**PPTs from other ML courses:**

**\*\*\*TODO use httrack and download all from:** [**http://ce.aut.ac.ir/~shiry/lecture/Advanced%20Machine%20Learning/**](http://ce.aut.ac.ir/~shiry/lecture/Advanced%20Machine%20Learning/)

**http://www.cs.ucsb.edu/~ambuj/Courses/165B/Lectures/**

[**http://www.cs.cmu.edu/~mgormley/courses/606-607-f18/**](http://www.cs.cmu.edu/~mgormley/courses/606-607-f18/)

**(\*\*\* TODO: search for his videos and/or send email and ask to share)**

[**http://www.ds100.org/fa18/**](http://www.ds100.org/fa18/)

**(\*\*\*TODO: Download soon before they reset. Even though, old ppt are here**

[**http://www.ds100.org/fa17/syllabus**](http://www.ds100.org/fa17/syllabus)

**In any case, they have great setup instructions**

**http://www.ds100.org/fa17/setup)**

**Website template:**

**https://harvard-ml-courses.github.io/cs281-web/**

[**https://davidrosenberg.github.io/ml2015/#home**](https://davidrosenberg.github.io/ml2015/#home)

**Learning Objectives**

[**http://www.cs.cmu.edu/~mgormley/courses/10601-s18/slides/10601-objectives.pdf**](http://www.cs.cmu.edu/~mgormley/courses/10601-s18/slides/10601-objectives.pdf) **(used for YU ML Objectives)**

**Other courses:**

**http://comp562fall18.web.unc.edu/syllabus/**

**http://www.cs.ox.ac.uk/people/varun.kanade/teaching/ML-HT2016/index.html#**

[**http://www.cs.cornell.edu/courses/cs4780/2015fa/index.html**](http://www.cs.cornell.edu/courses/cs4780/2015fa/index.html)

[**https://www.psi.toronto.edu/~jimmy/ece521/syllabus.pdf**](https://www.psi.toronto.edu/~jimmy/ece521/syllabus.pdf)

[**http://www.cs.colorado.edu/~mozer/Teaching/syllabi/ProbabilisticModels2013/**](http://www.cs.colorado.edu/~mozer/Teaching/syllabi/ProbabilisticModels2013/)

[**http://www.cs.colorado.edu/~mozer/Teaching/syllabi/ProbabilisticModels/**](http://www.cs.colorado.edu/~mozer/Teaching/syllabi/ProbabilisticModels/)

[**http://www.ntu.edu.sg/home/cspun/mh4510.html**](http://www.ntu.edu.sg/home/cspun/mh4510.html)

**Source:** [**http://www.cs.cmu.edu/~mgormley/courses/10601-s18/about.html**](http://www.cs.cmu.edu/~mgormley/courses/10601-s18/about.html)

**Learning Outcomes:** By the end of the course, students should be able to:

* Implement and analyze existing learning algorithms, including well-studied methods for classification, regression, structured prediction, clustering, and representation learning
* Integrate multiple facets of practical machine learning in a single system: data preprocessing, learning, regularization and model selection
* Describe the the formal properties of models and algorithms for learning and explain the practical implications of those results
* Compare and contrast different paradigms for learning (supervised, unsupervised, etc.)
* Design experiments to evaluate and compare different machine learning techniques on real-world problems
* Employ probability, statistics, calculus, linear algebra, and optimization in order to develop new predictive models or learning methods
* Given a description of a ML technique, analyze it to identify (1) the expressive power of the formalism; (2) the inductive bias implicit in the algorithm; (3) the size and complexity of the search space; (4) the computational properties of the algorithm: (5) any guarantees (or lack thereof) regarding termination, convergence, correctness, accuracy or generalization power.

**3. Recommended Textbooks**

* [*Machine Learning*](http://www.cs.cmu.edu/afs/cs.cmu.edu/user/mitchell/ftp/mlbook.html), Tom Mitchell.
* [*Machine Learning: a Probabilistic Perspective*](http://www.cs.ubc.ca/~murphyk/MLbook/), Kevin Murphy. Full online access is [free through CMU’s library](https://ebookcentral.proquest.com/lib/cm/detail.action?docID=3339490) – for the second link, you must be on CMU’s network or VPN.
* [*A Course in Machine Learning*](http://ciml.info/), Hal Daumé III. Online only.

The core content of this course does not exactly follow any one textbook. However, several of the readings will come from the Murphy book (available free online via the library) and Daumé book (only available online). Some of the readings will include new chapters (available as free online PDFs) for the Mitchell book.

Reference: <https://harvard-ml-courses.github.io/cs281-web/syllabus.pdf>

Objectives This course has the following aims: • Use the language of probabilistic modeling to describe and represent real-world problems. • Understand different ML algorithm in terms of the underlying inference challenges. • Implement a variety of inference techniques in simple and declarative ways. • Seamlessly combine non-linear methods, e.g. neural networks, into generative models.

Reference: http://www.cs.bilkent.edu.tr/~koyuturk/cs464\_f17\_syllabus.pdf

Learning Objectives • Conceptual understanding of learning applications, formulation of learning tasks as computational problems, and methods that are designed to solve these problems • Understanding the commonalities and differences between different learning tasks and different approaches to learning • Understanding the trade-offs in developing solutions • Thorough understanding of rigorously evaluating the performance of learning algorithms • Ability to manipulate, extend, and apply machine learning methods and algorithms in the context of real-world problems

* Students will learn the fundamentals of machine learning
* Students will learn to implement machine learning algorithms
* Students will learn to evaluate how to apply machine learning to different settings

to something like this:

* Implement and analyze existing learning algorithms, including well-studied methods for classification, regression, structured prediction, clustering, and representation learning
* Integrate multiple facets of practical machine learning in a single system: data preprocessing, learning, regularization and model selection
* Describe the the formal properties of models and algorithms for learning and explain the practical implications of those results
* Compare and contrast different paradigms for learning (supervised, unsupervised, etc.)
* Design experiments to evaluate and compare different machine learning techniques on real-world problems
* Employ probability, statistics, calculus, linear algebra, and optimization in order to develop new predictive models or learning methods
* Given a description of a ML technique, analyze it to identify (1) the expressive power of the formalism; (2) the inductive bias implicit in the algorithm; (3) the size and complexity of the search space; (4) the computational properties of the algorithm: (5) any guarantees (or lack thereof) regarding termination, convergence, correctness, accuracy or generalization power.

Week 1. Overview of Machine Learning: history, relation to classical statistics. Textbook: Chapter 1.

Learning Objectives:

* Formulate a well-posed learning problem for a real-world task by identifying the task, performance measure, and training experience
* Describe common learning paradigms in terms of the type of data available and when, the form of prediction, and the structure of the output prediction
* Identify examples of the ethical responsibilities of an ML expert

- explain the difference between supervised and unsupervised learning

- explain the difference between Classification and regression

1. formulate a well-posed learning problem for a real- world task by identifying the task, performance measure, and training experience

how probability can play a useful role in machine learning.

2. Describe common learning paradigms in terms of the type of data available, when it’s available, the form of

prediction, and the structure of the output prediction

And during the lecture I will discuss for example for 1.

Well-Posed Learning Problems

Three components <T,P,E>:

1. Task, T

2. Performance measure, P

3. Experience, E

Definition of learning: A computer program learns if its performance at tasks in T, as measured by P, improves with experience E.

Engaging activity and assessing the learning problem:

Example Learning Problems

3. Learning to beat the masters at chess

1. Task, T:

2. Performance measure, P:

3. Experience, E: