Conclusion

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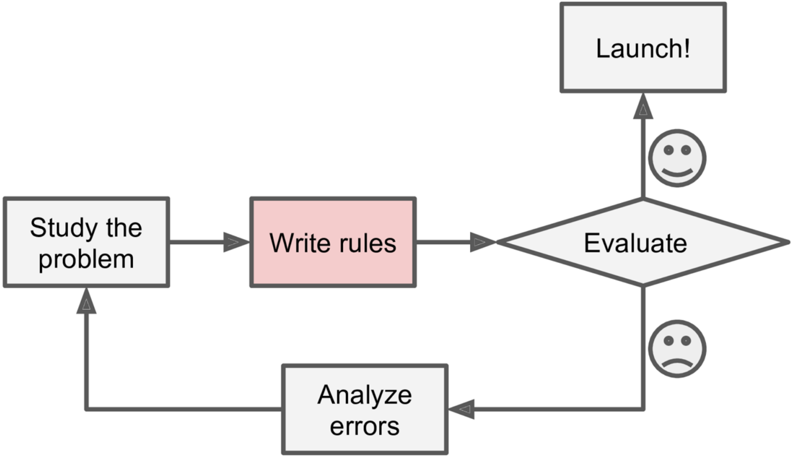
Summary of This Course

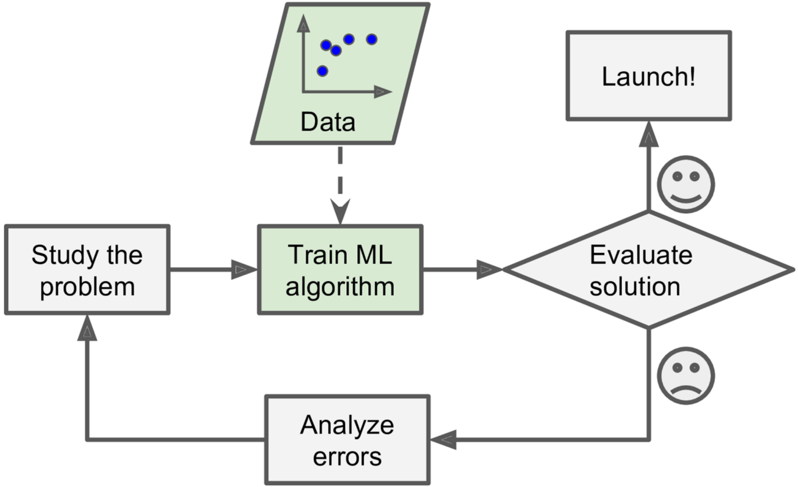
Rule-based approach

Code an algorithm



Machine learning approach

Learn from data



Machine learning vs rule-based approach

$$\text{data} \xrightarrow{\text{learning algorithm}} \text{model}$$

- Machine learning is the main driving force of modern AI.
- Shift from specifying *how to* solve the problem to *what* the solution looks like.
- Promise: *generalization* to unseen examples.

Typical machine learning recipe

Model A family of predictors that map from the input space to the action space:

$$f(x;\theta) = a. \tag{1}$$

Objective Empirical risk minimization:

$$\min_{\theta} \sum_{(x,y)\in\mathcal{D}_{\text{train}}} L(x,y,\theta). \tag{2}$$

Algorithm Stochastic gradient descent:

$$\theta \leftarrow \theta - \alpha_t \nabla_\theta L(x,y,\theta). \tag{3}$$

Models

Linear Perceptron, conditional probability models, SVMs

Non-linear Kernelized models, trees, basis function models, neural nets

How to choose the model family?

- Trade-offs:
  - approximation error and estimation error (bias and variance),
  - accuracy and efficiency (during both training and inference).
- Start from the task requirements, e.g. amount of data, computation resource

Objectives

Loss functions How far off a prediction is from the target, e.g. 0-1 loss, margin-based loss, squared loss.

Risk Expected loss - but expectation over what?

- Frequentist approach: expectation over data.
  - Empirical risk minimization, i.e. average loss on the training data.
  - Regularization: balance estimation error and generalization error.
- Bayesian approach: expectation over parameters.
  - Posterior: prior belief updated by observed data.
  - Bayes action minimizes the posterior risk.

Algorithms

Learning Find model parameters—often an optimization problem.

- (Stocahstic) (sub)gradient descent
- Functional gradient descent (gradient boosting)
- Convex vs non-convex objectives

Inference Answer questions given a learned model.

- Bayesian inference: compute various quantities given the posterior.
- Dynamic programming: compute $\arg\max$ in structured prediction.

Debugging Machine Learning Algorithms

Get it to work

- This course provides you a *toolbox*.
- Motivate a tool from the problem.
- Keep the solution as simple as possible.

How to start on a problem

Given a task, e.g., spam classification, how should we get started on the problem?

- Approach 1: Analyze the problem/dataset, design the right features/models/objectives carefully, then implement the algorithm.
- Approach 2: Implement a simple baseline quickly, see what's wrong with it and fix its problems.

In practice, often an *iterative process* with a mix of both approaches.

Reference: Andrew Ng's advice on applying ML.

Practical scenario

You build a logistic regression model with L2 regularization using bag-of-words features for the spam classification task. After running SGD for some iterations, validation error is 20%. What do you do now?

- Get more data.
- Better feature selection.
- Try another optimizer.
- Run SGD for longer.
- Tune weights on the regularizer.
- Try another model.
- ...

Setting expectations on performance

Lower bound What's the dumbest/simplest predictor you can build?

- Always predict the majority class / target mean.
- Decision/regression stump, i.e. use only one feature.
- Linear model (with regularization).

Upper bound What's the best performance you can get given the hypothesis space?

- Fit your model on the validation set without regularization, i.e. cheating.

Overfitting vs underfitting

Overfitting	Low bias, high variance
Underfitting	High bias, low variance

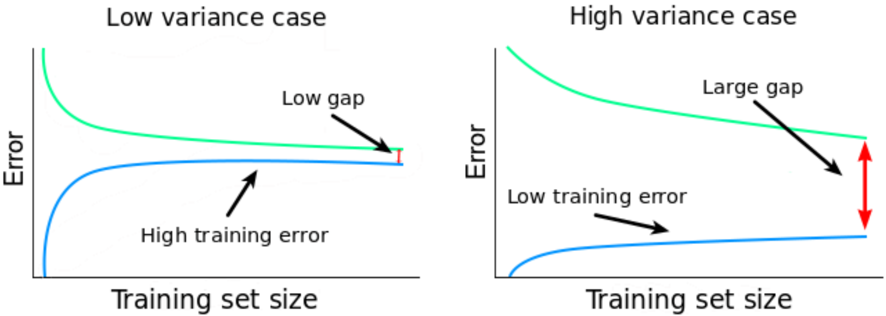


Figure: https://www.dataquest.io/blog/learning-curves-machine-learning/.

Fixes for high bias/variance

High variance

- More data, bagging
- Simpler feature, e.g., remove rare words, L1 regularization
- Simpler model, increase regularization strength

High bias

- Better feature, e.g., n-grams
- Increase model complexity, e.g., neural nets
- Reduce regularization strength

Optimization error

Is there a problem with optimization?

- Look at the learning curve. Is the loss decreasing?
- Verify initial loss, e.g., $p(y \mid x)$ is a uniform distribution.
- Add a cheating feature (i.e. the label), does it achieve zero training error?

Fixes

- Tune the hyperparameters, e.g., the learning rate.
- Try another optimizer.

Error analysis

Data **Look at your data, but only the training/validation data!**

- Preprocessing errors, data corruption.
- Label imbalance, noise.
- Look at misclassified examples.
- In general, print out as much information about the data as possible.

Model How much does each component help?

- **Ablation study**: change one thing at a time, e.g., how much does the performance change if you add/remove the component?
- **Oracle experiment**: use groundtruth information, e.g., how much gain do you get if the output of the component is perfect?
- Similar to how you would debug your code.

Summary

- Many things can go wrong: data, model, learning algorithm etc.
- Fixes should be motivated by a problem identified from your analysis.
- Verify that the fix actually fixes the problem it's intended to fix!
- Be creative.

Next Steps

Other courses offered by CDS

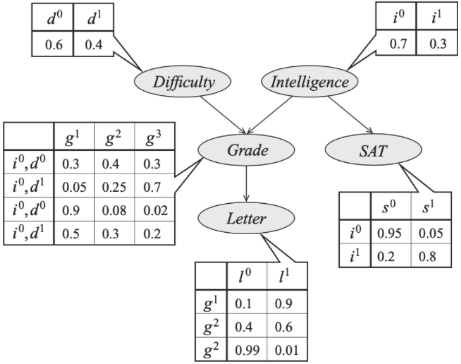
Foundations

- DS-GA 1005 Inference and Representation
- DS-GA 1008 Deep Learning
- DS-GA 1013 Mathematical Tools for Data Science
- DS-GA 3001 Special Topics in Data Science: Responsible Data Science

Applications

- DS-GA 1011 Natural Language Processing with Representation Learning
- DS-GA 1012 Natural Language Understanding and Computational Semantics
- DS-GA 3001 Special Topics in Data Science: Intro to Computer Vision
- DS-GA 3001 Special Topics in Data Science: Computational Cognitive Modeling

Probabilistic graphical models



d^0	d^1
0.6	0.4

i^0	i^1
0.7	0.3

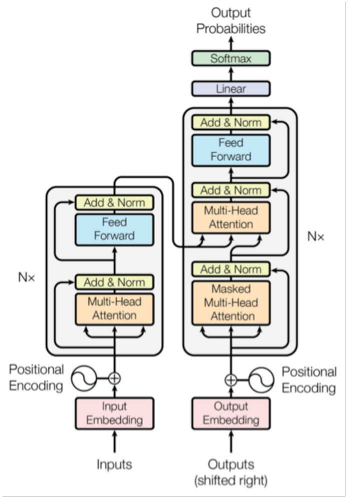
	g^1	g^2	g^3
i^0,d^0	0.3	0.4	0.3
i^0,d^1	0.05	0.25	0.7
i^0,d^0	0.9	0.08	0.02
i^0,d^1	0.5	0.3	0.2

	s^0	s^1
i^0	0.95	0.05
i^1	0.2	0.8

	l^0	l^1
g^1	0.1	0.9
g^2	0.4	0.6
g^2	0.99	0.01

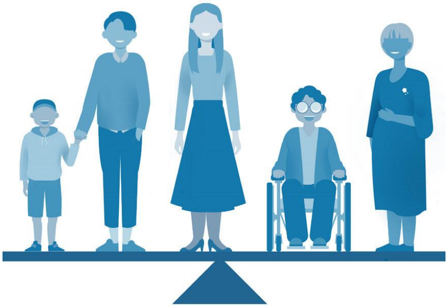
- DS-GA 1005
- Model: represent the world as a joint distribution of observed and unobserved variables.
- Learning: estimate parameters of the distribution from data, e.g., MLE.
- Inference: compute posterior distribution of the latent variables.

Deep learning



- DS-GA 1008
- Advanced neural network architectures: CNN, RNN, Seq2Seq, memory networks, Transformers etc.
- Deep generative models: auto-encoders, GANs, energy-based models.
- Representation learning: self-supervised learning.

Ethics



- DS-GA 3001.009
- Remember that the model we build will eventually impact *people*.
- Privacy: will the model/data leak user information?
- Fairness: does the model "discriminate" a group of people?
- Bias: does the model inherit bias in our society which generates the data?

Language

- DS-GA-10011, DS-GA-1012
- Goal: teach computers to understand human languages.
- Properties: discrete, compositional, ambiguous
- Representation: how do we represent words, sentences, and documents?
- Conditional sequence modeling: machine translation, summarization, dialogue etc.
- Language understanding tasks: information extraction, entailment, question answering.

Vision

- DS-GA 3001.005
- Goal: teach computers to see the world as we see it.
- Challenges:
  - Low-level input: large amounts of raw pixels.
  - Variations of the same object: illumination, view point, occlusion, scale etc.
- Tasks: object detection, video understanding, 3D vision etc.
- Many related areas: medical imaging, robotics.

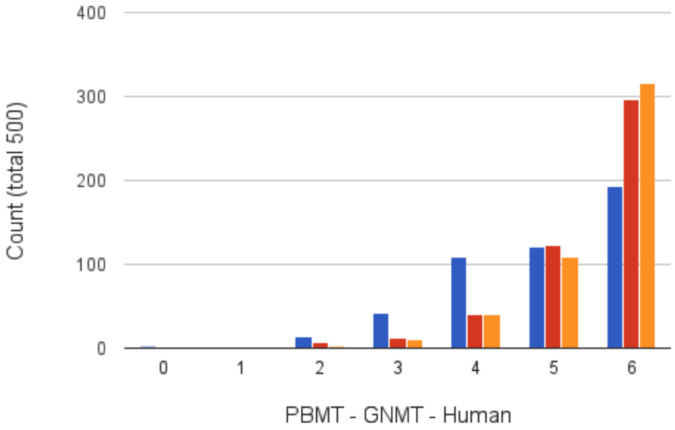
Cognitive modeling

- DS-GA 1016
- Goal: computational approaches to understanding human intelligence.
- Why should machine learning care?
    - Humans learn from a few examples—few shot learning.
    - Humans adapt to new concepts/environments quickly—transfer learning.
    - AI and cognitive science inform each other at both conceptual and technical levels.
        - Reinforcement learning, neural nets, Bayesian modeling etc.

Machine Learning in the Wild

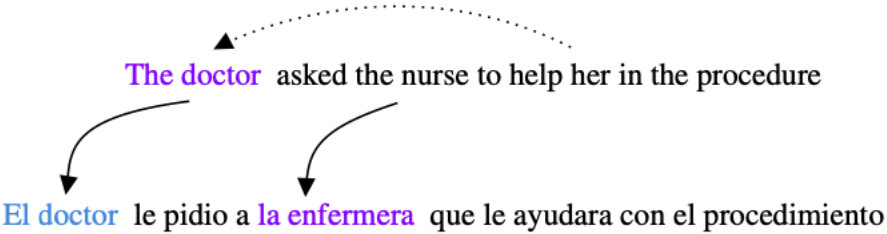
Google neural machine translation

Approaching human performance [Wu+ 2016].



Gender bias in MT

MT systems are prone to gender-biased translation errors [Stanovsky+ 2019].



The doctor asked the nurse to help her in the procedure

El doctor le pidio a la enfermera que le ayudara con el procedimiento

Object recognition

Lower error rate than humans on ImageNet.

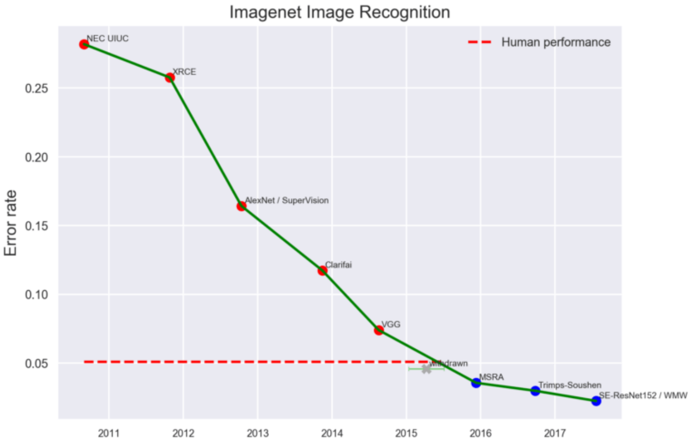
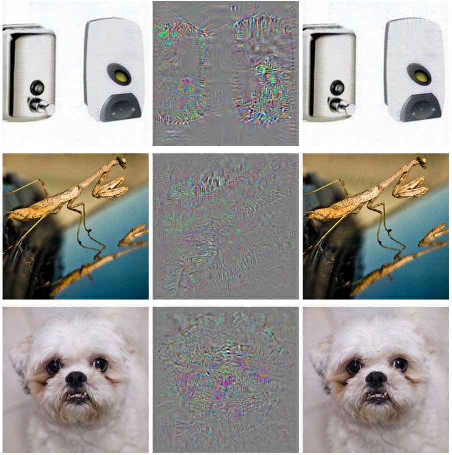


Chart from Measuring the Progress of AI Research by EFF (CC BY-SA).

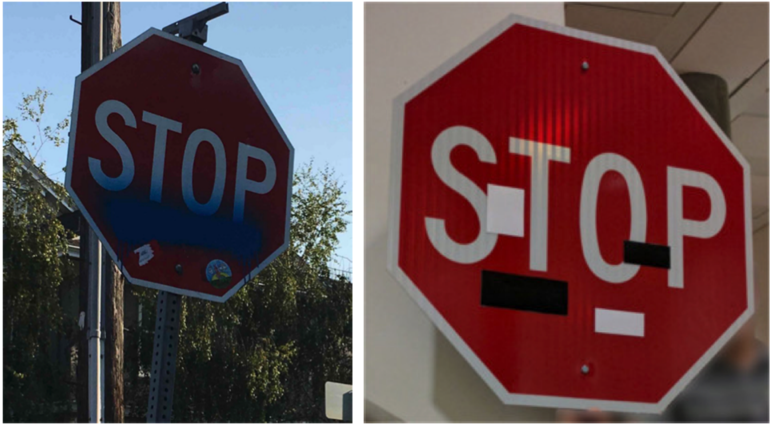
Adversarial examples

Left: correct. Middle: added noise. Right: ostrich. [Szegedy+, 2013]



Adversarial examples

Left: real graffiti. Right: advesarial patches. [Eykholt+, 2018]



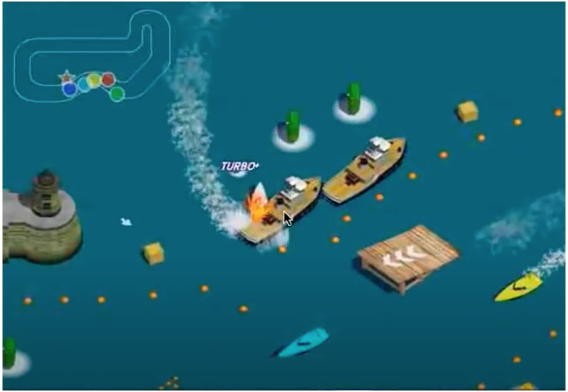
Reinforcement learning

Deepmind’s AlphaGo beats the world’s best human Go player.

Reward hacking

Instead of finishing the course, agent learns to circle and attack target repeated despite bumping into other boats.

https://openai.com/blog/faulty-reward-functions/



Ethics of Machine Learning

Ensure that the behavior of machines towards human users is ethically acceptable.

- Bias and accountability in high-stake decisions
    - Hiring, banking, legal, medical decisions etc.
- Unintended, long-term influences
    - Chat bots, recommender systems etc.
- Fairness: the system works well for a specific group of users
- Privacy: access to (private) data generated by users

Food for thought

- Should the learning objective be maximizing accuracy?
- Who is responsible and what to do when ML systems go wrong?
- How do we factor in humans when designing models?

Thank you!