DSC291: Machine Learning with Few Labels

Overview

Zhiting Hu

Lecture 1, April 1st, 2025

UC San Diego
HALICIOĞLU DATA SCIENCE INSTITUTE

Logistics

- Class webpage: http://zhiting.ucsd.edu/teaching/dsc291spring2025

Machine Learning with Few Labels

DSC 291 • Spring 2025 • UC San Diego

Machine learning is about computational methods that enable machines to learn concepts from experience. Many of the successful results of machine learning rely on learning with massive amounts of data labels. However, in many real problems we do not have enough labeled data, but instead have access to other forms of experience, such as structured knowledge, constraints, feedback signals from the environment, auxiliary models from related tasks, etc. This course focuses on those learning settings with few labels. This course is designed to give students a holistic understanding of related problems and methodologies (such as **large language/multi-modal models, world models, self/weakly/un-supervised learning, transfer learning, meta-learning, reinforcement learning, adversarial learning, knowledge constrained learning, panoramic learning**), different possible perspectives of formulating the same problems, the underlying connections between the diversity of algorithms, and open questions in the field. Students will read, present, and discuss papers, and complete course projects.

Logistics

Instructor: Zhiting Hu
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Location: HDSI 442

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Office hours: TBA
Location: TBA

- Discussion forum: Piazza
- Homework & writeup submission: Gradescope

Logistics: grading

- 2 Homework assignments (30% of grade)
- Paper presentation (20%)
- Course project (46%)
- Participation (4%)

Logistics: grading

- 2 Homework assignments (30% of grade)
  - Theory exercises, implementation exercises
  - 3 total late days without penalty
- Paper presentation (20%)
- Course project (46%)
- Participation (4%)

Logistics: grading

Depending on #enrollments

- 2 Homework assignments (30% of grade)
- Paper presentation (20%)
  - Each **student or pair** will give an oral presentation on a research paper
    - 6 mins = 5 mins presentation + 1 mins QA (*tentative*)
      - Timing -- hard time constraint: if you run over the expected time limit (5min), there will be no QA session for your presentation, and thus no credits for the QA component
    - **Critical thinking:** discuss both strengths and limitations of the paper
    - Sign up in a google sheet (TBA)
    - Design quiz questions for audience
  - **Peer grading:** other students will rate and give feedback (5% of grade)
  - Starting later part of the quarter, after the class size is stabilized
- Course project (46%)
- Participation (4%)

Logistics: grading

- 2 Homework assignments (30% of grade)
- Paper presentation (20%)
- Course project (46%)
  - 3 or 4-member (or larger) **team** to be formed and sign up in a google sheet (TBA)
  - Designed to be as similar as possible to researching and writing a **conference-style paper:**
    - Due to tight timeline, fine to use synthetic/toy data for proof-of-concept experiments + explanation of theory/intuition of why your approach is likely to work
  - **Proposal** : 2 pages excluding references (10%) -- due in 2 or 3 weeks (TBA)
    - Overview of project idea, literature review, potential datasets and evaluation, milestones
  - **Midway Report** : 4-5 pages excluding references (20%)
  - **Presentation** : oral presentation, 7-10mins (20%)
    - Peer grading (5%)
  - **Final Report** : 6-8 pages excluding references (50%)

Logistics: grading

- 2 Homework assignments (30% of grade)
- Paper presentation (20%)
- Course project (46%)
- Participation (4%)
  - Submission of quiz answers and feedback on paper/project presentations
  - Contribution to discussion on Piazza
  - Completion of final course evaluation
  - Any constructive suggestions

What is Machine Learning?

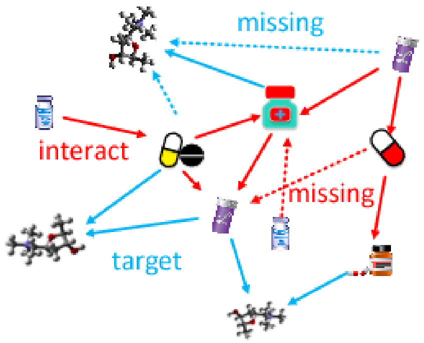
model

- Computational methods that enable machines to learn concepts and improve performance from **experience.**

Experience of all kinds

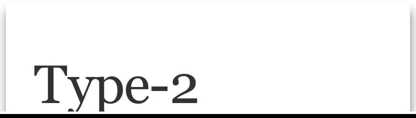
grammar

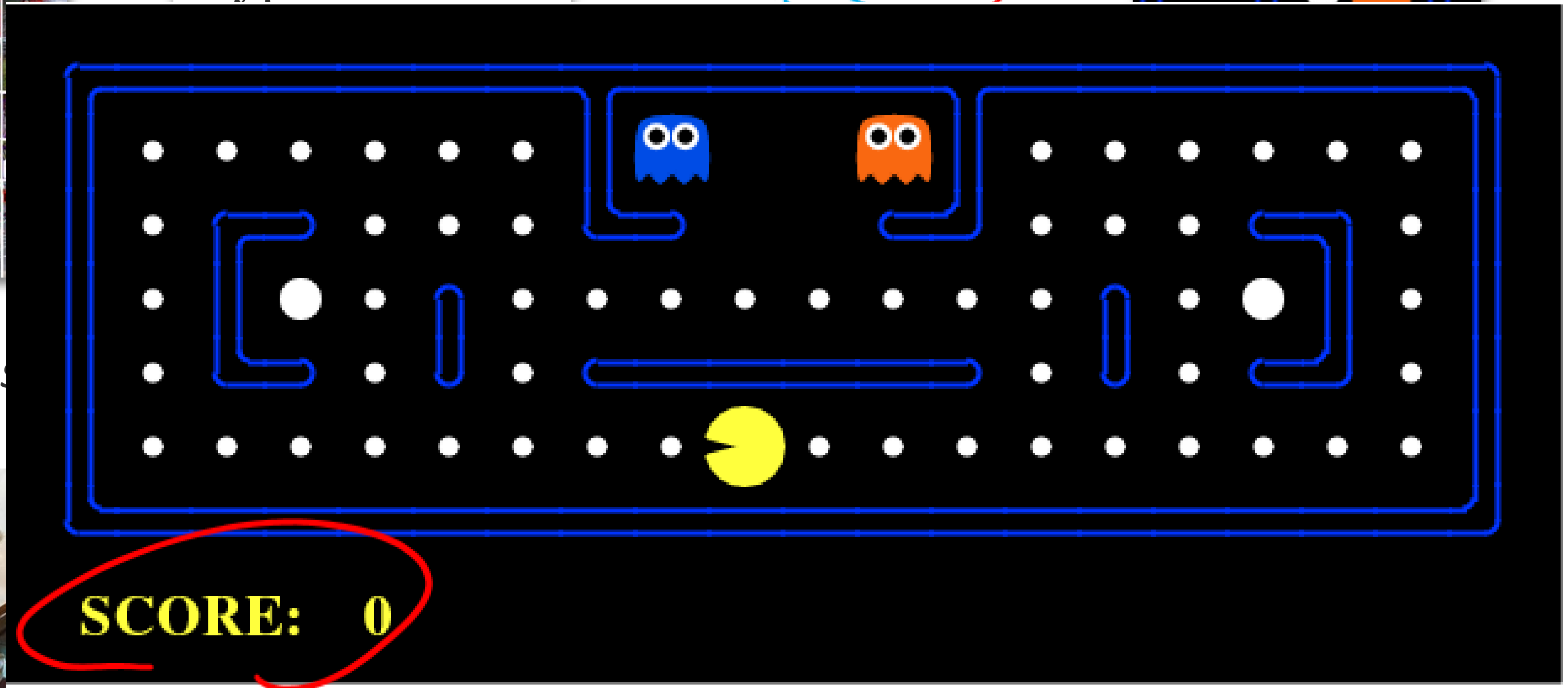
Type-2 diabetes is 90% more common than type-1



Data examples *Rules/Constraints* *Knowledge graphs* *Rewards*

Experience of all kinds

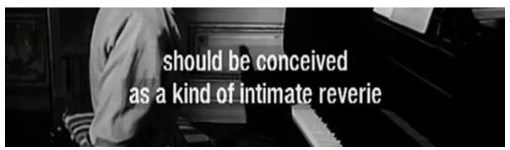




Data examples

Auxiliary agents

ations thereof

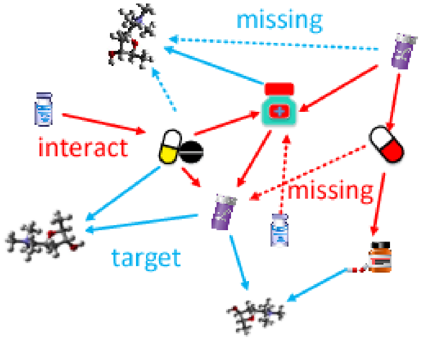


Adversaries

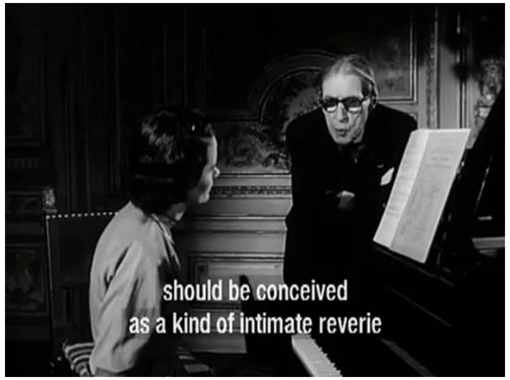
Master classes

Experience of all kinds

Type-2 diabetes is 90% more common than type-1



Data examples *Rules/Constraints* *Knowledge graphs* *Rewards* *Auxiliary agents*



...

And all combinations thereof

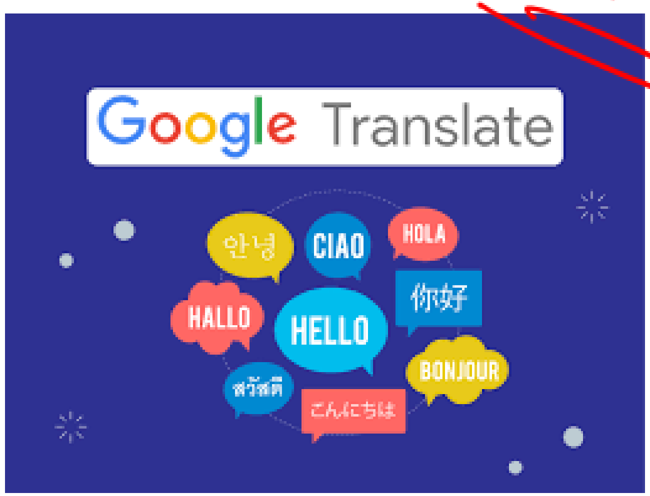
Adversaries *Master classes*

Experience: (massive) data examples

(English, French)

Image classification

2012 AlexNet



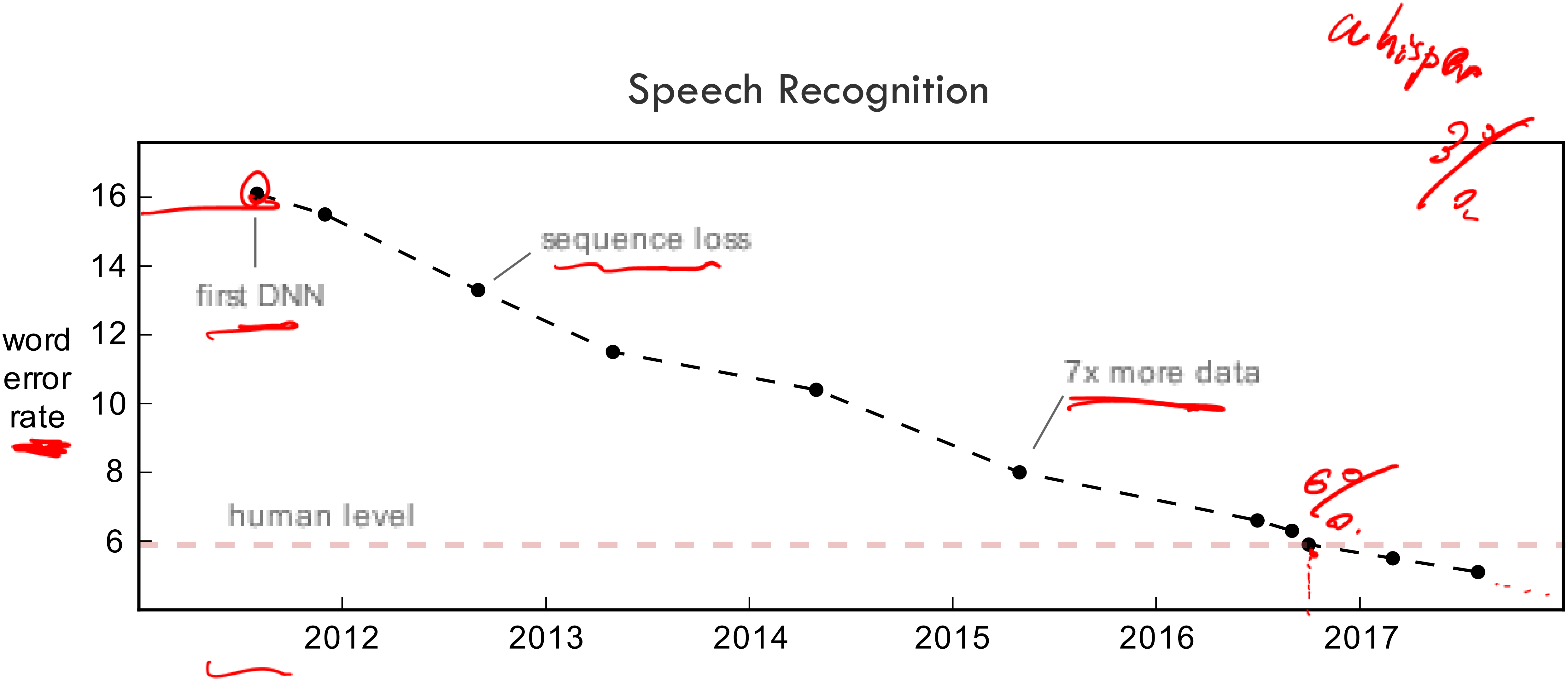
Machine translation

Language modeling
(BERT, GPT-2, GPT-3, GPT-4, …)

next-token prediction

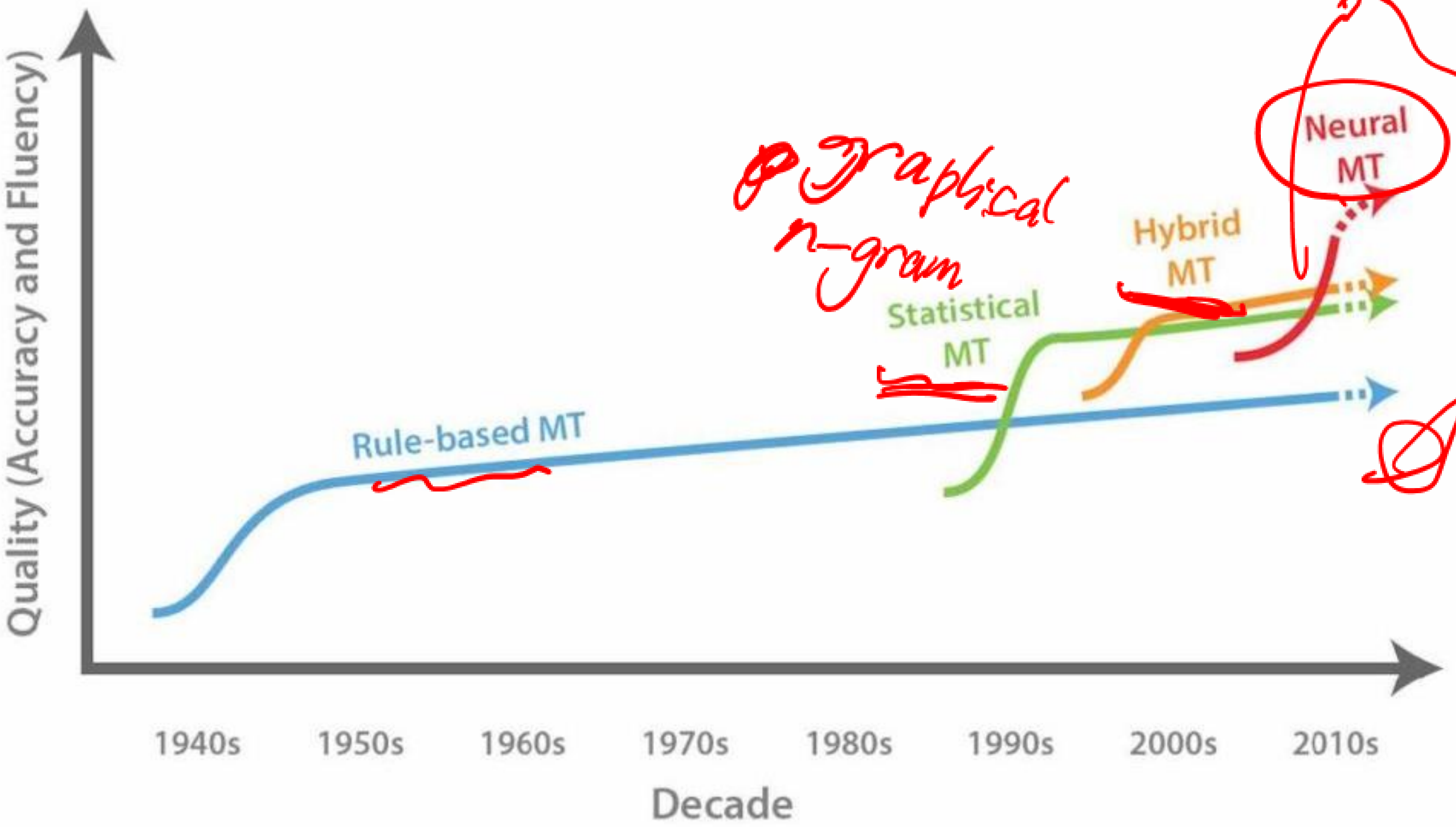
10s of trillions of text tokens: CommonCrawl, WebText, Wikipedia, corpus of books, …

Experience: (massive) data examples



Experience: (massive) data examples

Machine Translation



graphical n-gram

RNN

sequence-to-sequence (S2S)

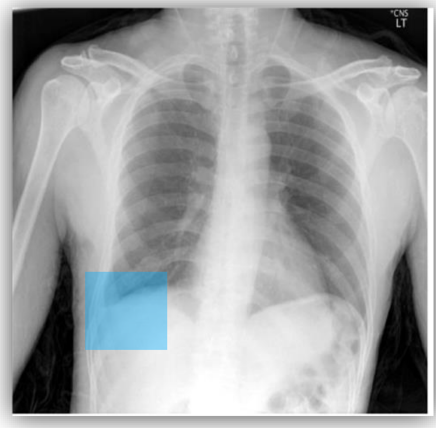
10-years ago

Transformers 2018.

Problems with few data (labels)

- Privacy, security issues

Assistive diagnosis



X-ray

Normal findings

Abnormal findings

``The heart size and mediastinal contours appear within normal limits. There is blunting of the right lateral costophrenic sulcus which could be secondary to a small effusion versus scarring …''

Problems with few data (labels)

- Expensive to collect/annotate

  Controllable content generation

Controlling sentiment

Pos	The film is full of imagination!
Neg	The film is strictly routine!

Controlling writing style

Plain	LeBron James contributed 26 points, 8 rebounds, 7 assists.
Elaborate	LeBron James rounded out the box score with an all around impressive performance, scoring 26 points, grabbing 8 rebounds and dishing out 7 assists.

Applications: personalized chatbot, live sports commentary production

Problems with few data (labels)

- Expensive to collect/annotate

Controllable content generation

Source image

Generated images under different poses

Applications: virtual clothing try-on system

Problems with few data (labels)

- Expensive to collect/annotate

Controllable content generation

pretraining

finetuning

o

post-training

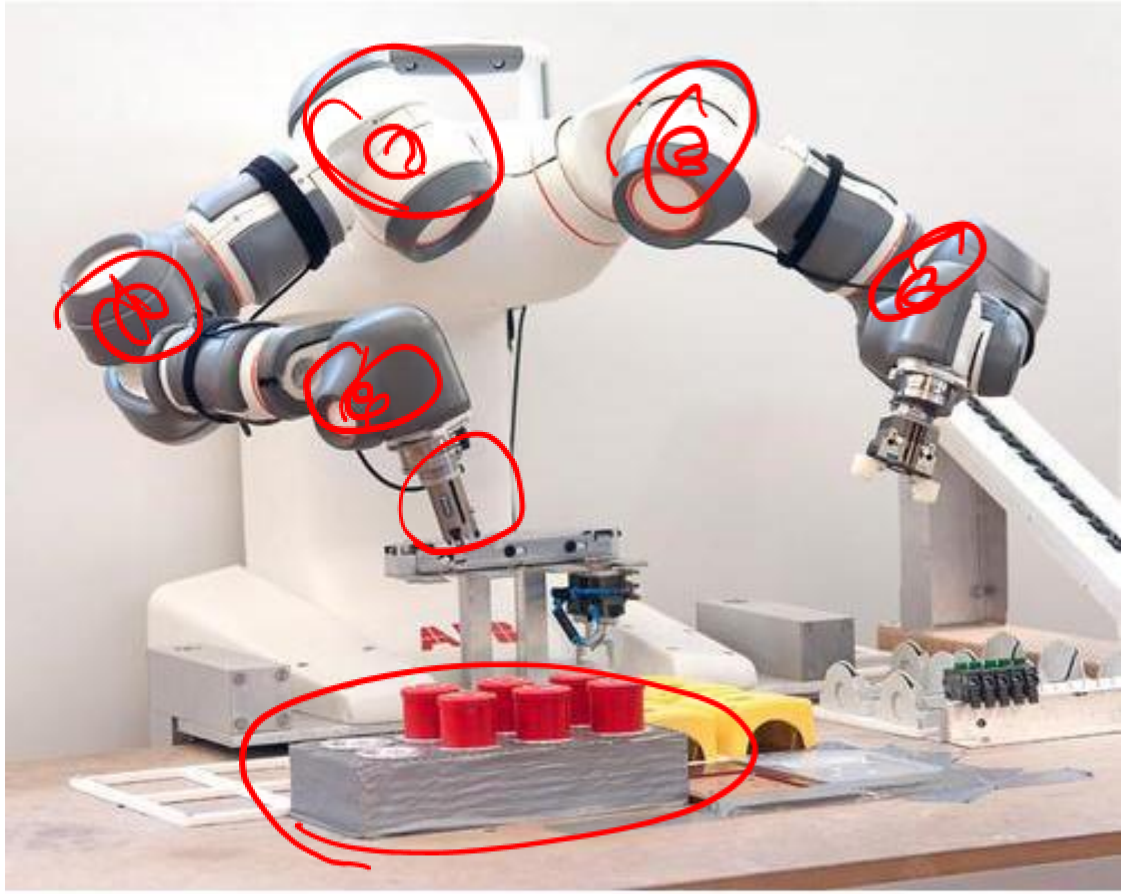
Source im

GPT-4o image generation/editing

Problems with few data (labels)

- Expensive to collect/annotate

Robotic control



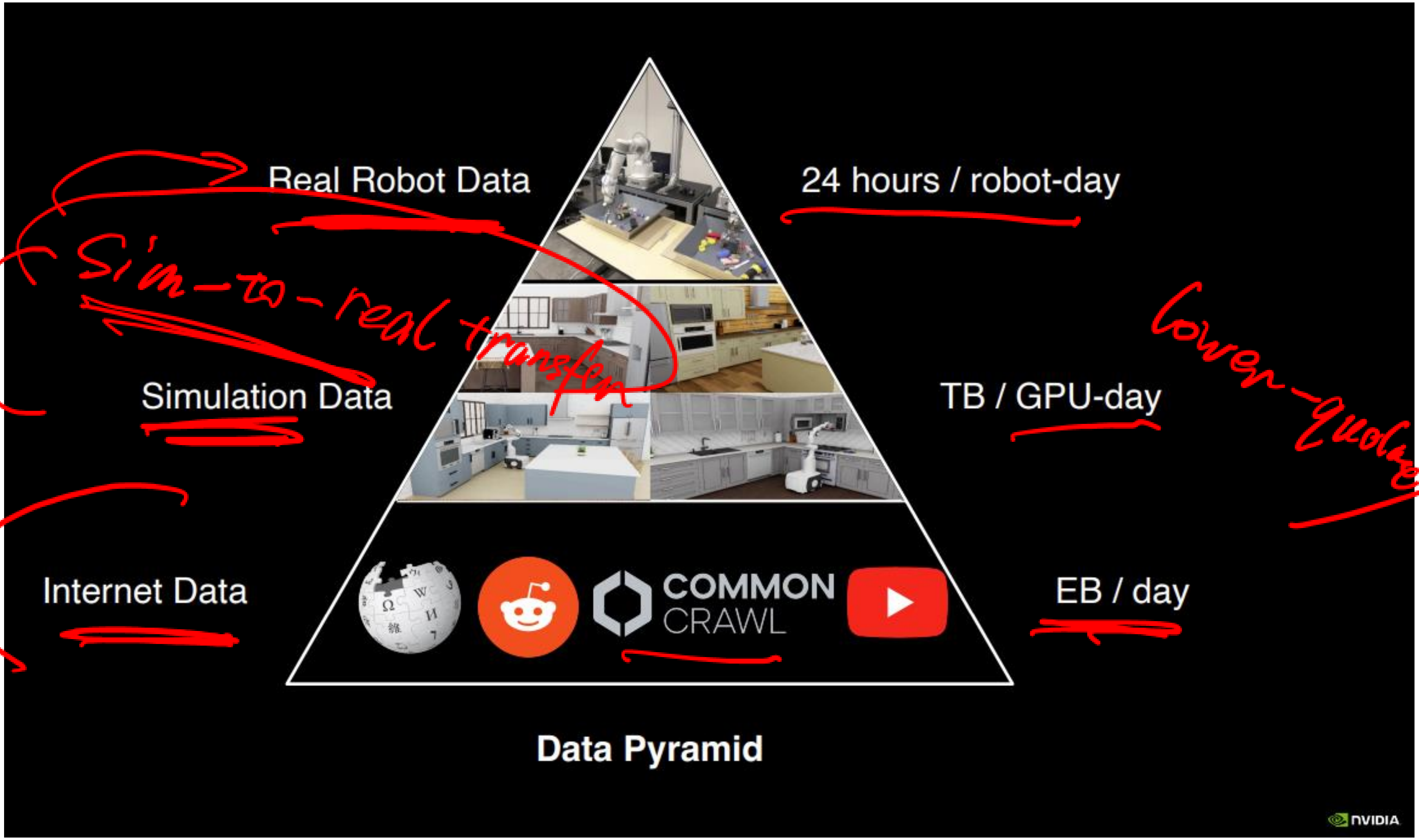
Problems with few data (labels)

- Expensive to collect/annotate

Robotic control

Post-training

Pretraining



Sim-to-real transfer

lower-quality

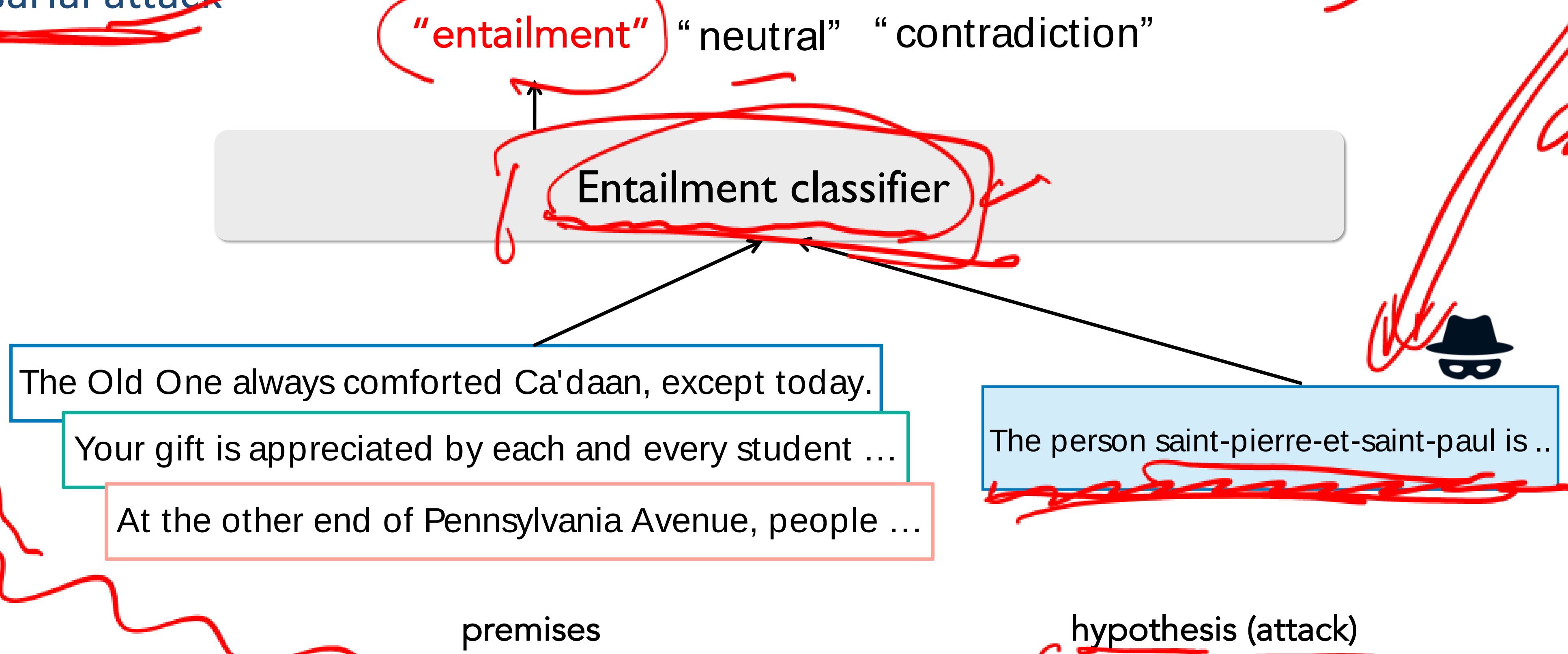
Problems with few data (labels)

- Difficult / expertise-demanding to annotate

Adversarial attack

attack model

3-way



universal attack

Applications: test model robustness

Problems with few data (labels)

prompt engineering

- Difficult / expertise-demanding to annotate

Prompt generation: automatically generating prompts to steer pretrained LMs

Pretrained LM
(e.g., GPT3)

Generate a story about cat: once upon a time, …

prompt | input | continuation

p-g

Problems with few data (labels)

- Specific domain

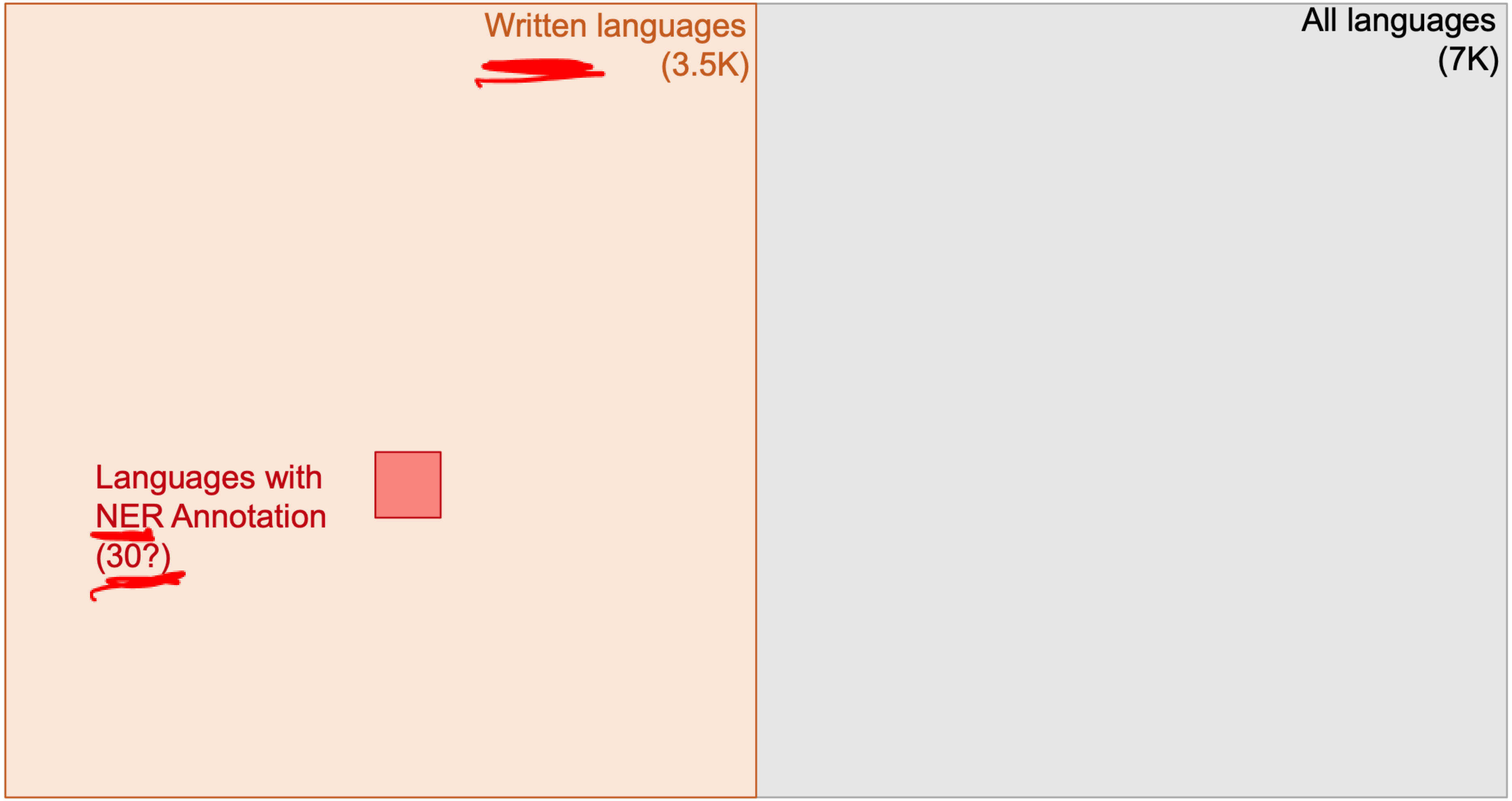
Low-resource languages

~7K languages in the world

NER: named entity recognition / study at UCSD University

Problems with few data (labels)

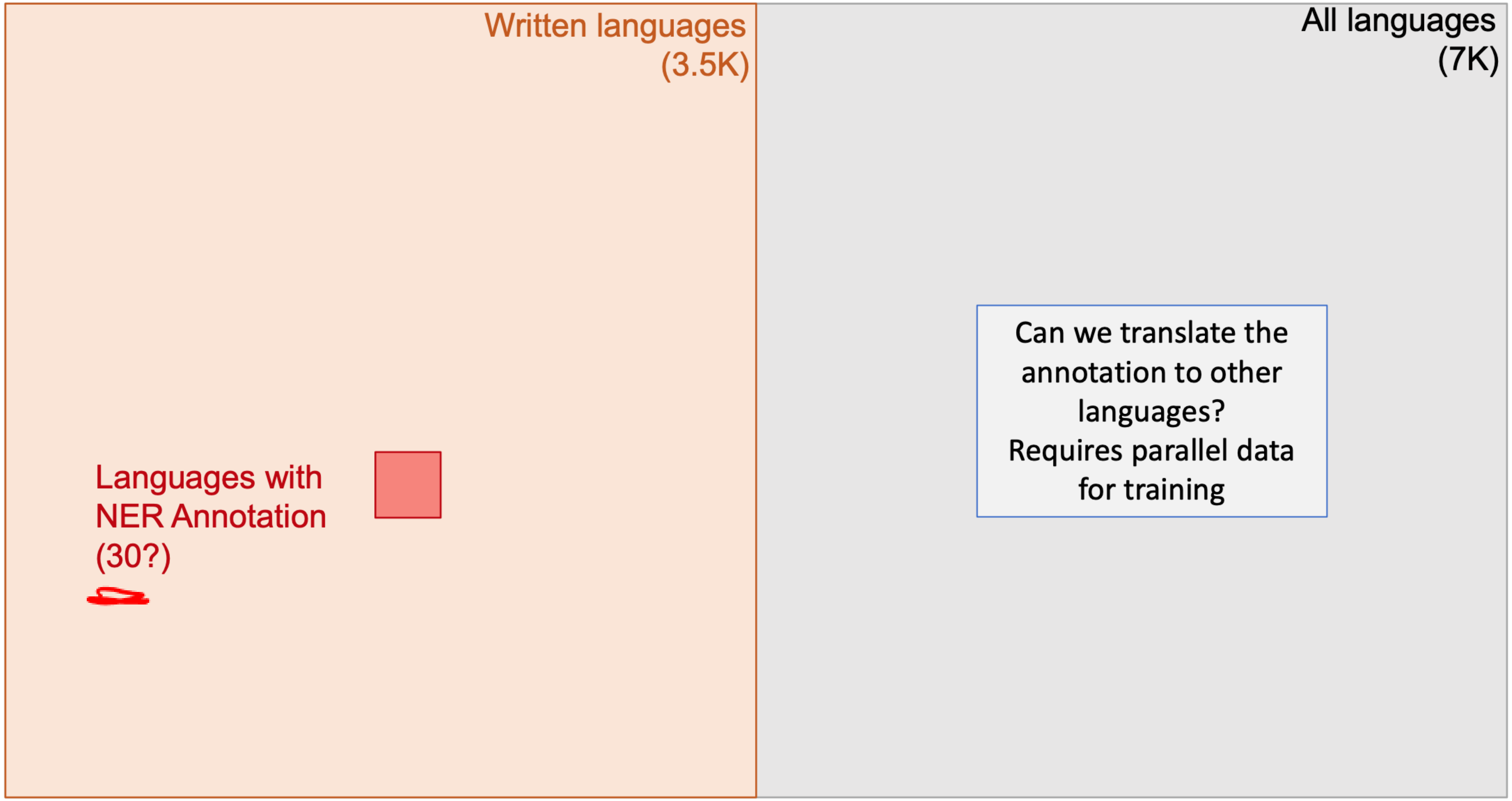
- Specific domain   Low-resource languages



[Figure courtesy: Dan Roth, CIS620]

Problems with few data (labels)

- Specific domain   Low-resource languages

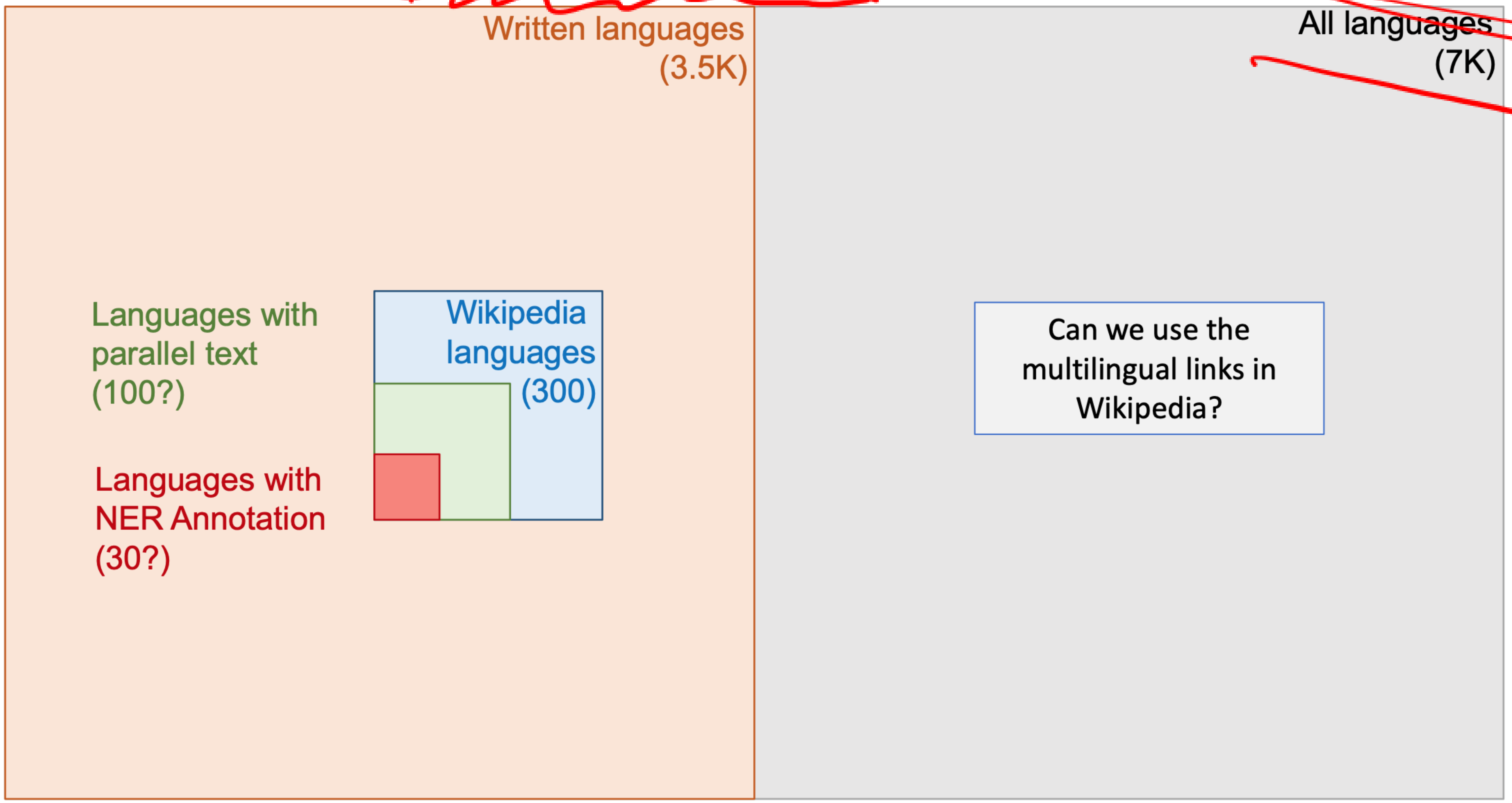


[Figure courtesy: Dan Roth, CIS620]

Problems with few data (labels)

Language documentation

- Specific domain Low-resource languages

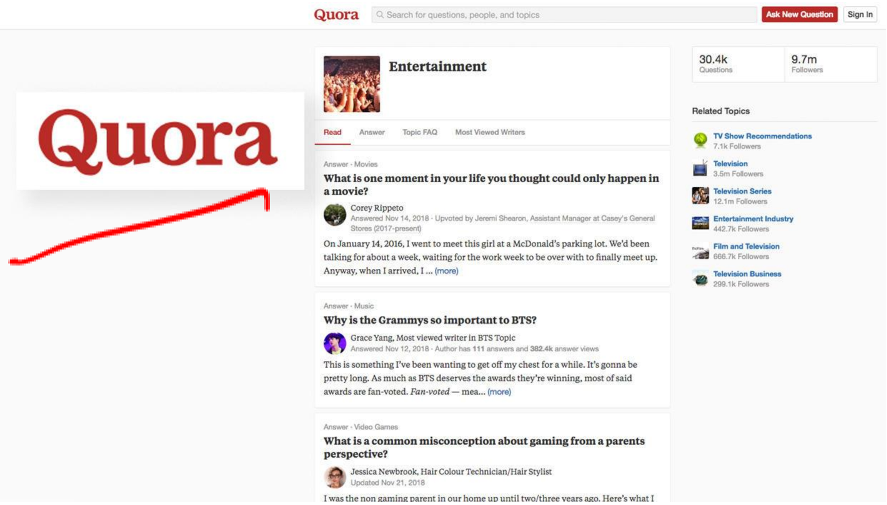


[Figure courtesy: Dan Roth, CIS620]

Problems with few data (labels)

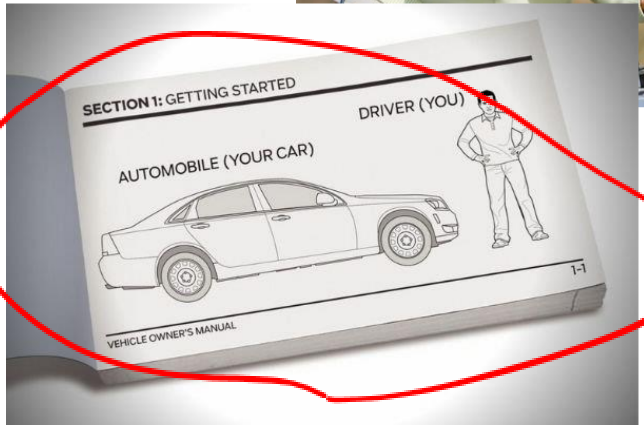
- Specific domain

Question answering



reddit

QA based on car manual?



Problems with few data (labels)

- Privacy, security issues
- Expensive to collect/annotate
- Difficult / expertise-demanding to annotate
- Specific domain

Machine learning solutions given few data (labels)

- How can we make more efficient use of data?
  - Clean but small-size
  - Noisy
  - Out-of-domain

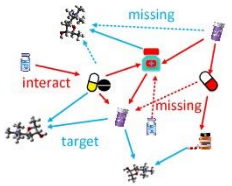
data examples

- Can we incorporate other types of experience in learning?

Data examples

Type-2 diabetes is 90% more common than type-1

Rules/Constraints



Knowledge graphs

Rewards

Auxiliary agents

Adversaries

Master classes

…

And all combinations thereof

Components of a ML solution (roughly)

- Loss
- Experience
- Optimization solver
- Model architecture

$$\min_{\theta} \mathcal{L}(\theta, \mathcal{E})$$

Optimization solver

Loss

Model architecture

Experience

Components of a ML solution (roughly)

- Loss
- Experience
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- Model architecture

This course does ***not*** discuss model architecture

$$\min_{\theta} \mathcal{L}(\theta, \mathcal{E})$$

Optimization solver

Loss

Model architecture

Experience

Components of a ML solution (roughly)

- Loss
- Experience
- Optimization solver
- Model architecture

This course does ***not*** discuss model architecture

Model of certain architecture whose parameters are the subject to be learned, $p_\theta(\boldsymbol{x}, \boldsymbol{y})$ or $p_\theta(\boldsymbol{y}|\boldsymbol{x})$

- Neural networks
- Graphical models
- Compositional architectures

Components of a ML solution (roughly)

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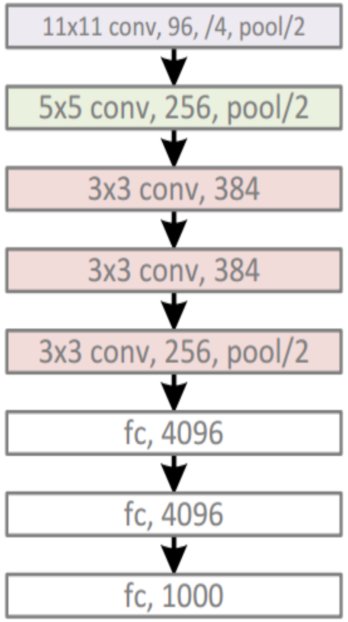
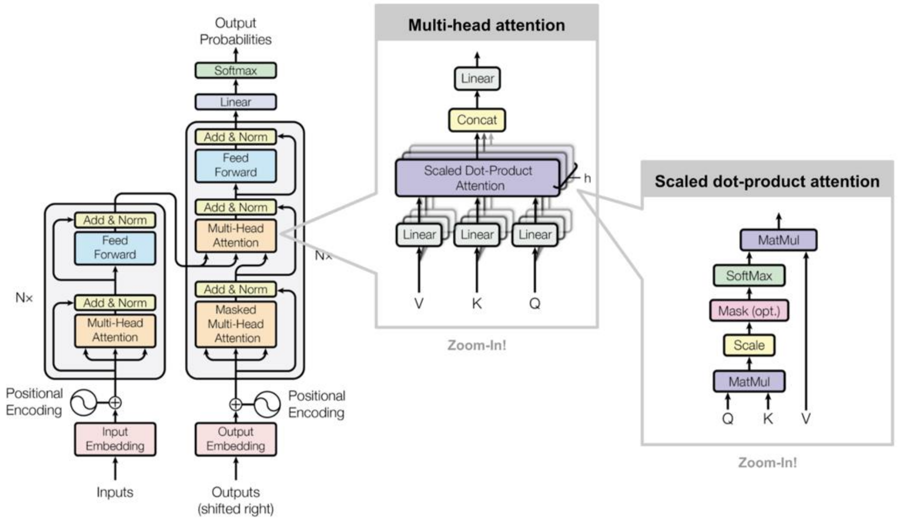


Convolutional networks



Transformers

Components of a ML solution (roughly)

- Loss
- Experience
- Optimization solver
- Model architecture

This course does ***not*** discuss model architecture

Model of certain architecture whose parameters are the subject to be learned, $p_\theta(\boldsymbol{x}, \boldsymbol{y})$ or $p_\theta(\boldsymbol{y}|\boldsymbol{x})$

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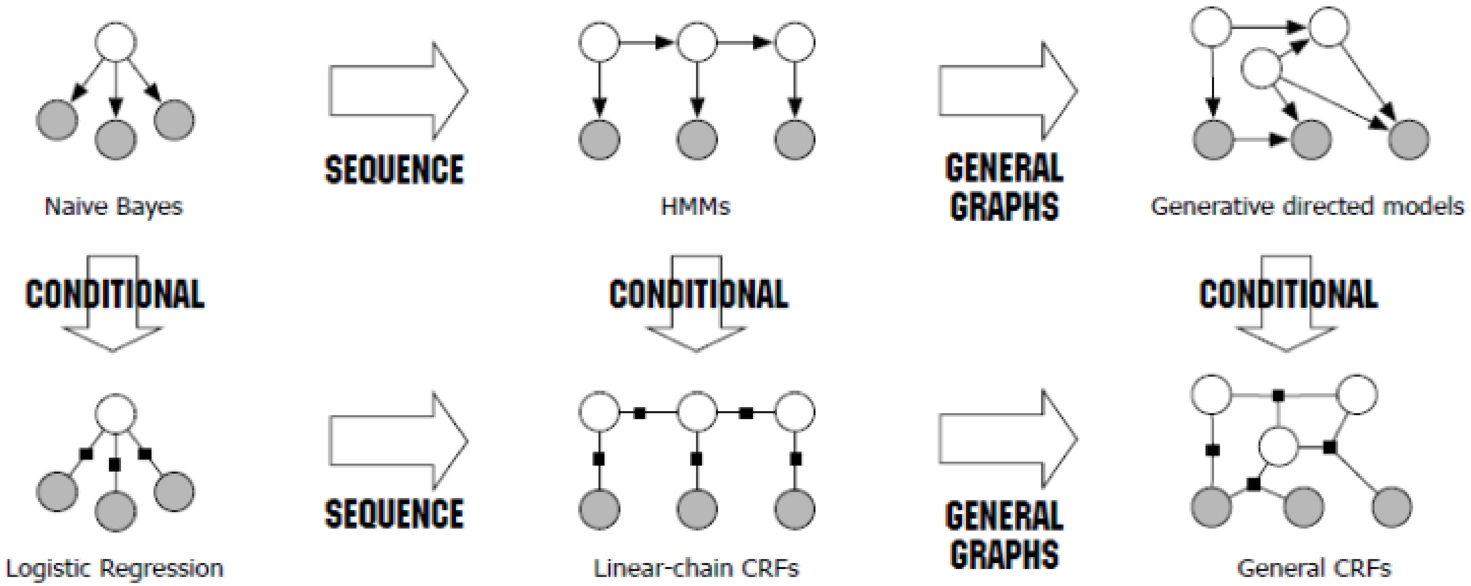


Components of a ML solution (roughly)

- Loss
- Experience
- Optimization solver
- Model architecture

This course discusses a *little* about optimization

Assuming you know basic procedures:

- (Stochastic) gradient descent
- Backpropagation
- Lagrange multiplier
- …

$$\min_\theta \mathcal{L}(\theta, \mathcal{E})$$

Optimization solver

Loss

Model architecture

Experience

Components of a ML solution (roughly)

- Loss
- Experience
- Optimization solver
- Model architecture

This course discusses *a lot* of loss & experience

Core of most learning algorithms

$$\min_{\theta} \mathcal{L}(\theta, \mathcal{E})$$

Optimization solver

Loss

Model architecture

Experience

Machine learning solutions given few data (labels)

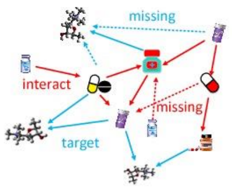
- (1) How can we make more efficient use of data?
  - Clean but small-size, Noisy, Out-of-domain

- (2) Can we incorporate other types of experience in learning?

Data examples

Type-2 diabetes is 90% more common than type-1

Rules/Constraints



Knowledge graphs

Rewards

Auxiliary agents

Adversaries

Master classes

…

And all combinations thereof

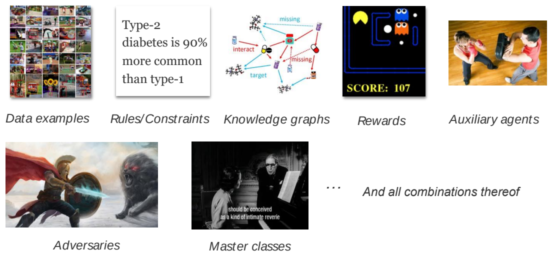
Machine learning solutions given few data (labels)

- (1) How can we make more efficient use of data?
  - Clean but small-size, Noisy, Out-of-domain, …
- Algorithms
  - **Supervised learning**: MLE, maximum entropy principle
  - **Unsupervised learning**: EM, variational inference, VAEs
  - **Self-supervised learning**: successful instances, e.g., BERT, GPTs, contrastive learning, applications to downstream tasks
  - **Distant/weakly supervised learning**: successful instances
  - **Data manipulation:** augmentation, re-weighting, curriculum learning, …
  - **Meta-learning**

Mostly first half of the course

Machine learning solutions given few data (labels)

- (2) Can we incorporate other types of experience in learning?
  - Learning from auxiliary models, e.g., adversarial models:
    - Generative adversarial learning (GANs and variants), co-training, …
  - Learning from structured knowledge
    - Posterior regularization, constraint-driven learning, …
  - Learning from rewards
    - Reinforcement learning: model-free vs model-based, policy-based vs value-based, on-policy vs off-policy, extrinsic reward vs intrinsic reward, …
  - Learning in dynamic environment *(not covered)*
    - Online learning, lifelong/continual learning, …



Second half of the course

Algorithm marketplace

Designs driven by: experience, task, loss function, training procedure …

maximum likelihood estimation
reinforcement learning as inference
data re-weighting
inverse RL
active learning
policy optimization
data augmentation
reward-augmented maximum likelihood
label smoothing
imitation learning
softmax policy gradient
actor-critic
adversarial domain adaptation
GANs
posterior regularization
knowledge distillation
intrinsic reward
constraint-driven learning
generalized expectation
prediction minimization
regularized Bayes
learning from measurements
energy-based GANs
weak/distant supervision

Where we are now? Where we want to be?

- Alchemy vs chemistry

maximum likelihood estimation
reinforcement learning as inference
data re-weighting
inverse RL
active learning
policy optimization
data augmentation
reward-augmented maximum likelihood
label smoothing
imitation learning
softmax policy gradient
actor-critic
adversarial domain adaptation
GANs
posterior regularization
knowledge distillation
intrinsic reward
constraint-driven learning
prediction minimization
generalized expectation
regularized Bayes
learning from measurements
energy-based GANs
weak/distant supervision

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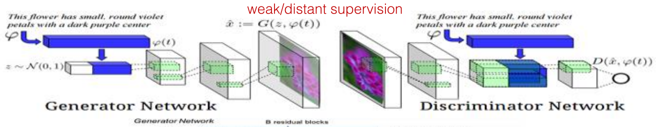

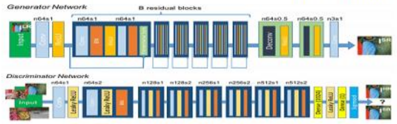

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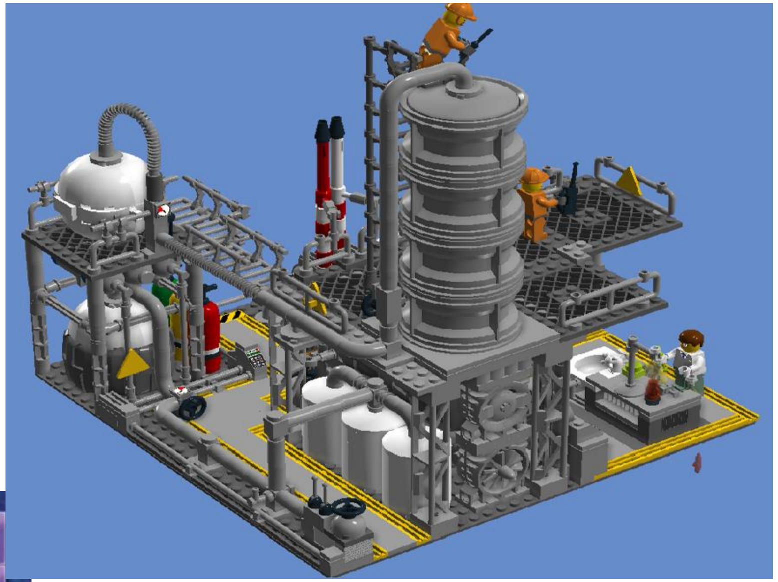

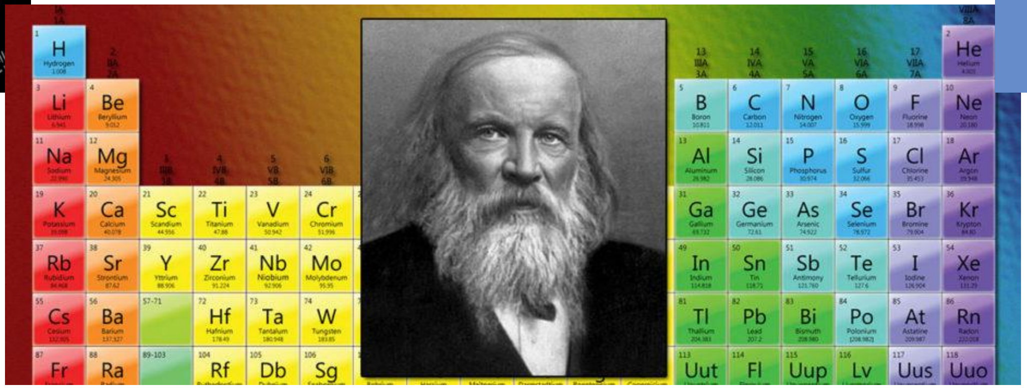

Quest for more standardized, unified ML principles

Machine Learning 3: 253–259, 1989
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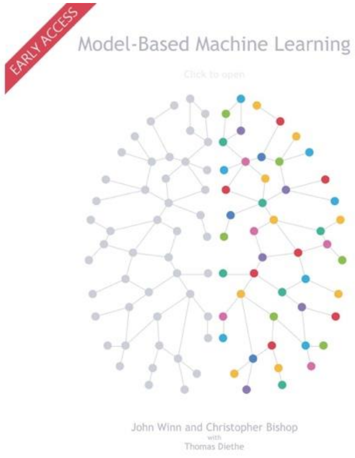
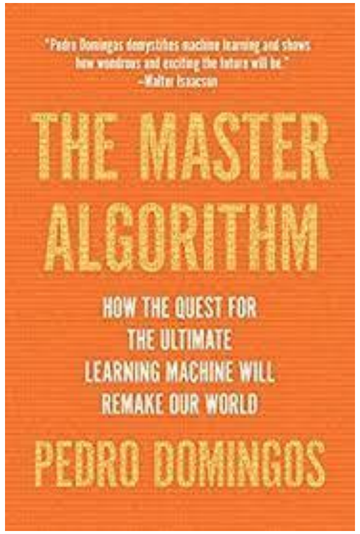
EDITORIAL

Toward a Unified Science of Machine Learning

[P. Langley, 1989]





REVIEW — Communicated by Steven Nowlan

A Unifying Review of Linear Gaussian Models

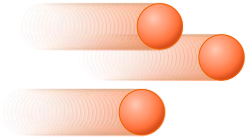
Sam Roweis*
Computation and Neural Systems, California Institute of Technology, Pasadena, CA 91125, U.S.A.

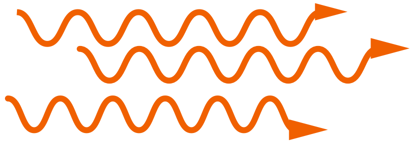
Zoubin Ghahramani*
Department of Computer Science, University of Toronto, Toronto, Canada

Physics in the 1800's

- Electricity & magnetism:
  - Coulomb's law, Ampère, Faraday, …

- Theory of light beams:
  - Particle theory: Isaac Newton, Laplace, Plank
  - Wave theory: Grimaldi, Chris Huygens, Thomas Young, Maxwell





- Law of gravity
  - Aristotle, Galileo, Newton, …

"Standard equations" in Physics

Diverse electro-magnetic theories

Maxwell's Eqns: original form

$e+\frac{df}{dx}+\frac{dg}{dy}+\frac{dh}{dz}=0$	(1)	Gauss' Law
$\mu\alpha=\frac{dH}{dy}-\frac{dG}{dz}$ $\mu\beta=\frac{dF}{dz}-\frac{dH}{dx}$ $\mu\gamma=\frac{dG}{dx}-\frac{dF}{dy}$	(2)	Equivalent to Gauss' Law for magnetism
$P=\mu\left(\gamma\frac{dy}{dt}-\beta\frac{dz}{dt}\right)-\frac{dF}{dt}-\frac{d\Psi}{dx}$ $Q=\mu\left(\alpha\frac{dz}{dt}-\gamma\frac{dx}{dt}\right)-\frac{dG}{dt}-\frac{d\Psi}{dy}$ $R=\mu\left(\beta\frac{dx}{dt}-\alpha\frac{dy}{dt}\right)-\frac{dH}{dt}-\frac{d\Psi}{dz}$	(3)	Faraday's Law (with the Lorentz Force and Poisson's Law)
$\frac{d\gamma}{dy}-\frac{d\beta}{dz}=4\pi p'$ $\quad p'=p+\frac{df}{dt}$ $\frac{d\alpha}{dz}-\frac{d\gamma}{dx}=4\pi q'$ $\quad q'=q+\frac{dg}{dt}$ $\frac{d\beta}{dx}-\frac{d\alpha}{dy}=4\pi r'$ $\quad r'=r+\frac{dh}{dt}$	(4)	Ampère-Maxwell Law
$P=-\xi p \quad Q=-\xi q \quad R=-\xi r$		Ohm's Law
$P=kf \quad Q=kg \quad R=kh$		The electric elasticity equation (**E** = **D**/ε)
$\frac{de}{dt}+\frac{dp}{dx}+\frac{dq}{dy}+\frac{dr}{dz}=0$		Continuity of charge

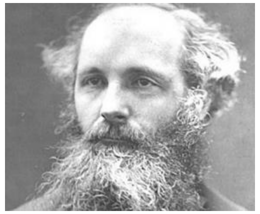
Maxwell's Eqns simplified w/ rotational symmetry

$$\nabla\cdot\mathbf{D}=\rho_V$$

$$\nabla\cdot\mathbf{B}=0$$

$$\nabla\times\mathbf{E}=-\frac{\partial\mathbf{B}}{\partial t}$$

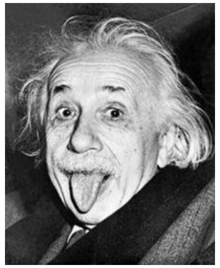
$$\nabla\times\mathbf{H}=\frac{\partial\mathbf{D}}{\partial t}+\mathbf{J}$$



Maxwell's Eqns further simplified w/ symmetry of special relativity

$$\varepsilon^{uvk\lambda}\partial_v F_{k\lambda}=0$$

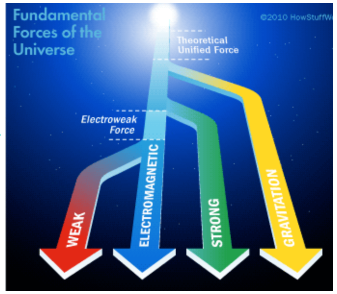
$$\partial_v F^{uV}=\frac{4\pi}{c}j^u$$



Standard Model w/ Yang-Mills theory and US(3) symmetry

$$\mathcal{L}_{\mathrm{gf}}=-\frac{1}{2}\operatorname{Tr}(F^2)=-\frac{1}{4}F^{a\mu\nu}F^a_{\mu\nu}$$

Unification of fundamental forces?



1861 — 1910s — 1970s — ?

A "standardized formalism" of ML

Data examples

Type-2 diabetes is 90% more common than type-1

Constraints

Rewards

Auxiliary agents

Adversaries

Imitation

$$\min_{q,\theta} \; -\mathbb{H} + \mathbb{D} - \mathbb{E}$$

Uncertainty Divergence Experience

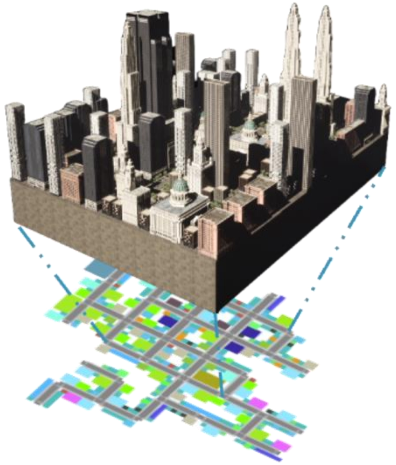
- Panoramically learn from all types of experience
- Subsumes many existing algorithms as special cases

Will discuss in later in the class

Possible Ideas of Course Project

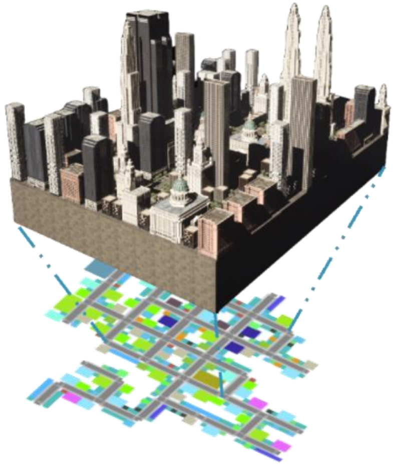
SimWorld: Open-ended world simulation with tens to millions of agents

Unreal Engine



In progress

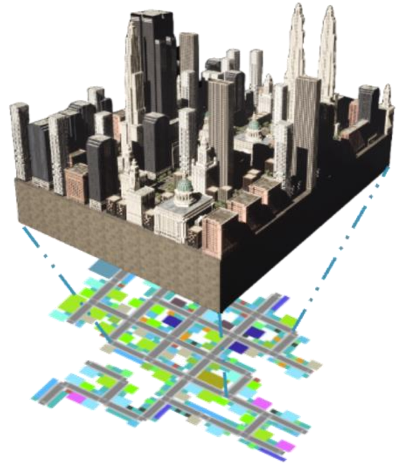
SimWorld: Open-ended world simulation with tens to millions of agents



In progress

SimWorld: Open-ended world simulation with tens to millions of agents

Robot dog controlled by GPT-4o



In progress

SimWorld: Open-ended world simulation with tens to millions of agents

LLM Reasoning and Agent

https://github.com/maitrix-org/llm-reasoners

LLM Reasoners

A library for advanced reasoning with large language models

Questions?