Deep Learning 2019: Project Topics

Deep Learning for Graphs

1. Inductive Node Classification
    - Project goals: Performing node classification using the GraphSAGE framework, changing/extending aggregators, experimenting with neighborhood sampling variants, e.g. sampling from higher-degree neighborhoods (prob. distr. over k-hop neighbors) or using all neighbors instead of a fixed number of samples
    - Paper reference: https://arxiv.org/abs/1706.02216
    - Dataset: Protein-Protein Interactions, citation networks, social networks (nodes with features and labels) **TBA**
    - Code reference: https://github.com/williamleif/GraphSAGE
2. Inductive node classification with Attention
    - Project goals: Performing node classification using Graph Attention networks (GAT), adding attention over other nodes (instead of only over direct neighbors, e.g. over neighbors of neighbors)
    - Paper reference: https://arxiv.org/abs/1710.10903
    - Dataset: Protein-Protein Interactions, citation networks, social networks (nodes with features and labels) **TBA**
    - Code reference: https://github.com/PetarV-/GAT
3. Multi-Task-Learning
    - Project goals: Performing node classification using the GraphSAGE framework, extending the architecture to perform multi-task-learning, i.e. optimizing multiple losses, e.g. a supervised node-classification loss + an unsupervised random walk based objective
    - Paper reference: https://arxiv.org/abs/1706.02216, https://arxiv.org/abs/1901.11504
    - Dataset: Protein-Protein Interactions, citation networks, social networks (nodes with features and labels) **TBA**
    - Code reference: https://github.com/williamleif/GraphSAGE
4. Generating Graphs with GANs
    - Project goals: Generating graphs using NetGAN, proposing changes to the Generator, e.g. changing the objective
    - Paper reference: https://arxiv.org/abs/1803.00816
    - Dataset: citation networks, social networks **TBA**
    - Code reference: https://github.com/danielzuegner/netgan
5. Predicting side-effects of drugs
    - Project goals: Using Graph Convolutional Networks (GCN) to model polypharmacy side effects. Proposing changes to the architecture.
    - Paper reference: https://cs.stanford.edu/people/jure/pubs/drugcomb-ismb18.pdf

- Dataset: http://snap.stanford.edu/biodata/ **TBA**
- Code reference: https://github.com/marinkaz/decagon

Deep Learning for Question Answering

1. Query to Question rewriting
    - Project goals: Train rewriting model(s) to transform queries to proper questions. Compare performance of QA/Reranking with different models/data augmentation approaches
    - Approach: Use data augmentation techniques, generate queries from questions, try to translate them back
    - Paper reference: Transformer: https://arxiv.org/abs/1706.03762, Query rewriting: https://www.aclweb.org/anthology/L18-1151
    - Dataset: https://www.kaggle.com/c/quora-question-pairs
    - Libraries: OpenNMT, tensor2tensor
2. Passage Retrieval
    - Project goals: Performing Passage retrieval, extending approaches, e.g. by splitting passages into sentences and accumulating scores
    - Paper reference: https://arxiv.org/pdf/1901.04085.pdf
    - Code reference: https://github.com/nyu-dl/dl4marco-bert, https://github.com/google-research/bert
    - Dataset: http://www.msmarco.org/dataset.aspx
3. Reading Comprehension
    - Project goals: Perform reading comprehension. Propose extensions/modifications to approaches
    - Paper reference: https://arxiv.org/abs/1611.01603
    - Code reference: https://github.com/allenai/bi-att-flow
    - Colab worksheet: https://worksheets.codalab.org/worksheets/0x37a9b8c44f6845c28866267ef941c89d/
    - Dataset: https://rajpurkar.github.io/SQuAD-explorer/
4. Open-domain Question Answering
    - See task 3. Reading comprehension, but using MS MARCO as the dataset
    - Dataset: http://www.msmarco.org/dataset.aspx

Interpretable Deep Learning

1. Right for the right reasons
    - Project goals: Training deep neural network based on background knowledge which is expressed as annotations indicating relevance between data dimensions and the label. Replicate results on images, try to apply to text (attention weights, modifying the loss function to conform the attention vector to the annotation)
    - Paper reference: https://www.ijcai.org/proceedings/2017/0371.pdf
    - Code reference: https://github.com/dtak/rrr

- Dataset: subset of 20 newsgroup dataset http://qwone.com/~jason/20Newsgroups

2. Sparse Interpretable Neural Embeddings
    - Project goals: Training a interpretable word embedding. The embedding is sparse and each active neuron of it is interpretable. The author provides an approach of retrofitting embedding on GloVe and Word2Vec of TensorFlow to interpretable versions. But their interpretable model optimizes a global loss, since the loss of GloVe and Word2Vec, as well as their properties take into effect in a local scope. Is it possible to retrofit the global loss function in SPINE into a local loss? Experiment with different regularization techniques.
    - Paper reference: https://arxiv.org/pdf/1711.08792.pdf
    - Code reference: https://github.com/harsh19/SPINE
    - Dataset: GloVe embedding: https://nlp.stanford.edu/projects/glove/, Word2Vec embedding: https://code.google.com/archive/p/word2vec/
3. Difference between neural models for images/text
    - Project goals: Compare reasons interpreted by various interpretation methods on the prediction of e.g. resnet50 or LSTM model. The key to interpret an NN model agnostically might hide in the images, on which reasons over different interpretation methods changes the most. This project consists of two tasks, one of which is comparing different reasons from interpretation methods in images classification tasks, and the other is comparing the reasons in text classification tasks.
    - Paper reference: SHAP: http://papers.nips.cc/paper/7062-a-unified-approach-to-interpreting-model-prediction, LIME: https://arxiv.org/abs/1602.04938, LRP: http://iphome.hhi.de/samek/pdf/BinICISA16.pdf, Fragility of interpretation on NNs: https://arxiv.org/abs/1710.10547
    - Tools: SHAP:https://github.com/slundberg/shap, LIME: https://github.com/marcotcr/lime, LRP: http://www.heatmapping.org/
    - Dataset: ILSVRC: http://image-net.org/challenges/LSVRC/2012/index, subset of 20 newsgroup dataset http://qwone.com/~jason/20Newsgroups/
4. Interpreting GANs through dissection and intervention
    - Project goals: The goal is to learn the interpretation of trained GAN network by reproducing the two experiments introduced in the GAN Dissection paper (ICLR 2019), which are 1). Understanding the units(featuremaps)-semantic concepts in the picture correlation by units-to-end dissection 2). Understanding the final effect of feature map on the generated picture by activate/ablate the unit of interests. A possible extension is implementing a custom brush.
    - Tools: Project webpage https://gandissect.csail.mit.edu/,
    - Code reference: https://github.com/CSAILVision/GANDissect
    - Paper reference: GAN Dissertation paper: https://openreview.net/pdf?id=Hyg_X2C5FX, The GAN paper (Goodfellow et. al. 2014) https://arxiv.org/abs/1406.2661, Progressive GAN: https://arxiv.org/abs/1710.10196

- Dataset: ADE20K scene dataset: http://groups.csail.mit.edu/vision/datasets/ADE20K/

Note that there is an option to propose your own topics. See the uploaded lecture slides “dl-lecture-projects.pdf” for more information.