

COS 484: Natural Language Processing

Final projects

Fall 2019

Announcements

- Assignment 4 due: Nov 18
- Problem 3: Neural MT (Nov 12 lecture)

Logistics

- Initial proposal due: Nov 11
- Proposal feedback meetings: Nov 12 Nov 15
- Milestone meetings: first/second week of Dec
- Final project presentations: around Jan 9 13
- Final report due: January 14 (Dean's date)
- Teams of 2 3 members

Decide the goal

- First, clearly define a **specific** goal/hypothesis of the project (more details the better!)
 - Good: "Adding a convolutional layer to the Transformer architecture will better capture positional information and improve machine translation"
 - Good: "Reimplement XYZ paper and verify the results on ABC tasks"
 - Bad: "Use BERT for analyzing financial news" (too vague/generic)
 - Bad: "Improve question answering for SQuaD" (how?)
- Important to pick an achievable goal (we can help!)

Considerations while picking a project

1. Availability of data

- DO NOT TRY TO COLLECT YOUR OWN DATA
 - Significant time (and money) investment (at your own risk!)
- 2. ML framework pick your favorite one
 - PyTorch, Tensorflow, Keras, etc.
- 3. Statistical model or neural network architecture
 - What are the inputs, outputs, functions, parameters?
- 4. ML Objective (Supervised? Unsupervised?)
- 5. Availability of compute

Finding inspiration

- 1. Do a thorough literature search almost certain that someone has attempted something similar before you
 - Google scholar, ACL anthology
 - Don't stop with just one search. Try variants e.g. "neural style transfer" vs "adapting models for different writing styles"
- 2. Search "awesome {NLP, RL, computer vision} papers github"
 - Example: https://github.com/mhagiwara/100-nlp-papers
 - Play around with code existing on github and see how readable/ usable it is if you want to build off
- 3. Project page with potential ideas: <u>nlp.cs.princeton.edu/cos484/</u> projects.html

Other sources

<u>https://paperswithcode.com/sota</u>

Browse > Natural Language Processing

Natural Language Processing

🗠 398 leaderboards • 217 tasks • 106 datasets • 3103 papers with code

Machine Translation



Question Answering



Brainstorming

- Have each team member flesh out 10-20 quick ideas before first meeting
- Filter out list by performing Google searches
 - Data availability
 - Has the same idea been done before (with possibly existing github code)?
 - How long and how much do the models need to be trained?
- Are there little tweaks or other experiments that haven't been done yet in existing work?
- Can you extend idea in one paper with an idea from another?
- Which idea allows for more experimentation/interesting conclusions?

Types of projects

- 1. Experiment with improving an architecture on a predefined task
- 2. Case study: Apply an architecture to a dataset in the real world (that has not been done before)
- 3. Compete in a predefined competition (SemEval 2020, Kaggle, etc.)
- 4. Stress test or comparison study of known models/architecture (e.g. when are RNNs better than Transformers for task XYZ?)
- 5. Design a novel NN layer, objective function, optimizer, etc.
- 6. Multi-domain NLP (RL + NLP, CV + NLP, ...)
- 7. Visualization/Interpretability study of deep learning models

Reading papers

- Don't read start to finish in order
- Tables, figures, captions provide a lot of useful information at first glance
- First pass: Abstract, Introduction, Experiments, Results
- Plenty of blogs, github repos, etc. that summarize several papers at once in a nice manner

Compute

- Some projects may require more CPU/GPU resources
- Tiger clusters: <u>https://researchcomputing.princeton.edu/</u> <u>systems-and-services/available-systems/tiger</u>
- CS Ionic clusters: <u>https://csguide.cs.princeton.edu/resources/</u> <u>clusters</u>
- Google cloud / Amazon AWS credits / Google Colab (1 free GPU)
- Request/get access to the above ASAP if you plan on using them!

Tips for successful projects

- 1. Clearly divide work between team members for optimal progress
- 2. Start early and work on it every 1-2 days rather than rush at the end
- 3. Set up work flow ASAP download data, verify data, set up base code
- 4. Have running code and fully trained baseline model by milestone
- 5. Have a clear, well-defined hypothesis to be tested (++ novel/creative hypothesis)
- 6. Conclusions and Results should teach the reader something
- 7. Meaningful tables, plots to display the key results
- ++ nice visualizations or interactive demos
- ++ novel/impressive engineering feat
- ++ good results

Come to office hours and talk to us!

Scenarios to avoid

- Data not available or hard to get access to, which stalls progress
- All experiments run with prepackaged source no extra code written for model/data processing
- Team starts late only draft of code up by milestone
- Just ran model once or twice on the data and reported results (not much hyperparameter search done)
- A few standard graphs: loss curves, accuracy, without any analysis
- Results/Conclusion don't say much besides that it didn't work
 - Even if results are negative, analyze them

Milestone goals

- 1. Have code up and running
- 2. Source of data explained correctly, along with true train/test/val split
- 3. What Github repo, or other code you're basing off of
- 4. Ran baseline model and have results
- 5. Brief discussion of initial, preliminary results
- 6. Reasonable literature review (2+ related papers)
- 7. 1-2 page progress report (not very formal)

Bonus points available for good milestone reports!