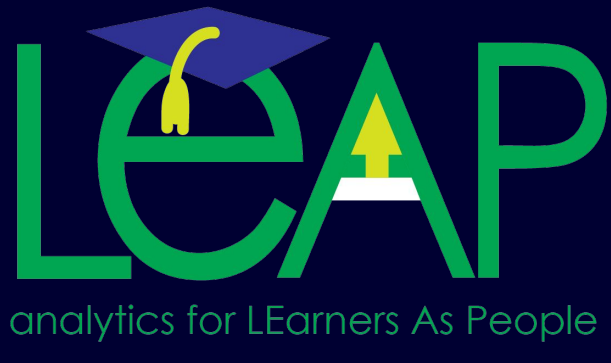




Relating Human Activities with Phrasal Embeddings

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Introduction

- Our everyday activities say a lot about who we are:
 - Personality [1]
 - Values [2]
 - Tweets
 - Facebook status updates
- We can't always directly observe human activities, yet people talk about what they are doing online. Examples:
 - Interests [3]
 - Future actions [4]
- However, reasoning about the relationships between activity phrases is not always straightforward:
 - go to a bar / attend church* (noun is important)
 - exercise / hit a punching bag* (type-of relationship)
 - sell a car / drive an SUV* (verb is important)
 - drink coffee / eat breakfast* (often done together)
- Our goal: Build a model that is able to determine the strength of semantic relationship between pairs of activity phrases.

Data

- To evaluate how well computational models are able to capture relationships between human activities, we create the Human Activity Dataset [5].
- Pairs of activities were annotated across four dimensions:

Similarity

- Semantic similarity in a strict sense.
- Example of high similarity phrases: *to watch a film and to see a movie.*

Relatedness

- A general semantic association between two phrases.
- Example of strongly related phrases: *give a gift and receive a present.*

Motivational Alignment

- The degree to which the activities are done with similar motivations.
- Example of phrases with potentially similar motivations: *eat dinner with family members and visit relatives.*

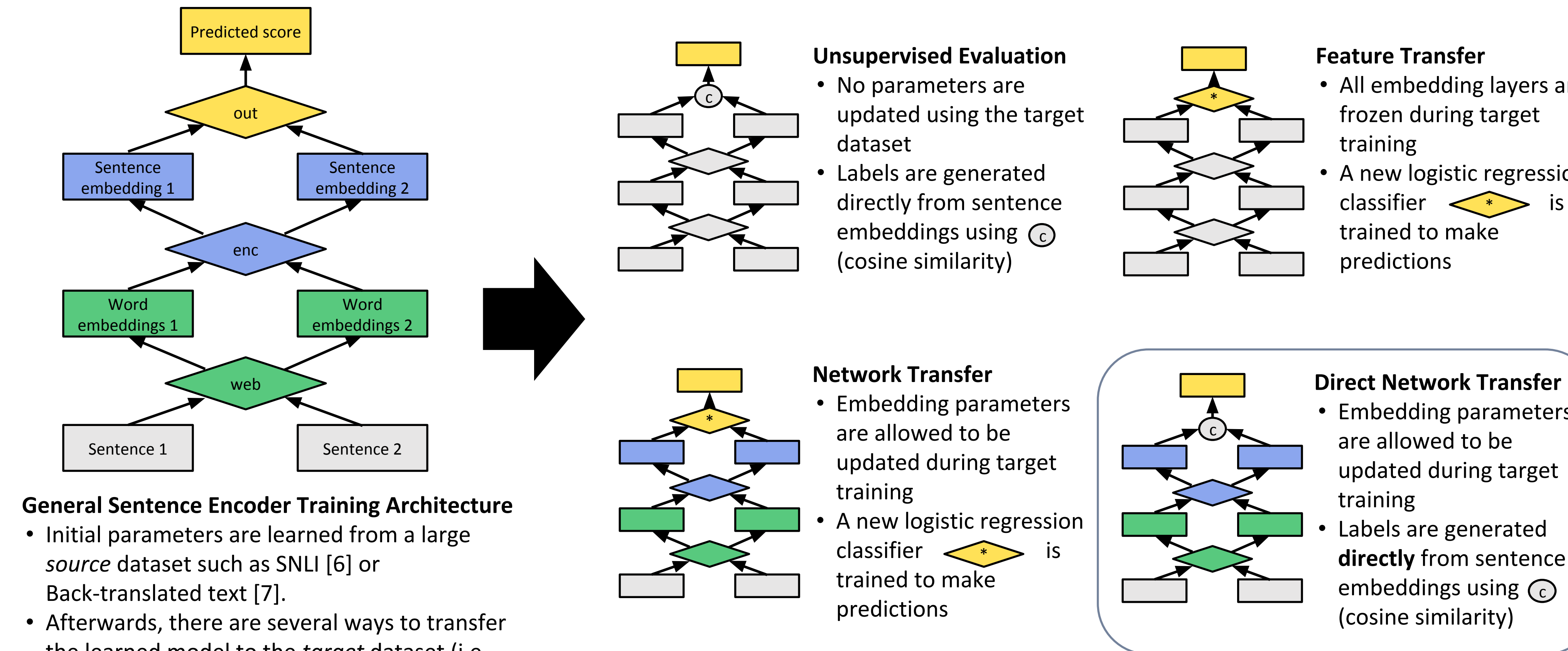
Perceived Actor Congruence

- Is someone who often does an activity also expected to do a second activity?
- Example of activities with high PAC score: *travel and pack a suitcase.*

Activity 1	Activity 2	SIM	REL	MA	PAC
go jogging	lift weights	1.67	2.22	2.89	1.11
read to one's kids	go to a bar	0	0	0	-1.29
take transit to work	commute to work	3.38	3.5	3.38	0.5
make one's bed	organize one's desk	0.58	1.29	1.57	0.71

Table 1: Sample of scores assigned to pairs of activities in the Human Activity Dataset. SIM, REL, and MA scores are in the range [0,4] and PAC scores lie in [-2,2]. Scores are averaged across 10 annotators.

Sentence Encoder Transfer Settings



Experimental Results and Analysis

Transfer Experiments

- We use the pre-trained InferSent model [8] to initialize our model parameters before transferring to each of the four dimensions in the Human Activity Dataset.

Transfer Setting	SIM	REL	MA	PAC
Unsupervised Evaluation	.701	.686	.652	.525
Feature Transfer	.655	.644	.608	.432
Network Transfer	.699	.692	.672	.537
Direct Network Transfer	.702	.722	.691	.572
Human Agreement	.768	.768	.745	.620

Table 2: Spearman's correlation between model predictions and human judgments for the four relational dimensions

- Direct Network Transfer is especially helpful when transferring to less traditional relational dimensions such as MA and PAC.

When Transfer Works

- We distinguish between two types of pairs for which transfer is helpful and show some illustrative examples:

Phrase 1	Phrase 2
have dinner with friends	eat dinner by oneself
go to a party	go to bible study
play football	play basketball
go to the movie theater	go to office to work
take long walks	go on a walk
take care of one's dogs	groom one's dog
read books	visit a bookstore
go to the doctor	see the doctor

Importance Analysis

- We use the leave-one-out importance analysis introduced in [9] as a basis for the following definition of the irrelevance of a word w for model m_1 trained only on the source data and model m_2 after transferring to the target data:

$$irrelevance(w, p_1, p_2, m_1, m_2) = m_2(p_1^{-w}, p_2) - m_1(p_1^{-w}, p_2)$$

where p_1 and p_2 are phrases that form a training instance, p^{-w} is phrase p with the word w removed, and $m(p_1, p_2)$ is the model's prediction of the relationship between p_1 and p_2 .

- This allows us to quantify the extent to which the model treats each word different after transfer.
- Using this approach, we explore the effect of Direct Network Transfer to the PAC dimension:

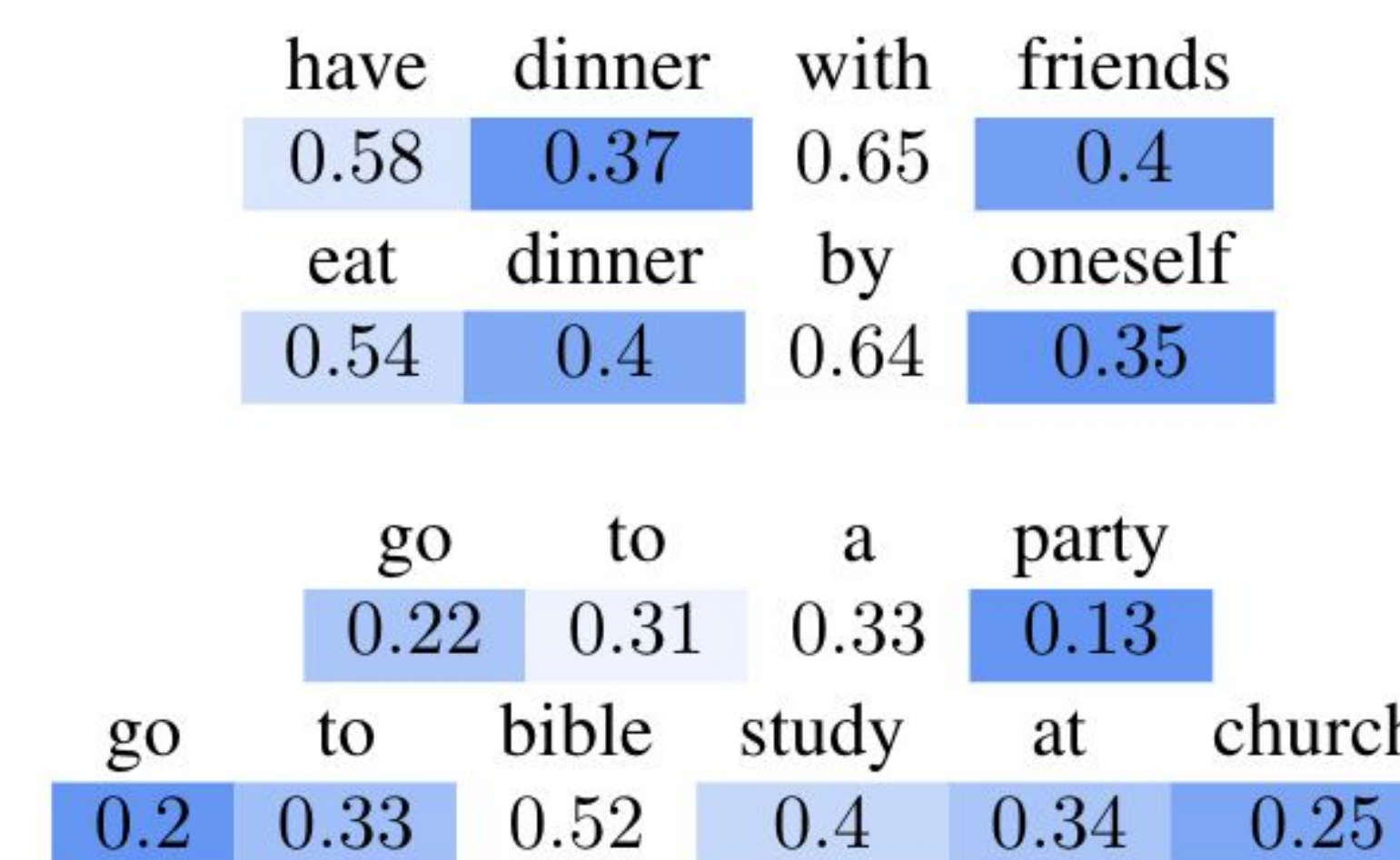


Figure 1: Heatmap of irrelevance scores showing the effect of Direct Network Transfer to the PAC dimension. Darker boxes indicate words that became more relevant during transfer.

Transfer to the STS Benchmark

- We also test the ability of Direct Network Transfer to fine-tune models for other datasets, such as the Semantic Text Similarity Benchmark [9]:

Transfer Setting	Dev	Test
Unsupervised Evaluation	.791	.783
Feature Transfer	.779	.746
Network Transfer	.836	.810
Direct Network Transfer	.852	.824
Previous Best [10]	.847	.810

Table 3: Pearson correlation with ground truth labels on the STS Benchmark evaluation.

Conclusions

- Our Human Activity Dataset [5] serves as a resource for the training and evaluation of semantic similarity methods in the domain of human activities.
- Experimental results show that transfer learning allows us to accurately model the relationships between human activities by leveraging information learned from very large text corpora, even if the domain varies.
- We introduce the *Direct Network Transfer* setting, which gives the best results on the Human Activity Dataset and is successful on other datasets, including state-of-the-art performance on the STS Benchmark.

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