# Course Project

## Due Dates, Deliverables, and Grade Weights

Check mycourses for most up-to-date due dates.

```
Due         Course Grading                        Activity
-----------------------------------------------------------------------
3/31 8AM                                  A. Group registrations in MyCourses
4/3 8AM                                   B. Model definition due
4/7 8AM                                   C. Proof-reader group definition due
4/14 8AM    (10%) Milestone 1             1. Project Proposal document due
4/14-4/19   (10%) Milestone 2             2. Live Proposal presentation
4/20 8AM                                  D. Proposal Peer Evaluation
5/1         (10%) Milestone 3             3. Final report and Project code due
Finals -1   (10%) Milestone 4             4. Online/Asychronous final presentation
Finals                                    E. Final Presentation Peer Evaluation
```

Percentages shown are the percentage of your final grade.

## Overview

All students will complete a group project for the course. This project involves reviewing existing literature, designing, executing and analyzing experiments using machine learning models.

After groups are formed, groups will propose an experiment using a sketch of their final report, along with a proof of viability for their chosen implementation and data set. The final implementation and write-up will be submitted before the finals week. An asynchronous virtual 10-minute presentation will be given by each group during the exam week (the hard deadline is the scheduled day of exam). No late submissions will be accepted.

More details on each stage of the project are provided below.

## Pre-proposal

The course project will be completed in **groups of 4 students.** Students who know their groups should sign up for one of the numbered groups in MyCourses, under `Groups -> Project Groups`.

Groups will be paired, and each group will proof-read and provide feedback to the other paired group. Feedback is encouraged **at any time**.

Group team registrations is our first project due date (check myCourses). **Students who have not joined a group will be automatically placed in groups by the instructor.**

Your group will need to choose a paper from a top-tier conference or journal. A paper can only be chosen by a single group.

If you need ideas on machine learning fields of research, here is a non-comprehensive suggestion of categories to look for:

- ML Systems and Operations: Foundation models, Distributed ML optimization, Neural architecture search, Neural Network performance prediction, Neural Network initialization, Hyper parameter learning
- Meta learning: Transfer learning, Weak supervision / Few shot learning, Zero shot learning / Unsupervised models, Model explainability
- Natural Language: Sentiment detection, Topic categorization, Text summarization, Dialog and text generation, Code completion, Knowledge graphs link prediction, Question answering
- Computer vision: Image classification, Object detection, Image to text, Text to image, Diffusion models

# Detailed Project Milestones

## 1. Project Proposal Writeup (10% of Final Grade)

The project proposal main goal is to replicate existing results of the chosen model (e.g. Neural Network). **You can use one of the settings/experiments present in the original paper.** Each group will submit a proposal as a PDF document through MyCourses by the due date. The proposal will be graded out of 50 points.

- The proposal will be a **6 page sketch (draft) of the final report, with one page per section of the final report, one page for references, and a 1-page section specific to the proposal ('Viability').**
- **Format:** The full document should be six pages long, with each section **on a separate page** (11pt font, 1 inch margins).

### Proposal Sections

- **Section 1: Task Definition, Evaluation Protocol, and Data.** Capture the intended task, data set, and metrics, and include an associated reference.
- **Section 2: Neural Network Machine Learning Model.** Identify the learning model to be used, along with the associated references. A draft outline of how the model will be summarized in this section is required, along with a description of any figures or tables to be used. **Model constraints:**
  - The neural model used should not be covered directly as examples in the Charniak book, or be a model very close to those.
  - No model simpler than a *deep* convolutional neural network should be used. Take this as an opportunity to explore more complex models (e.g., transformer models such as BERT, ViT, etc.).
  - See example of Python machine learning frameworks that can be used in the description of the full proposal below. Good venues to search for research papers on current systems are provided in the Recommendations section at the end of this write-up. – note that dblp is particularly helpful for this, **and you should only use systems with an available and *working* implementation** (see Viability section below).
  - If a framework does not run relatively easily for your group after **carefully reading the documentation** on how to install run, and retrain it, or it is difficult to see where parameters and hyper-parameters might be changed – **do not use this model**.
- **Section 3: Experiment Design.** A table briefly sketching the research question, variables, and hypothesis as described in the write-up requirements below, along with a bullet-point summary of expected modifications/code needed to run your experiment.
- **Section 4: Experimental Results and Discussion.**
  - Summary of the results that will be collected, and the tables and figures that you will use to present results.
  - How results will be used to test your hypothesis, and what you expect to learn about your research question if the hypothesis is (1) confirmed, (2) contradicted, or (3) not clearly confirmed or contradicted. We want to avoid outcome (3) – thinking about the possibility often helps improve our experiment designs.
- **Section 5: References.** 1 page, with references for Sections 1, 2, and optionally Section 3.
- **Section 6: Viability Test.**: This is intended to confirm that you will be able to work with your intended model.
  - Provide output or a screen shot showing that you are able to run the model as provided in the framework that you are using. **Also include the time needed to run the model on the test set, and the test set size for your task.** The model does not need to be fit to the whole data.
  - Provide a second output or screen shot that clearly shows that you are able to train the model for 1 epoch over the data set. **Also include the time required to train for the one epoch, and the number of training samples.**

## 2. Proposal Presentation (10%)

The project proposal presentations will take place in our regular classroom during lecture time. The presentation will be graded out of 50 points (10 points per required talk element below, plus 10 points for questions).

Each group will have **exactly** 10 minutes each to present a summary of their project work to date.

**Required 10-Minute Presentation Content:**

8 minute talk (**maximum; this will be timed**); 2 mins for questions. All group members should speak for at least 2 minutes.

1. Learning task and research question
2. Learning model
3. Experiment design (including dataset)
4. Preliminary results, how they relate to the research question

**Hints:**

- Target your talk at the members of the class – inform them of what you've done, taking what we've covered in the course as a starting point.
- **Avoid repeating material from class** – tell us *new* information about the background and execution of your project.
- It is perfectly okay to share challenges that you've encountered – use this as an opportunity to get information and feedback from the class.
- It is strongly recommended that you **rehearse your talk a couple of times, even if only over Zoom.** Make edits to the talk as you discover things that are awkward or unclear.
- Do not read from your slides – use slides to capture short bullet points, and to share helpful figures that help drive discussion.
- You are welcome to use text and figures from your report in your talk and vice versa.

## 3. Final Report and Project Code (10%)

The report and code are expected to be prepared by the group as a whole (i.e., all students should contribute to both the code and final report).

**Note that for the write-up,** the technical depth, analysis, and clarity of the writing (including design, placement and formatting of figures and graphics) will be roughly equally weighted factors in the assigned grade.

**For evaluating code,** the thoughtful use of existing operations built into the framework, code organization, and style will be factors in grading.

### 3.1. Final Code/Implementation

The implementation will be graded out of 50 points; a rubric will be available through MyCourses showing specific criteria.

A .zip file containing your code, along with a README explaining how to install and run your system **on a CS server** is required. If your code requires a GPU, make sure you include this requirement as part of your README.

Students are highly encouraged to start from an existing Python framework. A (highly) partial list of possible frameworks include:

- TensorFlow https://www.tensorflow.org/
- PyTorch https://pytorch.org/
- SentenceBERT https://www.sbert.net/
- PyTorch Geometric (Graph Neural Networks) https://pytorch-geometric.readthedocs.io/en/latest/

In choosing their research question/topic, groups are strongly encouraged to download a framework or two that look interesting, try some of the provided examples, and then think about what would be interesting and does not appear in the available documentation for the tool.

### 3.2. Final Report Write-up

The final project report will be graded out of 50 points; a rubric will be available through MyCourses.

**Below are the required sections for the write-up,** along with notes regarding requirements for each section. **The writeup must be 8-10 pages in 11pt font, 1 inch margins, including figures, tables, and other graphics, and with 1 page for references.**

The page lengths shown below are encouraged, but may vary.

**Final Project Report Sections**

**(1 page) 1. Task Definition, Evaluation Protocol, and Data**

- **With one or two figures** illustrating the classification or regression task, and how evaluation is performed
- Include a reference for a paper or book defining the task and data set – preferably from those who created the data set in the form you are using. Cite this paper in your discussion, summarizing any other pertinent details of interest related to the task definition.

**(2 pages) 2. Neural Network / Machine Learning Model**

- Neural Network Learning Model Summary
  - Remember to include the loss metric used in training
  - **Material covered in class should be assumed:** focus on defining the model clearly, explaining key piece of the 'new parts.'
- Use figures where it will aid understanding. **Figures created by groups are preferred**; where figures, tables, etc. are taken from other documents, they must be explicitly cited so this is clear.
- Focus your presentation on the parts of the algorithm that you will modify, to help motivate and provide context for your experiment.
- 1-3 reference(s) defining the model
  - Cite and summarize this in your discussion

**(2 pages) 3. Experiment**

- The **research question** that your experiment addresses (but does not necessarily answer) – put another way, what do you hope to learn from the experiment?
- **Design:**

- Explicitly identify (organization in subsections and/or tables is fine):
  - **Hypothesis**: a falsifiable statement about the expected outcome of the experiment based on your understanding of the learning model, which is clearly motivated by your research question. This should be closely tied to the pertinent mathematical, algorithmic, and data/storage properties of the model associated with your research question.
  - **Independent variables (Experimental Settings)** that you will manipulate (e.g., hyper-parameters, model form, other learning parameters),
  - **Control variables (Biases and Modeling assumptions)** that will be held constant, but might alter the experiment outcome if this was not true, and
  - **Dependent variables (Results Analysis)** for observations made during and after systems are trained (e.g., performance metrics, learning curves, convergence intervals in number of epochs, etc.)

- **Methodology.** Identify the specific implementation/code base used, any required data processing, and a summary of modifications / code required for your available implementation to create and run the different conditions of your experiment.

- *Requirements*:
  - You must make use of a baseline that you will compare your modifications ('conditions') against. This can include modifications to the original model, diferent dataset or different experimental settings. The choice of baseline must be motivated by your research question and the models involved,
  - **Your research question can be simple, but must be focused on building understanding of a learning model.** "Will A perform better than B?" asks for a single observation in isolation; it does not test expected behavior based on a formal understanding ('model'), and so is not a *scientific* research question.
  - The experiment should contain at least 3 conditions for one variable (not including grid-search or other methods to tune hyper-parameters for each condition), to keep your effort focused and manageable in the available time frame. The conditions should be defined by changing one variable, e.g., network architecture embedding size, different activation functions.

**(2-3 pages) 4. Experimental Results and Discussion**

Your analysis should read like a clear narrative – roughly, a well-guided tour of the results, whether they confirm or contradict your hypothesis, and what this tells you about your research question.

- Numeric results from your experiments in tables and/or figures. Include specific metric values wherever possible (e.g., at the top of bars in bar graphs).
- Visualizations of results where helpful (e.g., learning curves, tables of metrics, etc.)
- A discussion of whether these results support or contradict your hypothesis, and how this informs your understanding of the original research question, and possible next steps.

**(1 page) References**

## 4. Final Presentation

The final presentation will be done asychoronously. The group will be required to record the presentation, upload to youtube and generate a youtube link (it is ok to make it accessible only via the URL). The due date for making the links available is the day before the final exam date, as defined on SIS. In the following 24h, the presentation recordings will be peer-reviewed. Questions can be done during this 24h period using the discord server before the deadline. The peer-review form need to be completed within this 24h period. The link to the peer-review form will be shared in mycourses.

The recorded final presentation should follow the proposal presentation format, but will be now limited to 10-minutes. Each group member is required to speak for at least 2 minutes. As in the proposal presentation, your final presentation should include:

1. Learning task and research question
2. Learning model
3. Experiment design (including dataset and experiment settings modifications from the proposal)
4. Results, how they relate to the research question

## Recommendations

To make the project effort productive, manageable and successful, here is a (**strongly recommended**) approach for this project. A key requirement is to find another group willing to serve as proof-readers.

1. Create a group ASAP – while waiting to finalize your group, review the proposal requirements in the next Section, and take **substantial time (i.e., hours)** to carefully explore models both on your own and with group members to identify a model to experiment with.

2. Begin drafting the proposal, while carefully formulating your experiment.
   - To produce a stronger report in your available time for the project, **alternate** between drafting different sections of the proposal, rather than writing the report front-to-back.
   - Details of your proposal **will change across sections** as you learn more, so plan your work around this.

3. Make final edits/rewrites to make your proposal clear.
   - As a final check on clarity, have another group proof-read your draft.
   - Based on their feedback, revise and submit your proposal.

4. As soon as possible, work with your group members to alternate between:

   (1) **Writing.** Preparing your experiment write-up,

   (2) **Implementing models and the experiment. Debugging** and running the models and experiment code,

   (3) **Preparing visualizations and analysis.** Preparing code for metrics and visualizations to be used in the analysis of results (these are best prepared **before** experiments are finished), along with a sketch of expected outcomes and how you will examine the data for expected cases of interest.

5. Prepare your group presentation, sharing slides with another group for feedback.
   - Compile answers to questions you might receive – extra slides at the end of your slide deck are helpful for this.
   - Rehearse the talk as a group a couple of times.

6. **Final Deliverables.**
   - Prepare the final code submission (removing unecessary output, making sure to include a README, etc.).
   - Before submitting the final project report, again use members from another group as proof-readers and rewrite/edit as needed.

7. **Venues to Look for Machine Learning papers**
   - Here is a non-comprehensive list of top machine learning venues: ICML, NeurIPS, ICLR, COLT, JLM, TPAMI, SIGIR, KDD, CVPR, ACL anthology, TNN, CHI, ICRA, WWW, AAAI.
   - If you are interested in a paper that is a pre-print (e.g. arXiv), **get express authorization from the instructor**.
   - Use DBLP to search for the papers by title first, by abstract second.
   - You have access to most papers if you use RIT network. If you can not access the paper, try using IEEE eXplore, ACM Digital Library or Springer Link.
   - You can also use the RIT Library webpage to search for papers and even request access for papers that are not part of a portal subscription that RIT is part of.

8. Even though you are not required to, it is always a good idea to use Latex. Here are two good resources to learn Latex:
   - https://www.learnlatex.org/en/
   - https://www.overleaf.com/learn/latex/Learn_LaTeX_in_30_minutes

9. You have access to CS servers, including servers with multiple GPUs. Check the most up to date listing at:
   - https://wiki.cs.rit.edu/index.php/ClientNodes

10. To make your life easier, install conda on your home directory following these instructions:
    - https://docs.conda.io/projects/conda/en/latest/user-guide/install/linux.html

11. A few useful packages to install using conda:
    - conda install tensorflow numpy matplotlib pandas scikit-learn tdqm argparse statistics