# RecSys Summer School 2017 - Deep Learning hands-on session

#### Task:

Implement a hybrid recommender in theano

- Flip recommendation (user-to-item) scenario
- Find users to an item for whom it is a good recommendation

#### **Architecture:**

- Content representation learning
- Item representation learning (embedding)
- Merging of the two representations
- Compute preferences of all users over the input item

## **Content representation learning**

- Based on movie plots
- Choose one of the following
  - o (a) TF-IDF weighted pretrained wordvectors (beginner)
    - Optional extension: fine tuning
  - o (b) Pretrained paragraphyectors (intermediate)
    - Requires implementing and running paragraph2vec on the movi plots
    - Optional extension: fine tuning
  - o (c) Paragraphyector with end-to-end training (advanced)
    - Jointly train the item representations (paragraph vectors) with the preference model
    - Requires experimentation for balancing the loss
  - (d) GRU/LSTM with end-to-end training (expert)
    - Same as above, but using recurrent neural networks
    - The architecture of the RNN is as you see fit

# Item representation learning

- Parameter matrix including a feature vector for all items
- To be index by the item Ids

## Merging

- Concatenation
- Sum:
  - The content representation is to be translated to the same dimensionality as the item mebedding by using another weight matrix

### **Preference computations**

- Optional processing layers of the representation
- Product with learned user feature vectors (embeddings)

## **Loss options**

- Weighted MSE: 1/0 for users with/without events on the item with  $\alpha$  and 1 as weights  $(\alpha \gg 1)$ 
  - o Optional: sampling of negative users
- Pairwise loss (e.g. BPR): Select a positive user and several negatives and compute the average BPR loss
- Listwise loss: Select a positive user and several negatives, compute softmax over their scores and use cross-entropy as the loss

### **Features**

- Mini-batch training
- Adaptive learning rates (suggestion: adagrad)
- ELU activations ( $\alpha = 1$ )
- Dropout
  - o Separate parameters on user/item/content embedding and in the processing layers

#### Data

• <a href="http://tinyurl.com/rsss17dl-data">http://tinyurl.com/rsss17dl-data</a>