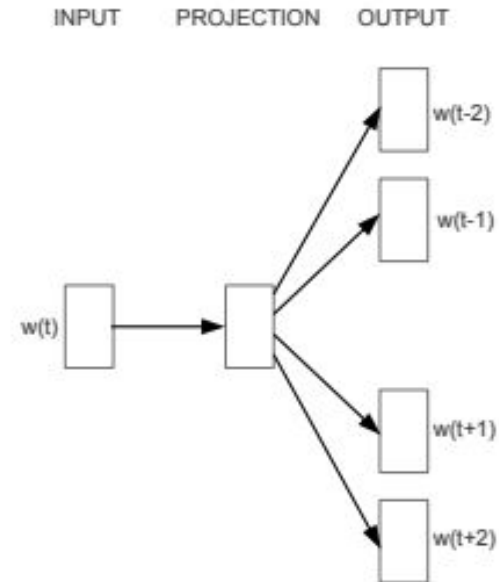
Map actions to an embedding space

- Pull similar actions closer together
- Based on the surrounding actions (context)
- Weighted Word2Vec

Word2Vec

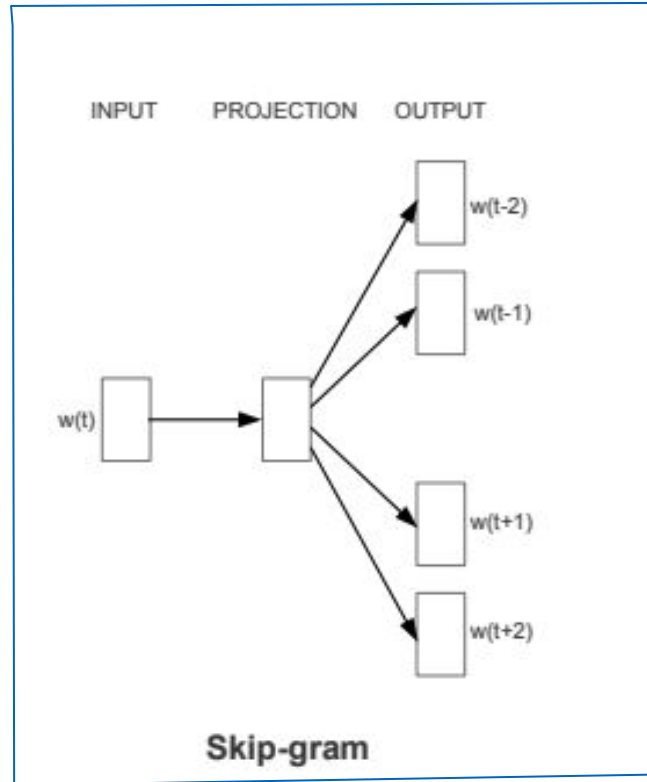
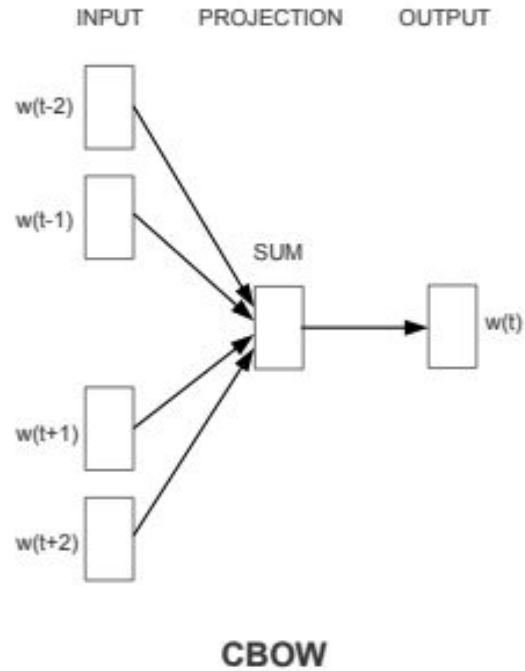


CBOW



Skip-gram

Word2Vec



Training objective

Word2Vec

$$C(\theta) = \frac{1}{T} \sum_{t=1}^T \sum_{-k \leq j \leq k, j \neq 0} L(w_t, w_{t+j}; \theta)$$

Time2Vec

$$C(\theta) = \frac{1}{T} \sum_{t=1}^T \sum_{c_j \in S_t} \alpha(c_t, c_j) L(c_t, c_j)$$

Training objective

Word2Vec

$$C(\theta) = \frac{1}{T} \sum_{t=1}^T \sum_{-k \leq j \leq k, j \neq 0} L(w_t, w_{t+j}; \theta)$$

L is the loss when
we predict word
 w_{t+j} is in the
context of w_t

Time2Vec


$$C(\theta) = \frac{1}{T} \sum_{t=1}^T \sum_{c_j \in S_t} \alpha(c_t, c_j) L(c_t, c_j)$$

Training objective

Word2Vec

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Time2Vec

$$C(\theta) = \frac{1}{T} \sum_{t=1}^T \sum_{c_j \in S_t} \alpha(c_t, c_j) L(c_t, c_j)$$


Actions similarity

- Start time difference
- Duration difference
- Group Size difference
- Facility name used as concept name

Actions similarity

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- Duration difference
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Steps

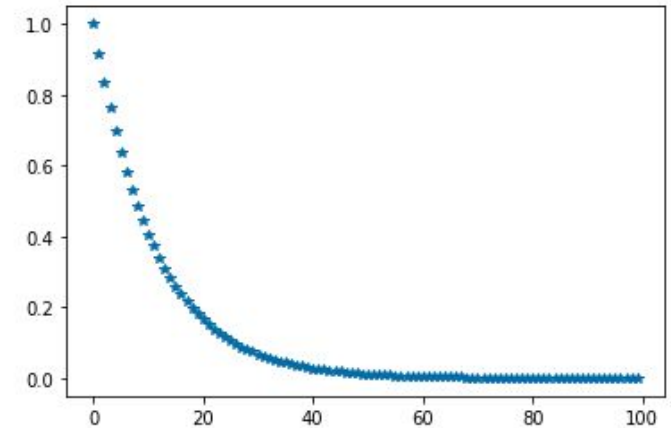
1. Build a vocabulary of concepts (map to indices)
2. Create pairs
3. Compute weights
4. Create the train file
5. Train embedding
6. Clustering and risk prediction

Inter-Action Weights

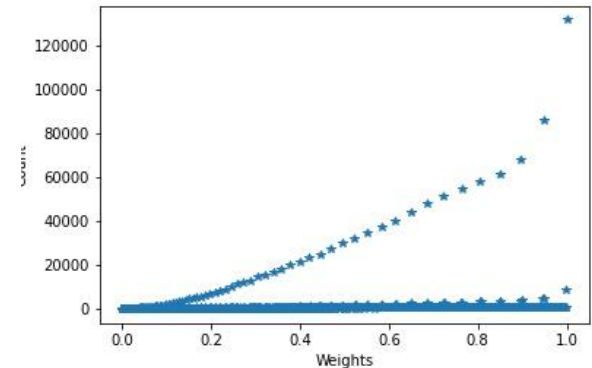
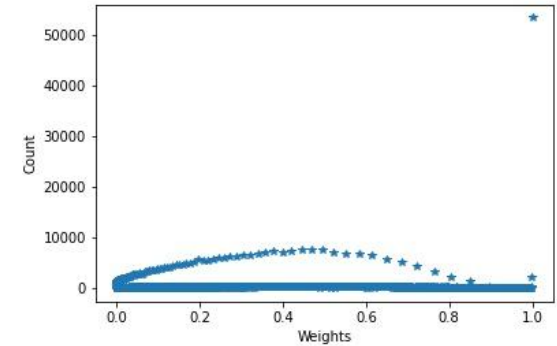
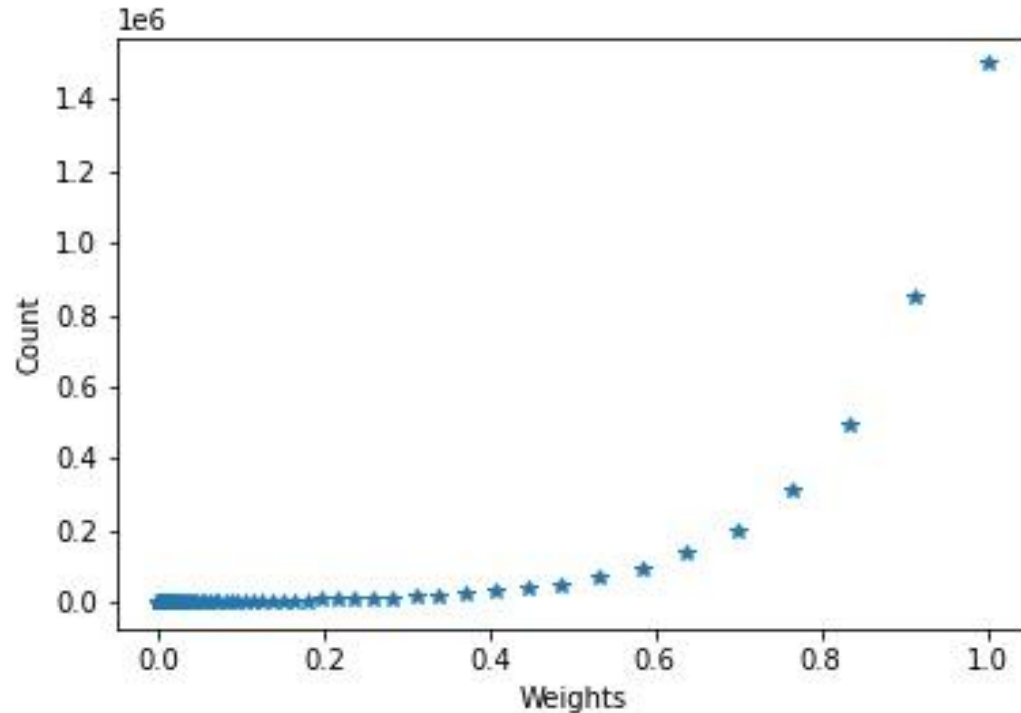
	input	target	time_difference	duration_difference	group_size_difference
0	1234	5746	30558.0	25018.0	29.0
1	5746	1234	30558.0	25018.0	29.0
2	1234	5747	35456.0	29066.0	30.0
3	5747	1234	35456.0	29066.0	30.0
4	5746	5747	4898.0	4048.0	1.0

Exponential decay

Differences



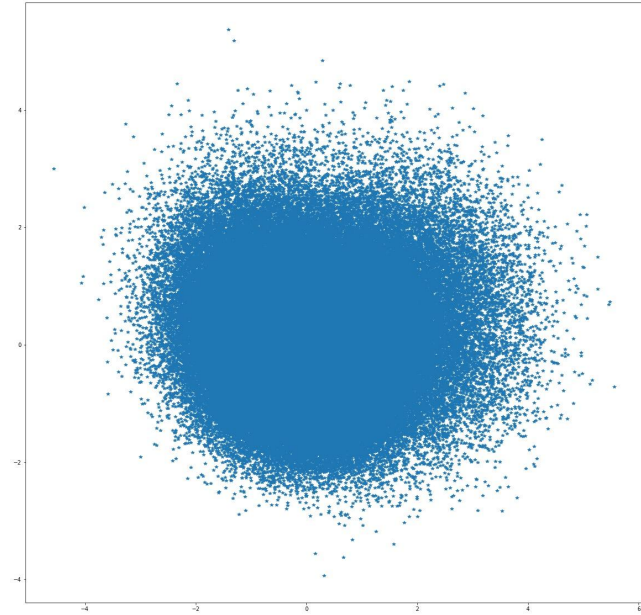
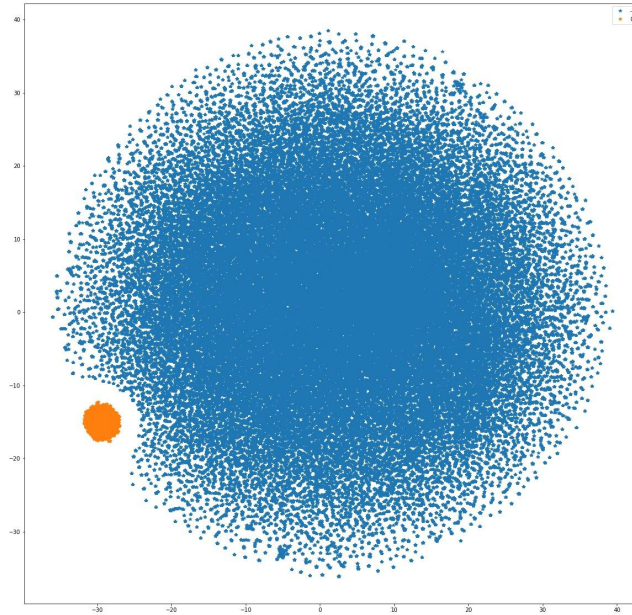
Apply exponential decay



Train embeddings

- ~211.000 concepts (facilities)
- Training time: 4 days (on CPU)
- Embedding dimensions: 50

Clustering (T-SNE and PCA)

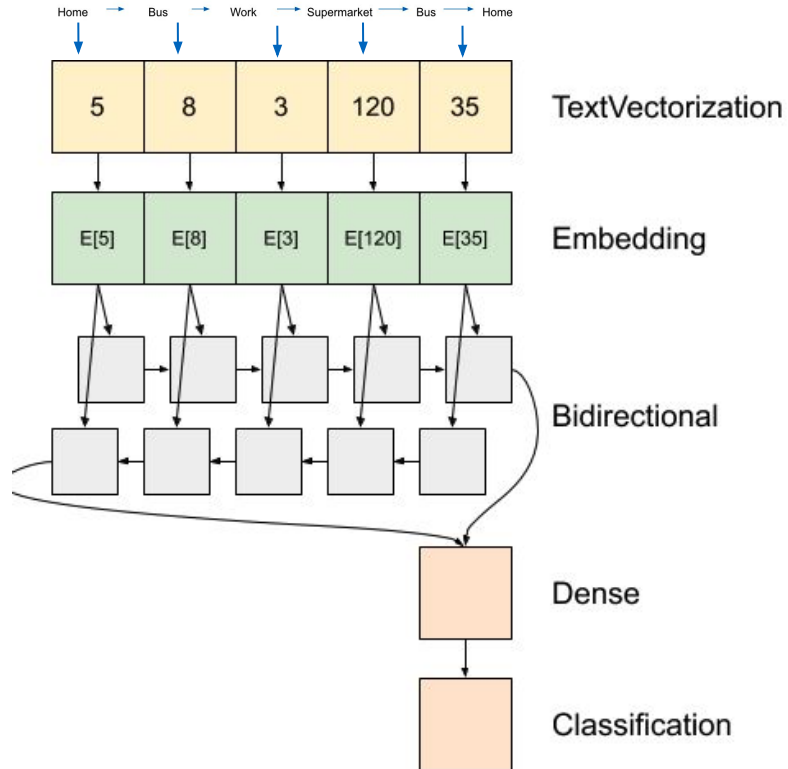


Risk prediction

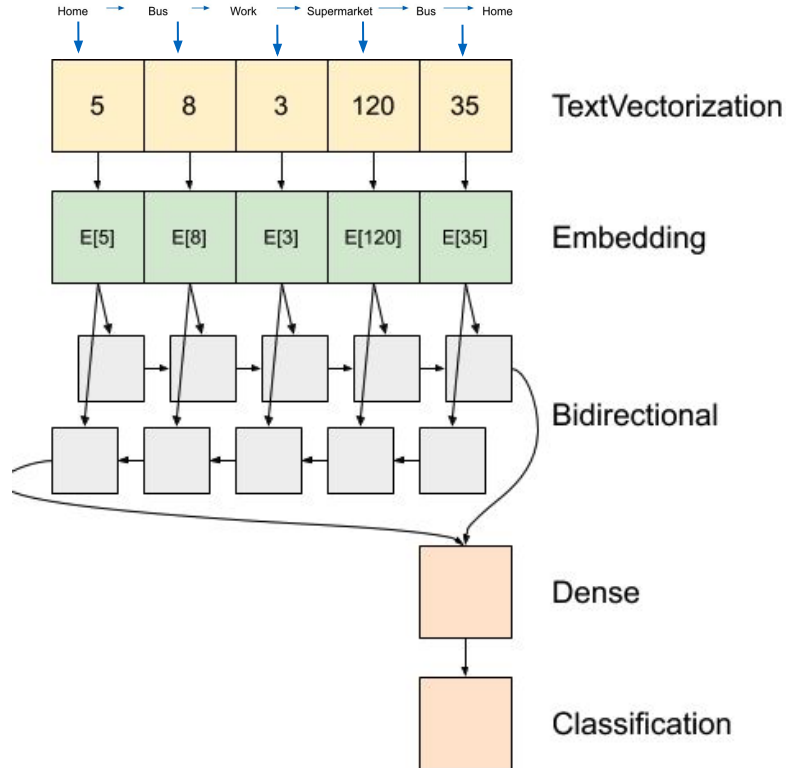
- Structure actions of a person as sentence
- Train a model to predict risk of infection given a sentence
 - Binary classification
 - Similar to sentiment analysis (Prediction of +/- sentiment)

Home → Bus → Work → Supermarket → Bus → Home

Models tried



Models tried



Models

- Trained with 1 BiLSTM (10 epochs)
- Trained with 2 BiLSTM (10 epochs)

Results

- Training remained at random (~50%)
 - No clear patterns in the data
 - Both models performed same

Conclusion

- The whole process needs to be redone → to improve performance

End