DSC190: Machine Learning with Few Labels

Overview

Zhiting Hu

Lecture 1, September 23, 2021

UC San Diego
HALICIOĞLU DATA SCIENCE INSTITUTE

Logistics

- Class webpage: http://zhiting.ucsd.edu/teaching/dsc190fall2021

DSC190-Fall2021 Logistics Lectures Homework Project

Machine Learning with Few Labels

DSC 190 • Fall 2021 • 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 supervised learning with massive amount 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 environment, auxiliary models from related tasks, etc. This course focuses on those learning settings with few labels, where one has to go beyond supervised learning and use other learning methods. This course is designed to give students a holistic understanding of related problems and methodologies (such as zero/few-shot learning, self/weakly-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
Email: zhh019@ucsd.edu
Office hours: Tuesday 3:00-4:00pm
Location: SDSC E247

TA: Meng Song
Email: mes050@eng.ucsd.edu
Office hours: Wednesday 2:30-3:30pm
Location: CSE 4109

- Canvas
- 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

- 2 Homework assignments (30% of grade)
- Paper presentation (20%)
  - Each student will give an oral presentation on a research paper
  - 10 mins = 8 mins presentation + 2 mins QA
  - Discuss both strengths and limitations of the paper
  - Sign up in a google sheet (TBA)
  - Starting October 26
- Course project (46%)
- Participation (4%)

Logistics: grading

- 2 Homework assignments (30% of grade)
- Paper presentation (20%)
- Course project (46%)
  - 3 or 4-member 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 Oct 12
    - Overview of project idea, literature review, potential datasets and evaluation, milestones
  - **Midway Report** : 4-5 pages excluding references (20%)
  - **Presentation** : oral presentation, 15-20mins (20%)
  - **Final Report** : 6-8 pages excluding references (50%)

Logistics: grading

- 2 Homework assignments (30% of grade)
- Paper presentation (20%)
- Course project (46%)
- Participation (4%)
  - Contribution to discussion on Piazza
  - Complete mid-quarter evaluation
  - Any constructive suggestions

Machine Learning

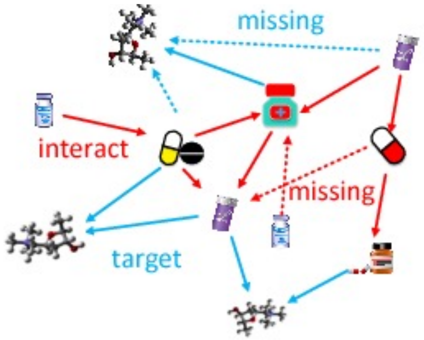
- Computational methods that enable machines to learn concepts and improve performance from **experiences**.

Experiences of all kinds

Data examples

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

Rules/Constraints

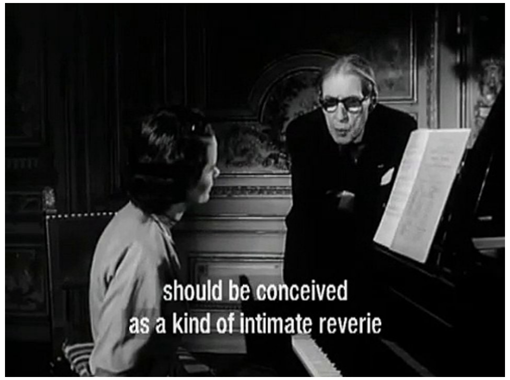


Knowledge graphs

Rewards

Auxiliary agents

Adversaries

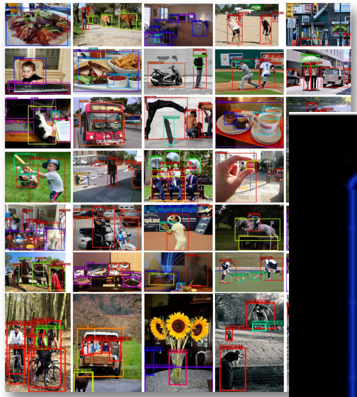


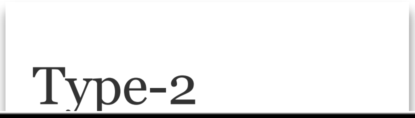
Master classes

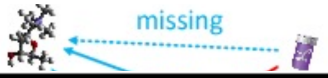
…

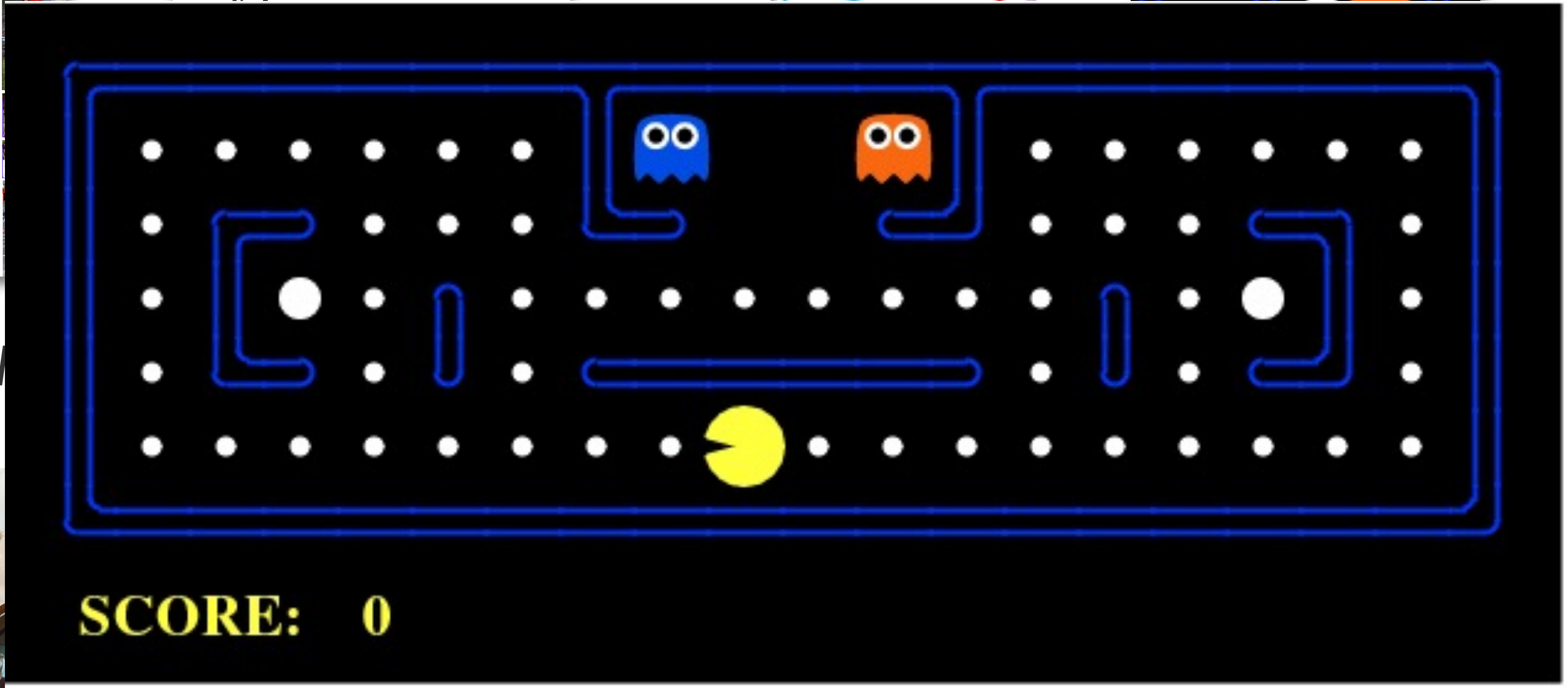
And all combinations thereof

Experiences of all kinds





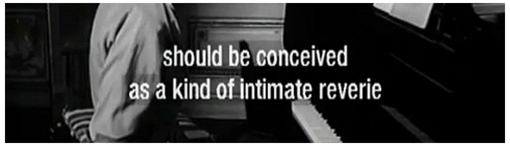




Data exampl

Auxiliary agents

ations thereof



Adversaries

Master classes

Experiences of all kinds

Data examples

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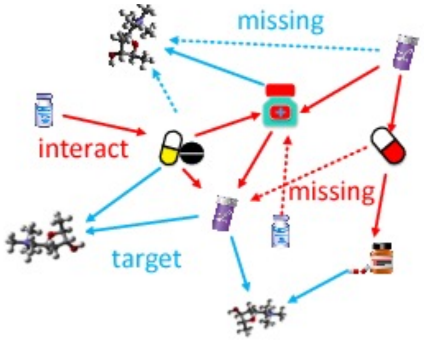
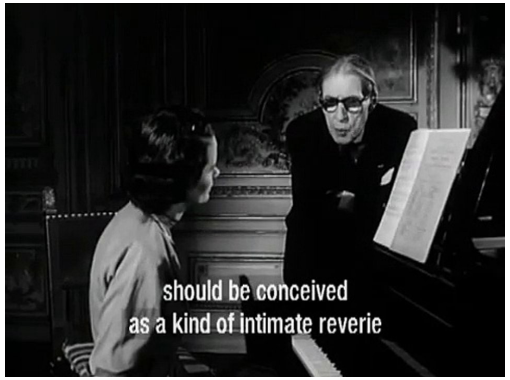


Knowledge graphs

Rewards

Auxiliary agents

Adversaries



Master classes

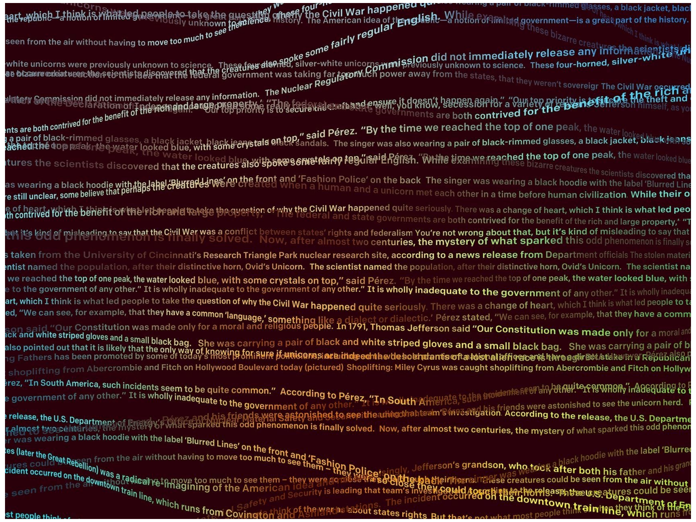
…

And all combinations thereof

Experiences: (massive) data examples

Image classification

Machine translation



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

45TB of text data: CommonCrawl, WebText, Wikipedia, corpus of books, …

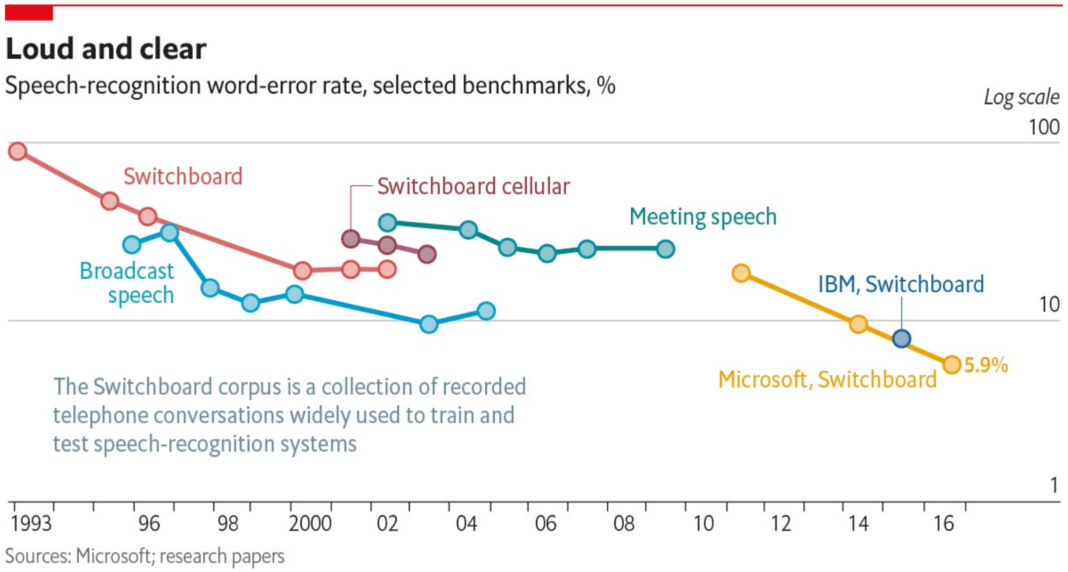
Experiences: (massive) data examples

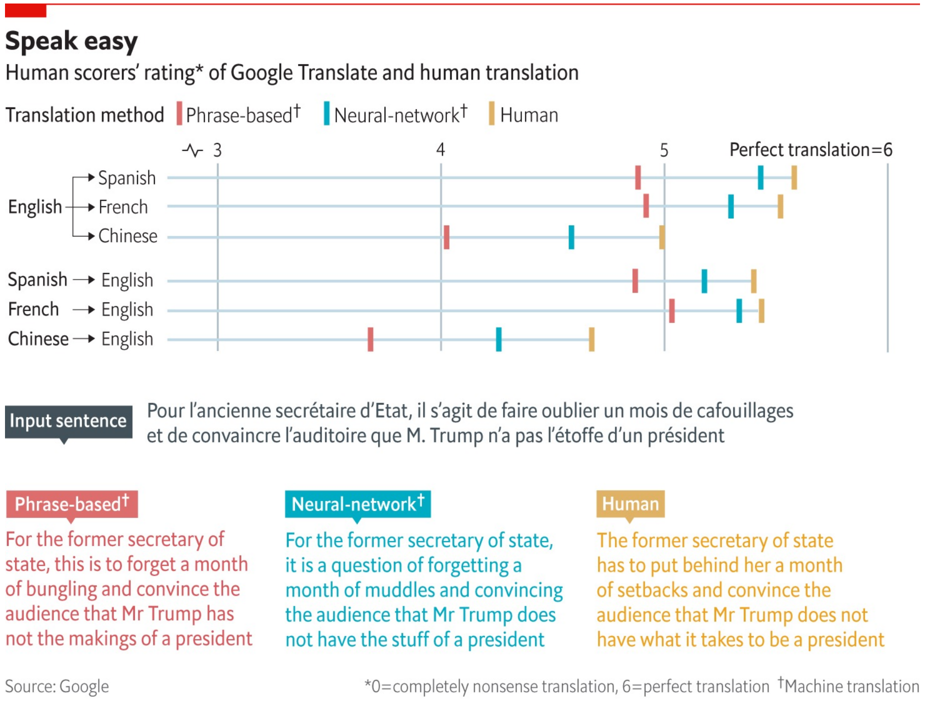
TECH ARTIFICIAL INTELLIGENCE

OpenAI's text-generating system GPT-3 is now spewing out 4.5 billion words a day

Robot-generated writing looks set to be the next big thing

By James Vincent | Mar 29, 2021, 8:24am EDT





[The Economist]

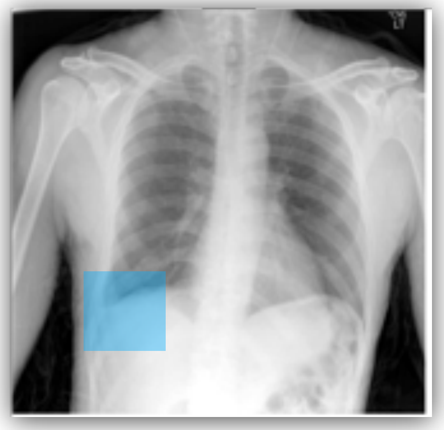
Problems with few data (labels)

- Privacy, security issues

Assistive diagnosis

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)

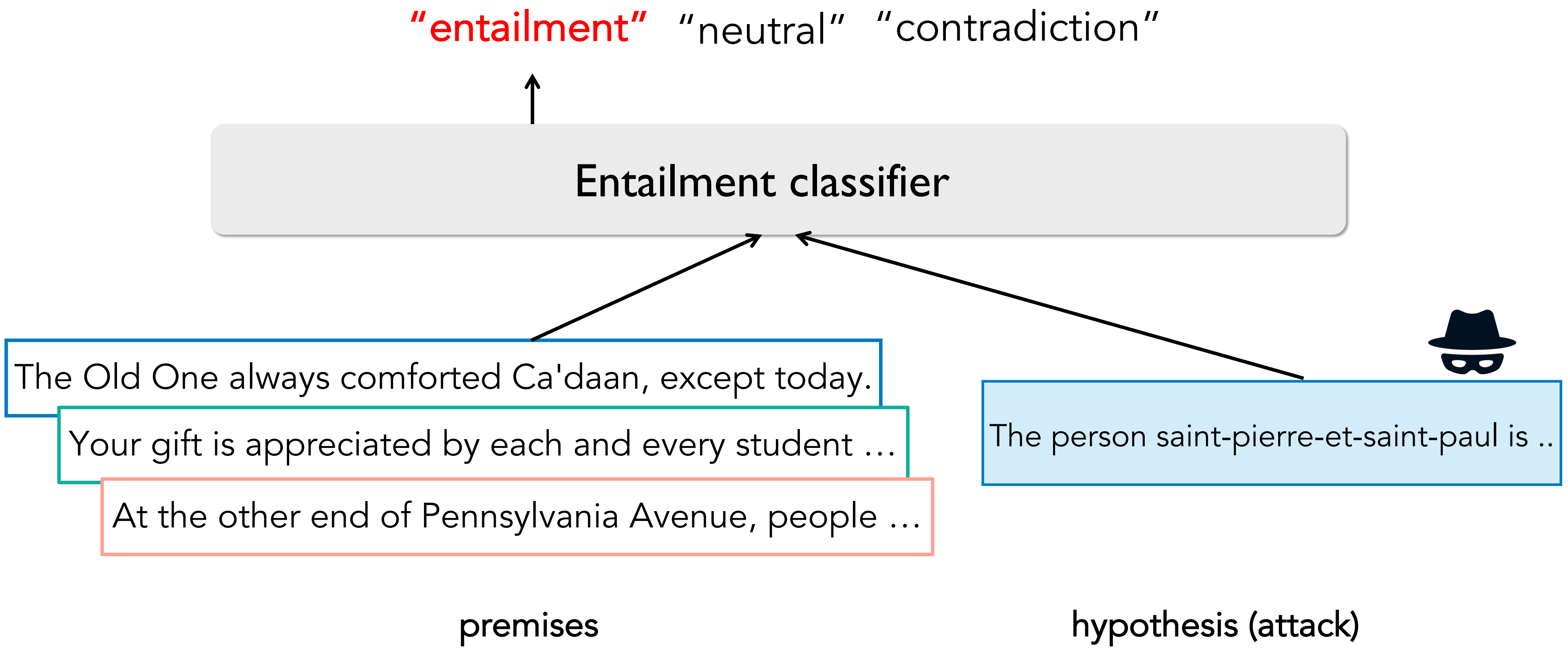
- Expensive to collect/annotate

Robotic control

Problems with few data (labels)

- Difficult / expertise-demanding to annotate

Adversarial attack

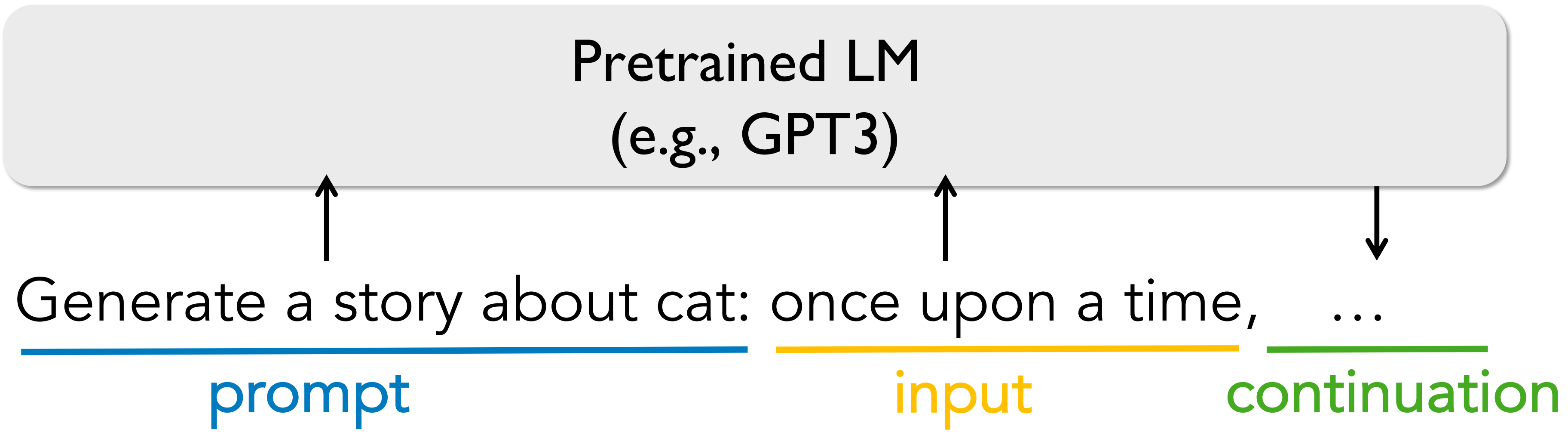


Applications: test model robustness

Problems with few data (labels)

- Difficult / expertise-demanding to annotate

Prompt generation: automatically generating prompts to steer pretrained LMs



Problems with few data (labels)

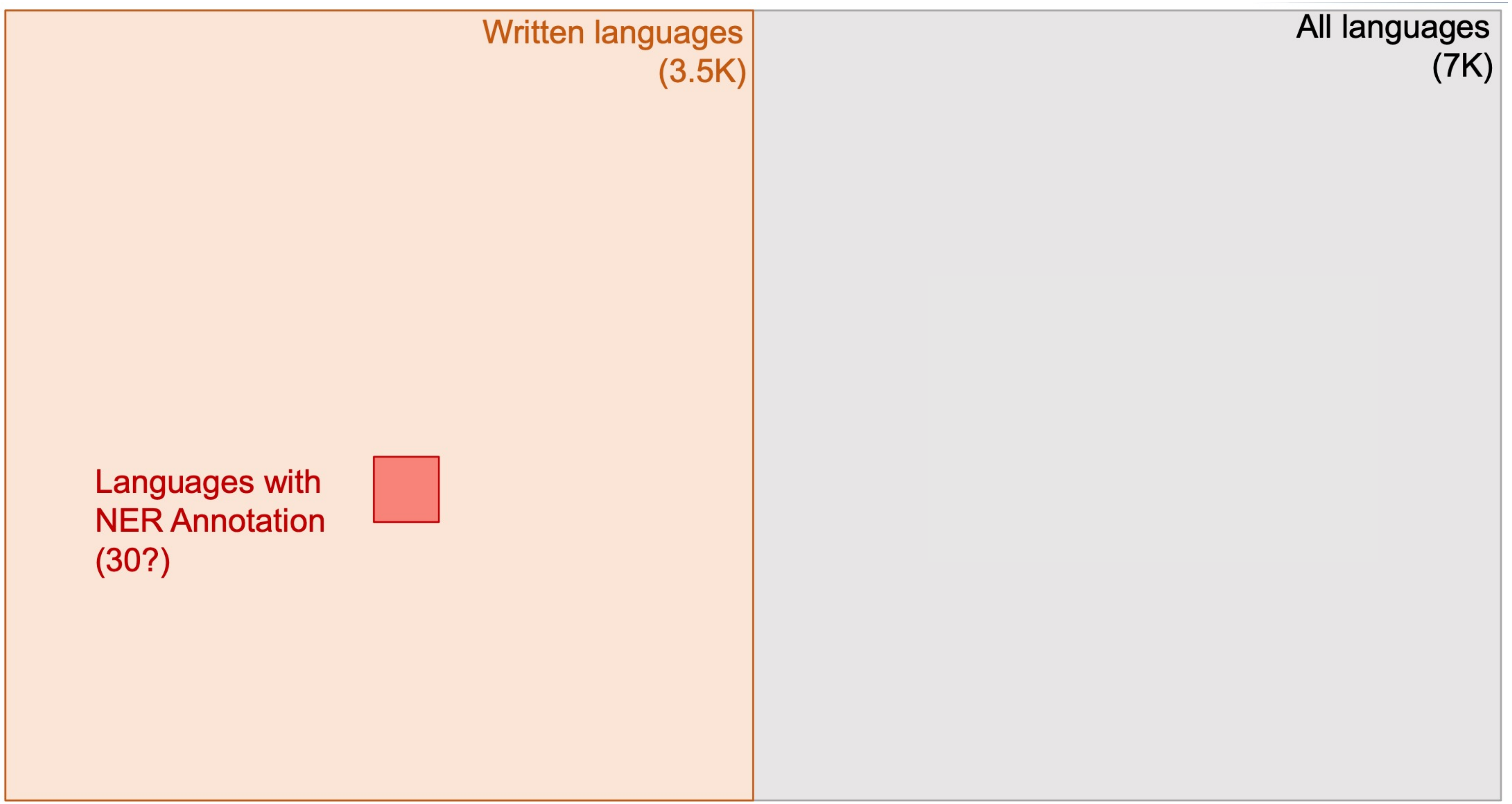
- Specific domain

Low-resource languages

~7K languages in the world

Problems with few data (labels)

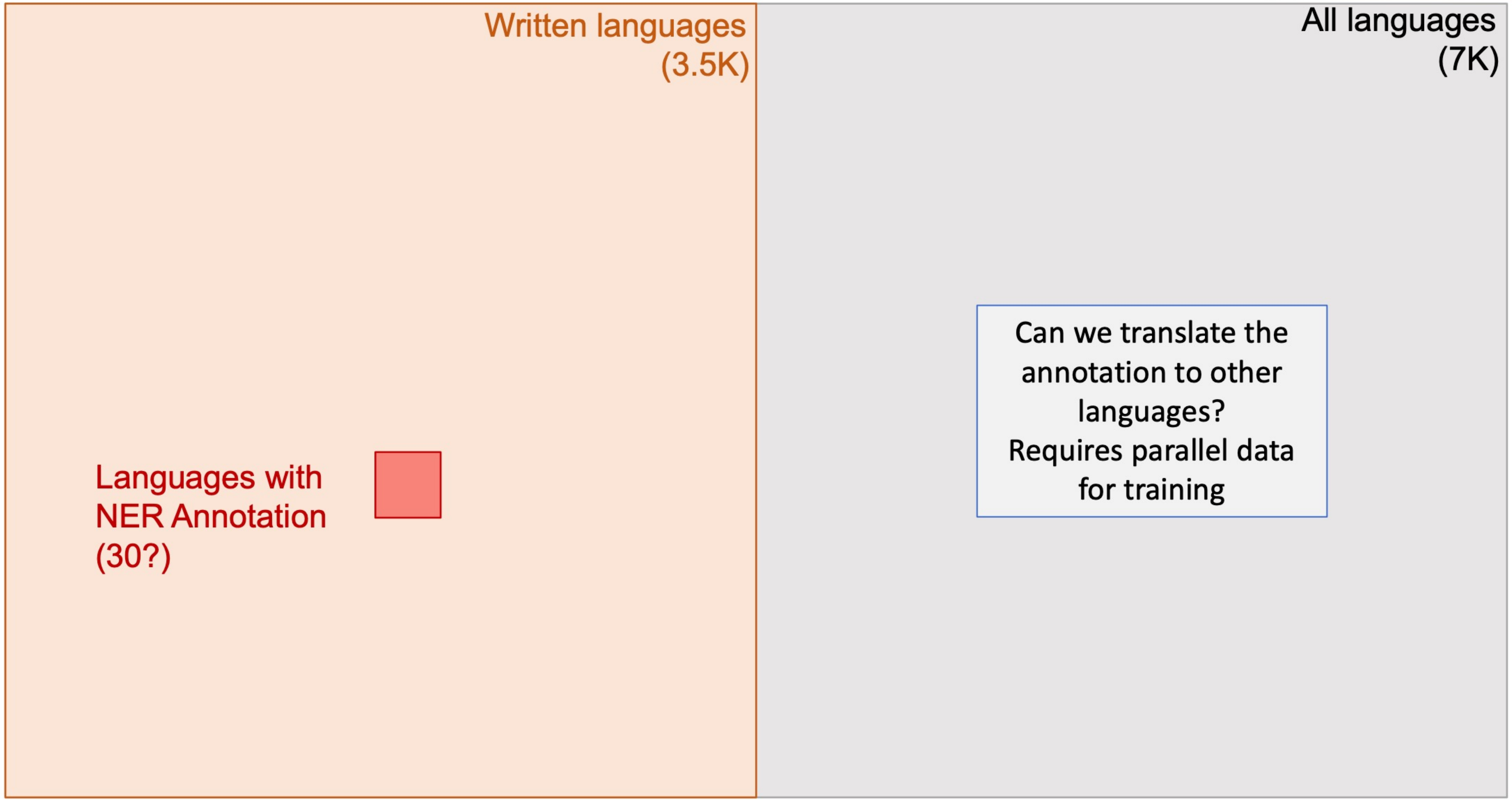
- Specific domain   Low-resource languages



[Figure courtesy: Dan Roth, CIS620]

Problems with few data (labels)

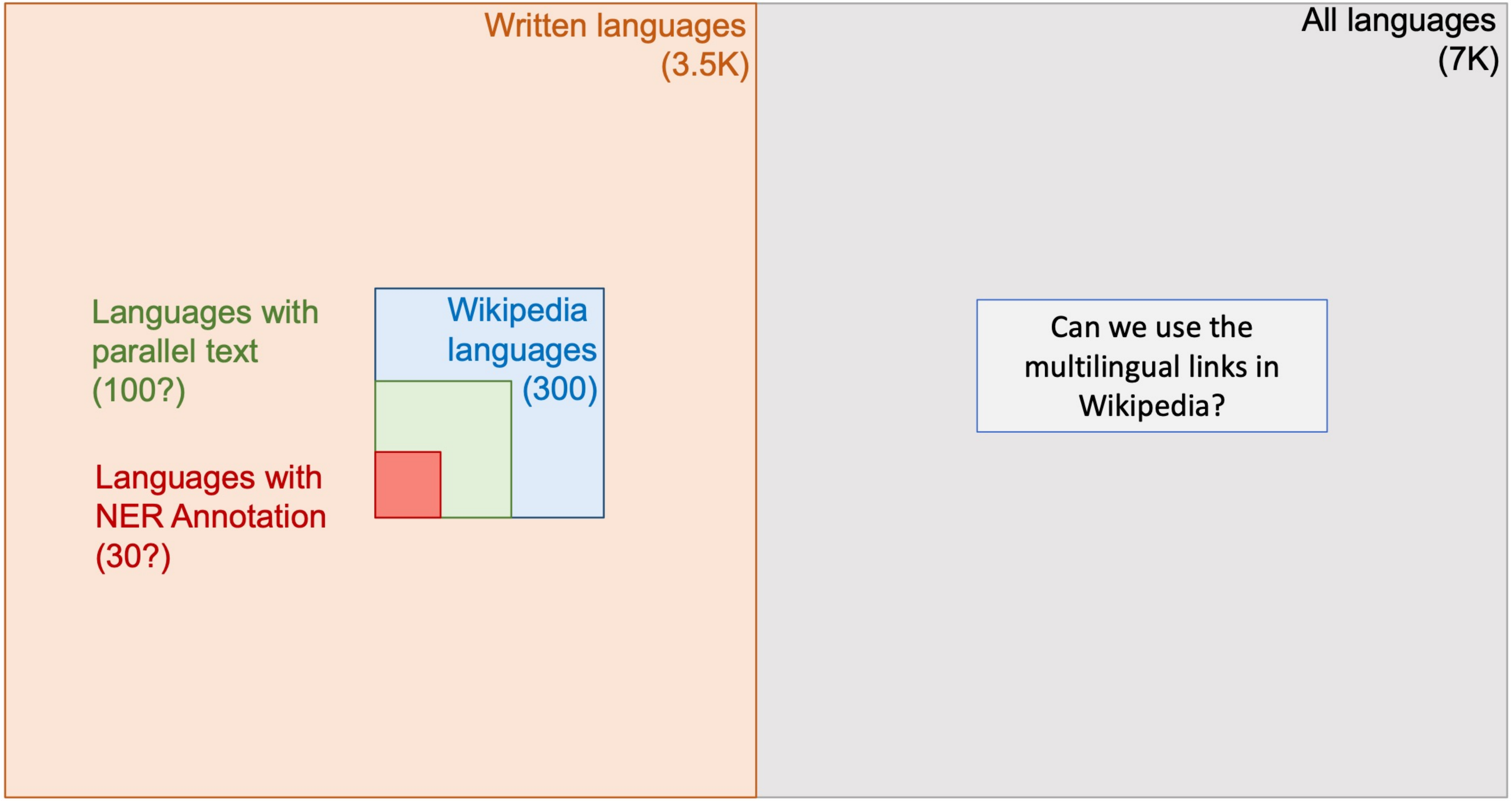
- Specific domain   Low-resource languages



[Figure courtesy: Dan Roth, CIS620]

Problems with few data (labels)

- Specific domain Low-resource languages

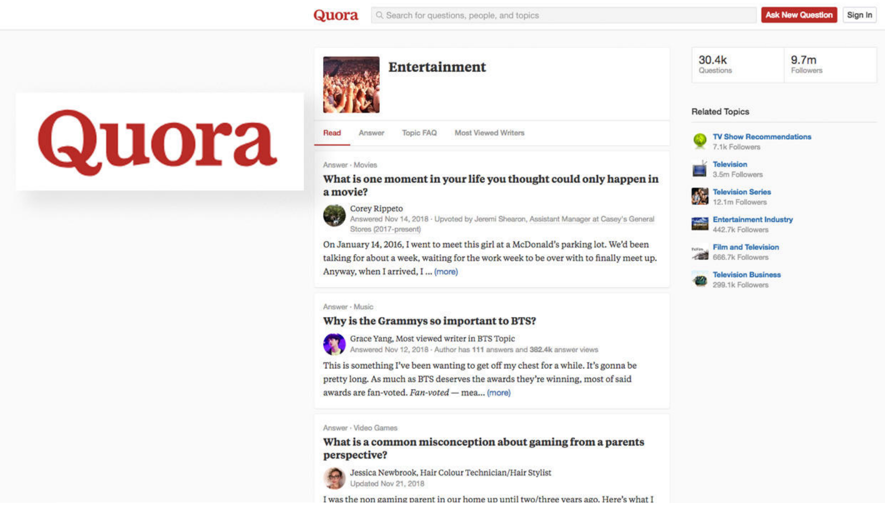


[Figure courtesy: Dan Roth, CIS620]

Problems with few data (labels)

- Specific domain

Question answering



QA based on car manual?

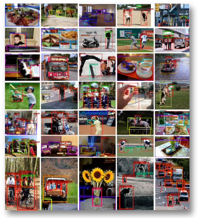
Problems with few data (labels)

- 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 the data?
  - Clean but small-size
  - Noisy
  - Out-of-domain

- Can we incorporate other types of experiences in learning?



Data examples

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

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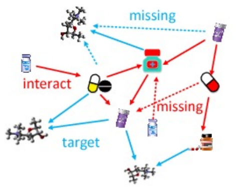

Knowledge graphs

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
- Optimization solver
- 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)

- Loss
- Experience
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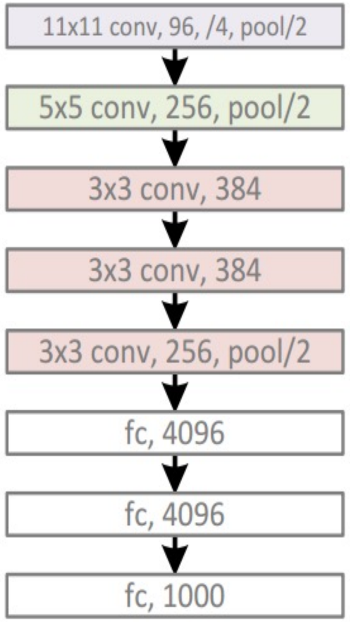
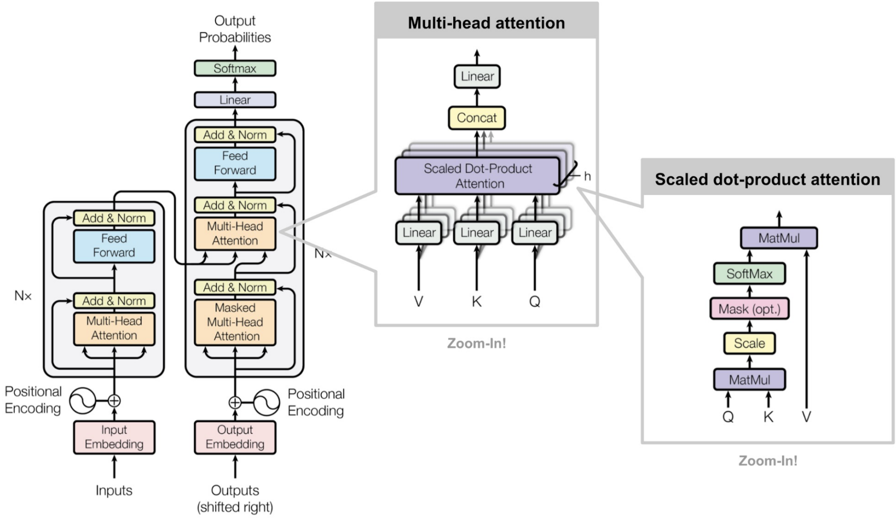


Convolutional networks



Transformers

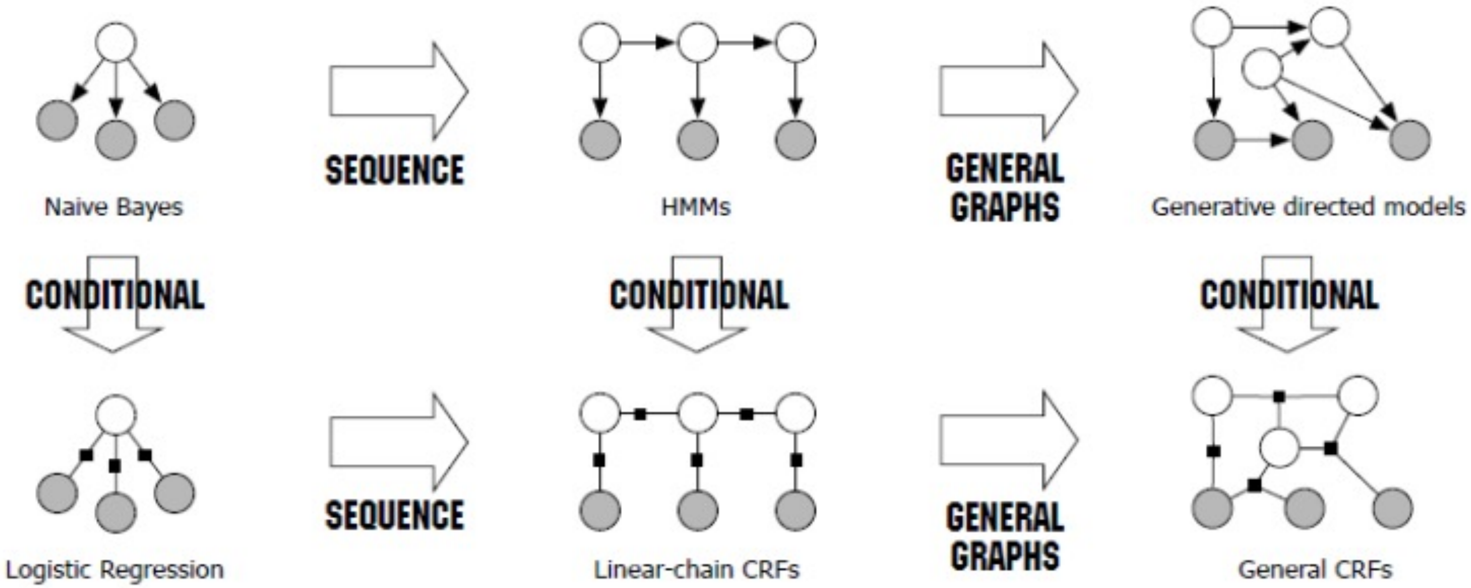
Components of a ML solution (roughly)

- 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 $p_\theta(\boldsymbol{y}|\boldsymbol{x})$

- Neural networks
- Graphical models
- Compositional architectures



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)

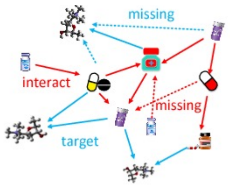
- (1) How can we make more efficient use of the data?
    - Clean but small-size, Noisy, Out-of-domain

- (2) Can we incorporate other types of experiences 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

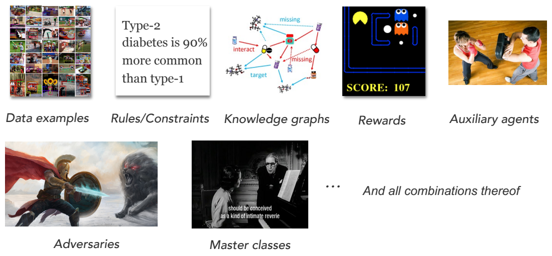
Machine learning solutions given few data (labels)

- (1) How can we make more efficient use of the 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, GPT-3, 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 experiences 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

prediction minimization

generalized expectation

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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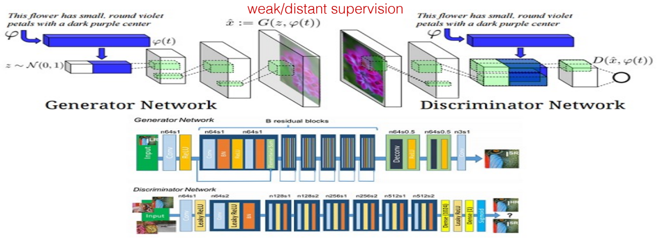

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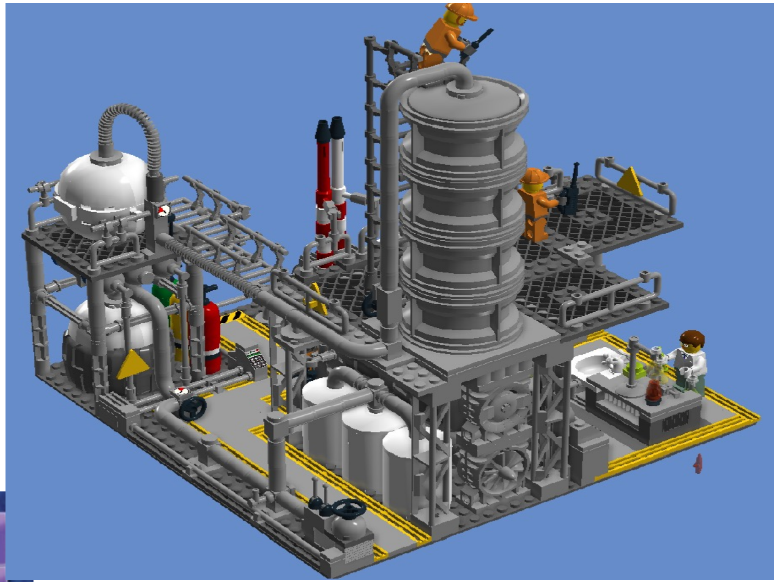

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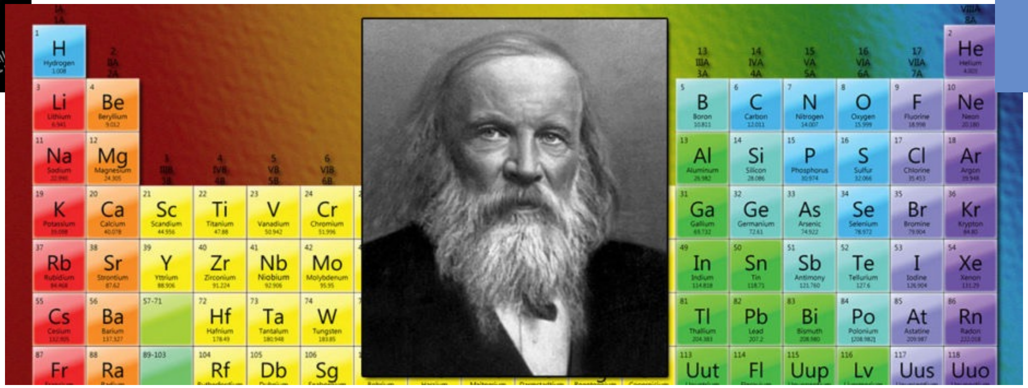


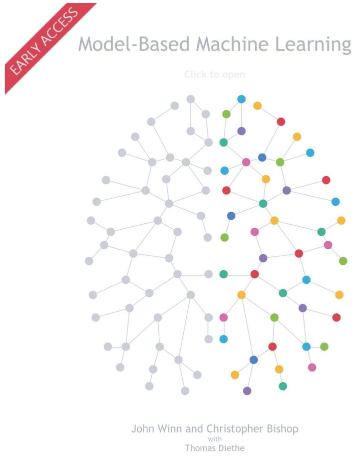
Quest for more standardized, unified ML principles

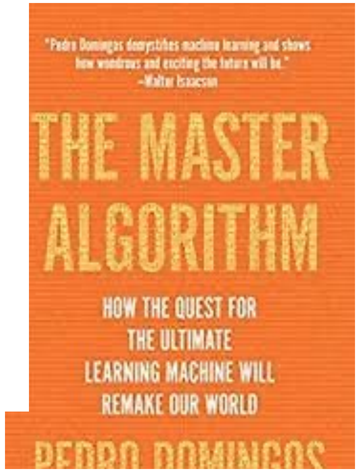
Machine Learning 3: 253–259, 1989

EDITORIAL

Toward a Unified Science of Machine Learning

[P. Langley, 1989]





REVIEW Communicated by Steven Nowlan

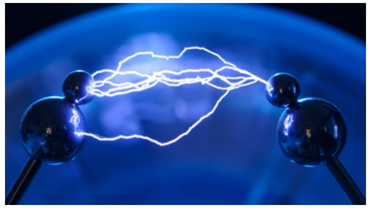
A Unifying Review of Linear Gaussian Models

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

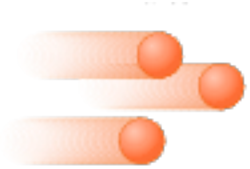
Zoubin Ghahramani*
Department of Computer Science, University of Toronto, Toronto, Canada

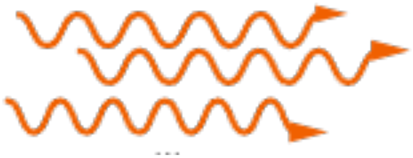
Physics in the 1800's

- 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

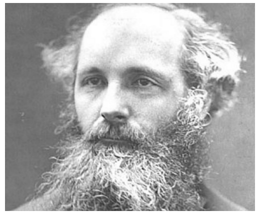
Maxwell’s Eqns simplified w/ rotational symmetry

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

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

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

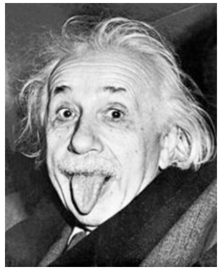
$$\nabla\times\mathbf{H}=\frac{\partial\mathbf{D}}{\partial t}+\mathbf{J}$$



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

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

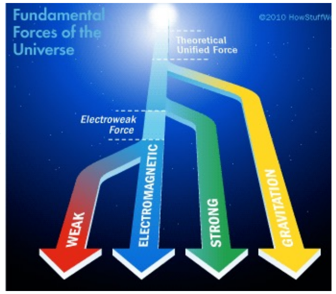
$$\partial_v F^{uV}=\frac{4\pi}{c}j^u$$



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

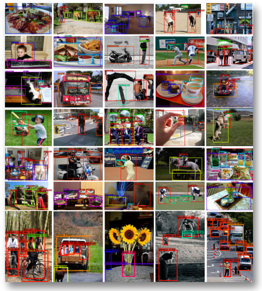
$$\mathcal{L}_{\rm gf}=-\frac{1}{2}\operatorname{Tr}(F^2)=-\frac{1}{4}F^{a\mu\nu}F^a_{\mu\nu}$$

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 experiences
- Subsumes many existing algorithms as special cases

Lecture #8

Questions?