DSC291: Machine Learning with Few Labels

Overview

Zhiting Hu

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UC San Diego
HALICIOĞLU DATA SCIENCE INSTITUTE

Possible Ideas of Course Project

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

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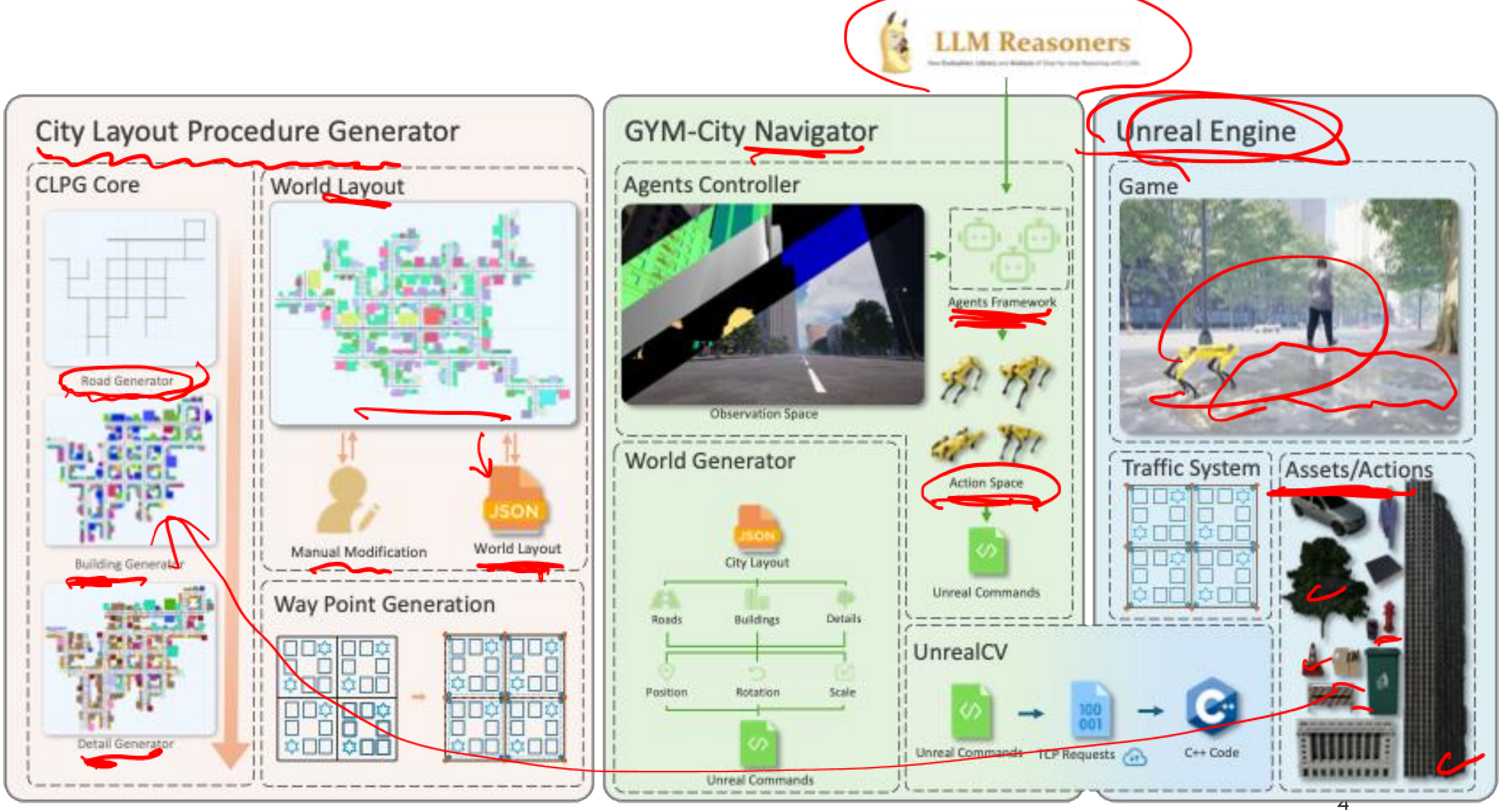


SimWorld: Open-ended world simulation with tens to millions of agents

City Generation

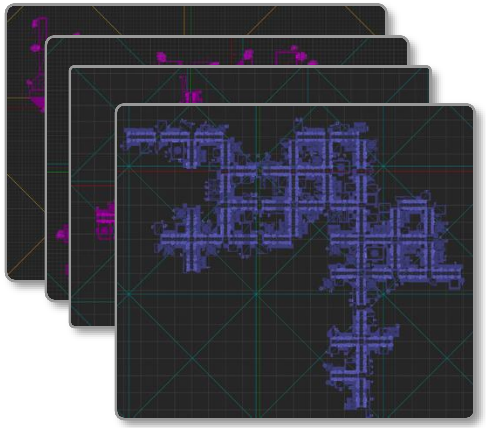
urban planning

- **Example projects (I): language-guided city/scene generation**

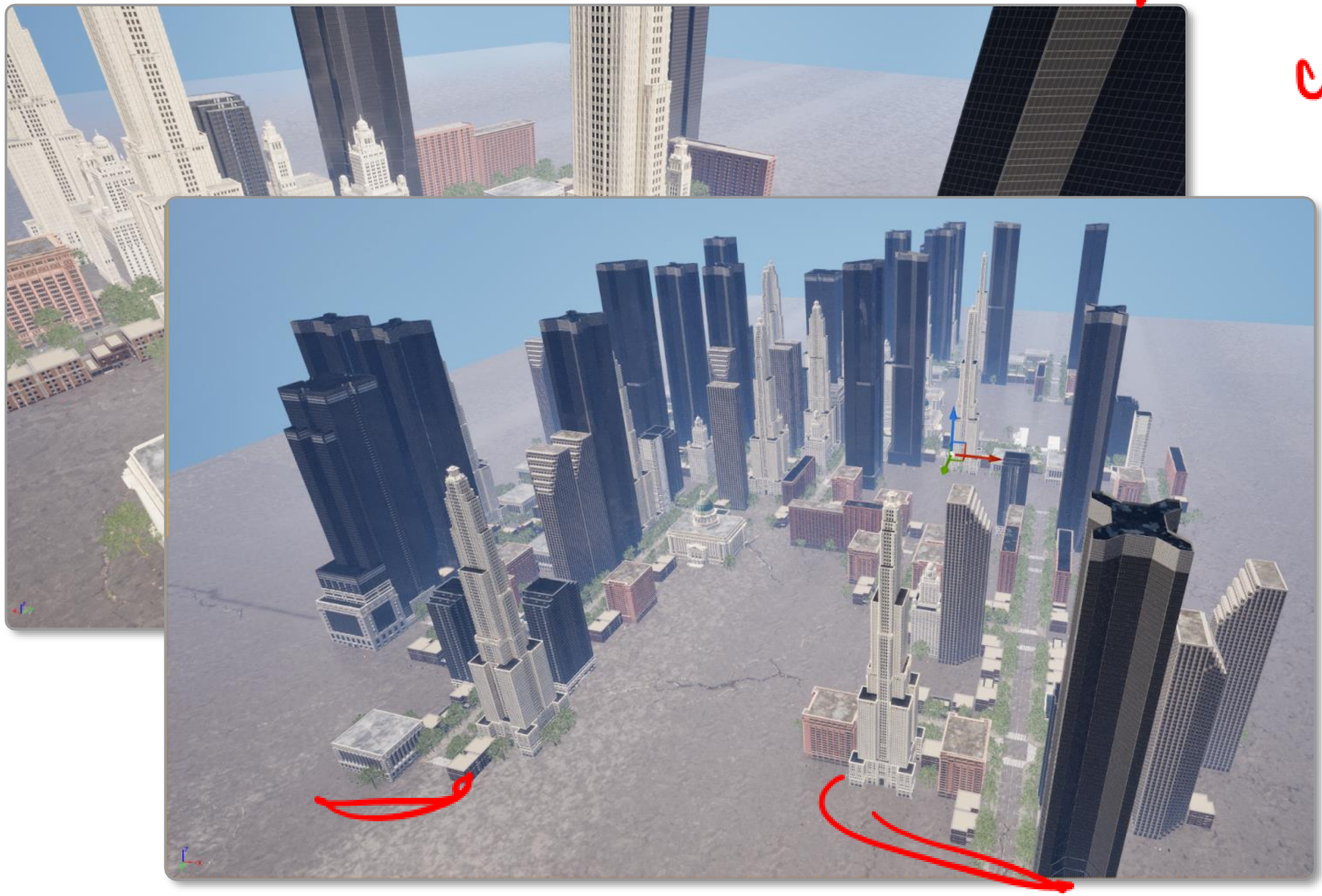
```python
import clpg

cfg = clpg.function_call.CityFunctionCall()
cfg.generate_city()
cfg.export_city("output_test")
```

4 lines of python code using CLPG



Generated layouts of cities



Rendered cities according to layouts in Unreal Engine

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

City Generation

- Example projects (I): language-guided city/scene generation

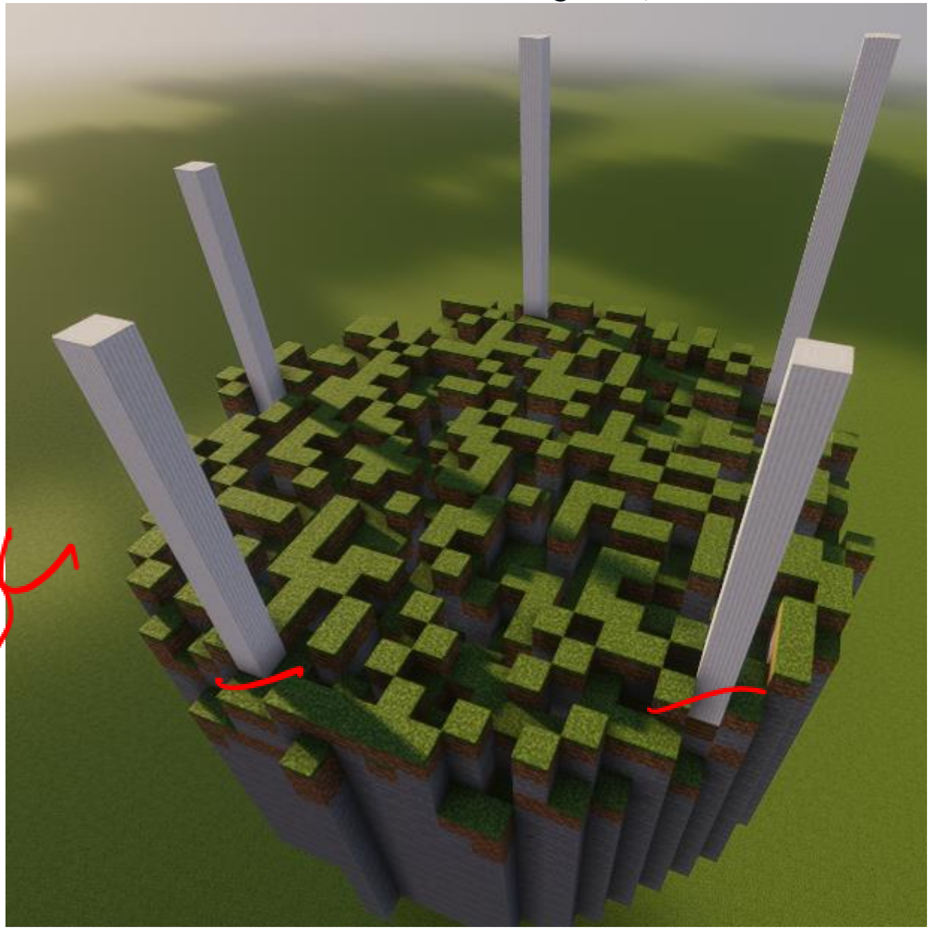
SimWorld: Open-ended world simulation with tens to millions of agents

City Generation

- **Example projects (I): language-guided city/scene generation**

“Build me an amazing, large, organic and epic floating island city right above you with a ton of detail. Make it a goal, iterate.”

o1



o3-mini-high

Simulator: Minecraft

https://x.com/adonis_singh/status/1885843774888108371?s=46&t=otWCD5-VRF8m4Zt94i4acA

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

- Example projects (II): embodied agent for navigation or other tasks

Robot dog controlled by GPT-4o

① benchmark

② agent

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

- **Example projects (III): multi-agent interactions**

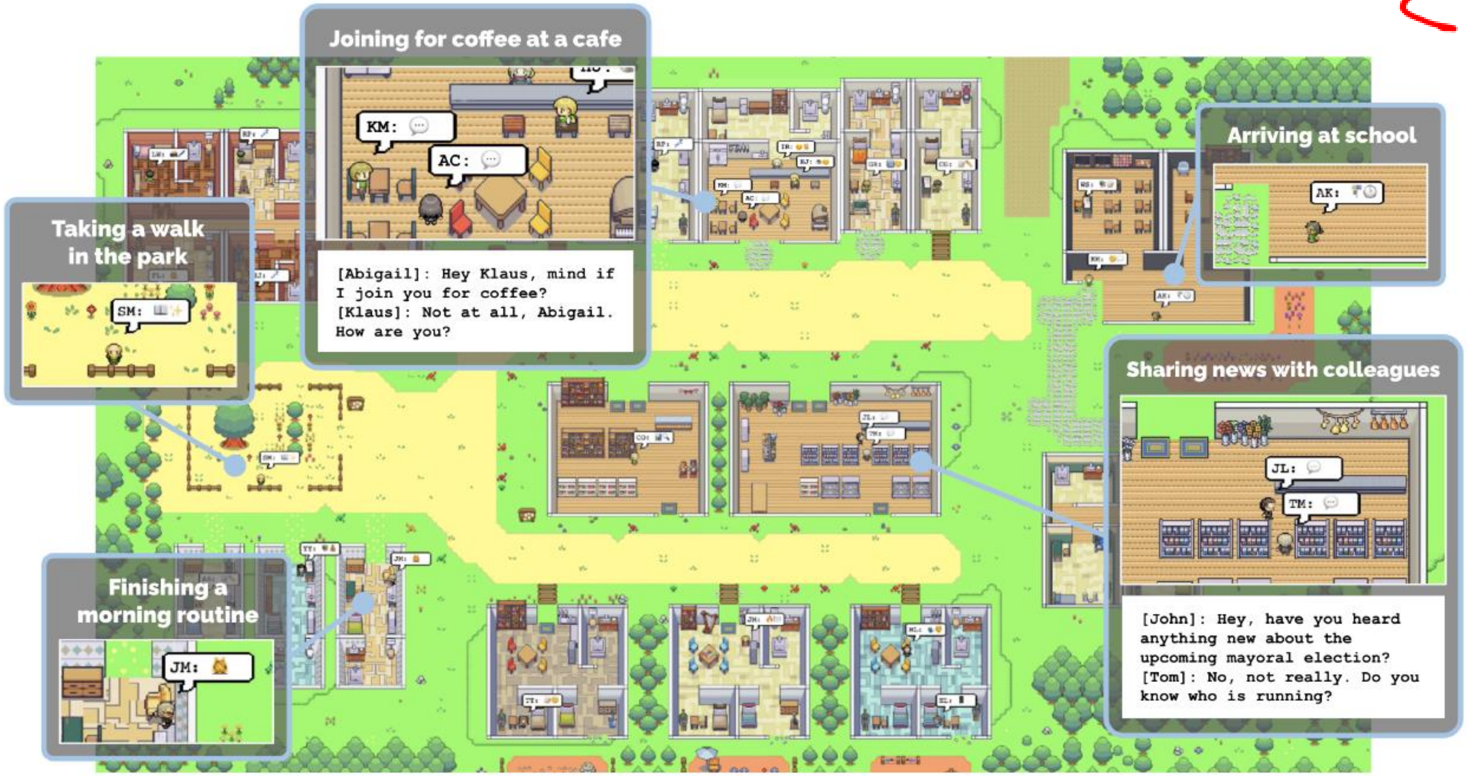
Two agents moving forward concurrently, controlled by our APIs

84 agents moving forward concurrently, no need to manual define them because we supply APIs to generate and control these agents

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

- **Example projects (III): multi-agent interactions**

LLM village



[Park et al., 2023]

HCI

25 agents, each controlled by individual LLM, converse with each other

- For studying emerging communication behaviors

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

- **Example projects (III): multi-agent interactions**

Project Sid: Exploring the First AI-Driven Virtual World with Autonomous Agents

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

LLM Reasoning and Agent

LLM Reasoners

A library for advanced reasoning with large language models

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

- Example projects (IV): web-agent
    - https://github.com/maitrix-org/llm-reasoners/tree/main/examples/browsergym

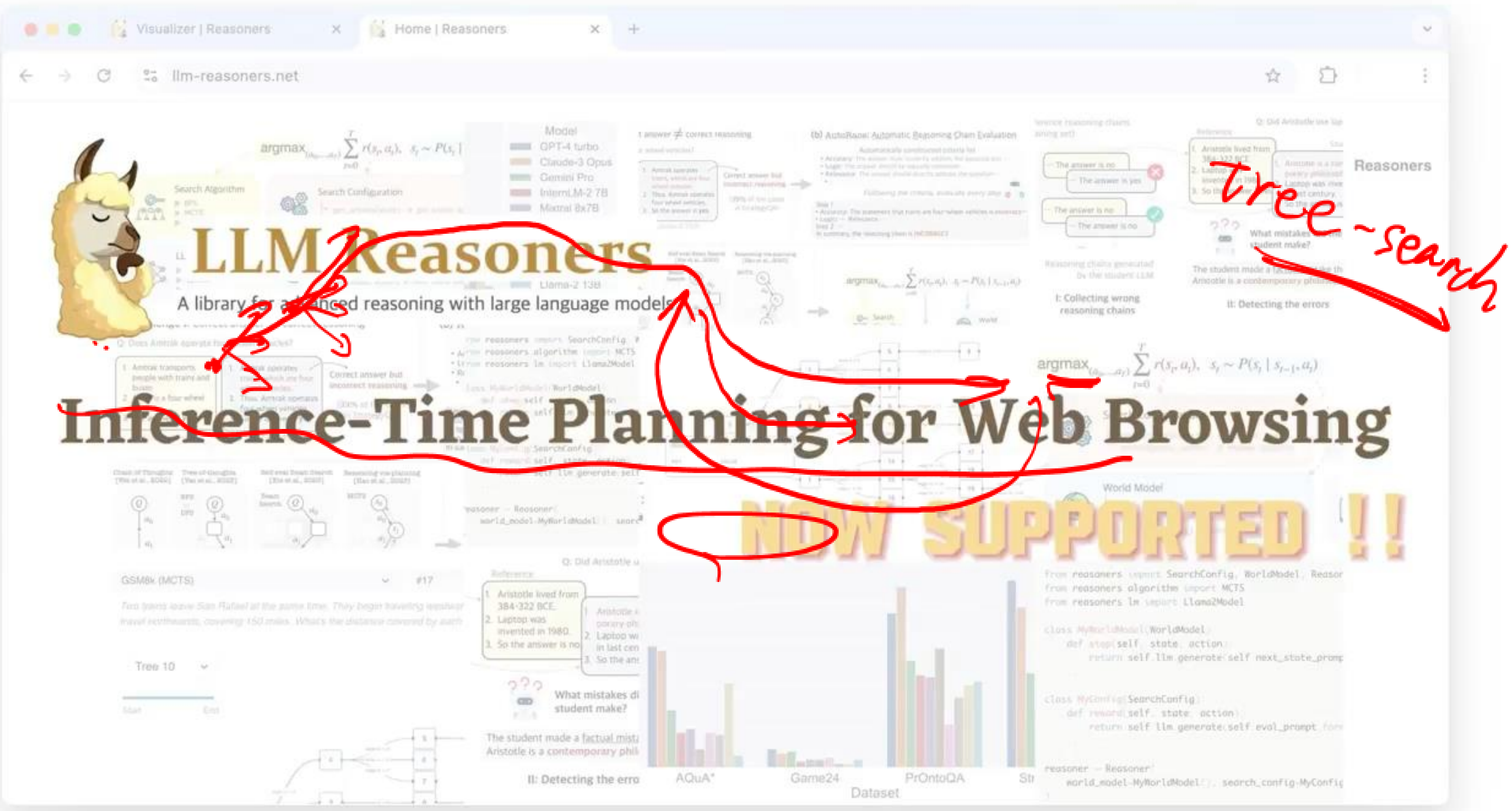
LLM Reasoning and Agent

LLM Reasoners

A library for advanced reasoning with large language models

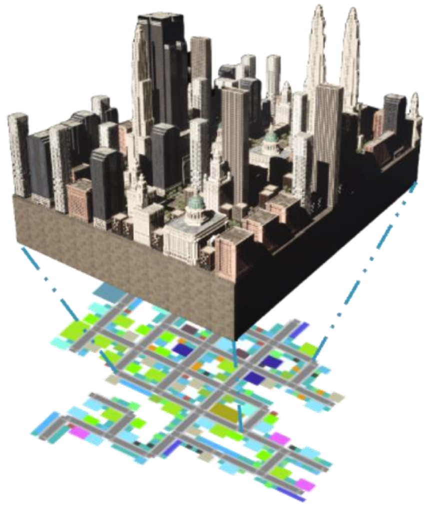
https://githu

- Example
  - https://g



Possible Ideas of Course Project

- (I): language-guided city/scene generation
- (II): embodied agent for navigation or other tasks
- (III): multi-agent interactions
- (IV): web-agent



LLM Reasoners

A library for advanced reasoning with large language models

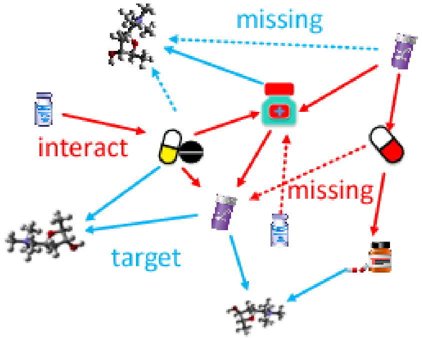
Overview

Recap: What is Machine Learning?

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

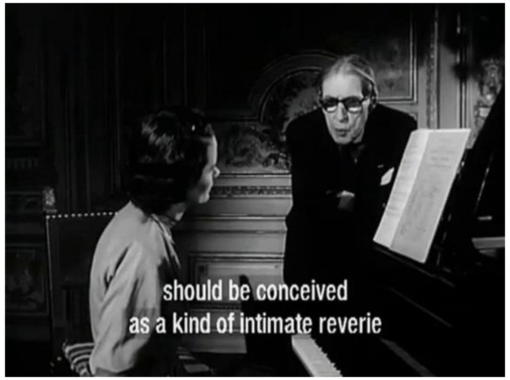
Recap: Experience of all kinds

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



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

Adversaries



Master classes

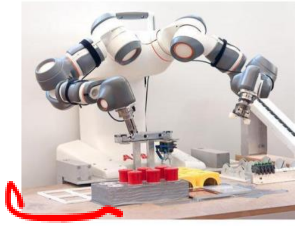
...

And all combinations thereof

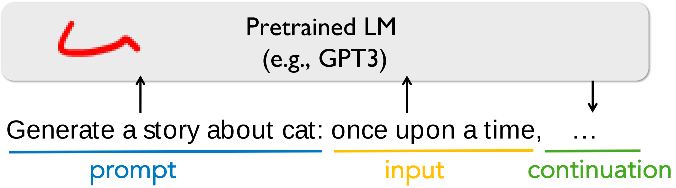
Recap: Problems with few data (labels)

- Privacy, security issues

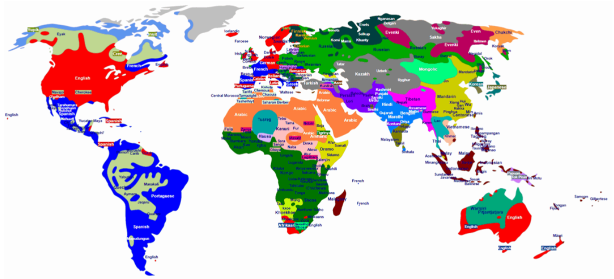
- Expensive to collect/annotate



- Difficult / expertise-demanding to annotate



- Specific domain



Machine learning solutions given few data (labels)

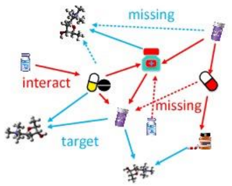
- How can we make more efficient use of data?
  - Clean but small-size
  - Noisy
  - Out-of-domain

- 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

objective

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

$$P(y|x) = \frac{P(x,y)}{P(x)}$$

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

- Neural networks
- Graphical models
- Compositional architectures

$P(y)$ image

Components of a ML solution (roughly)

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

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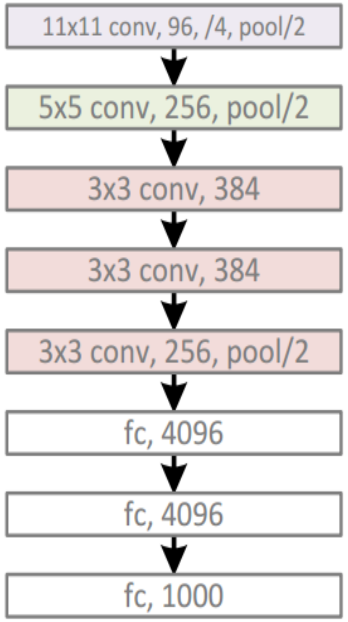
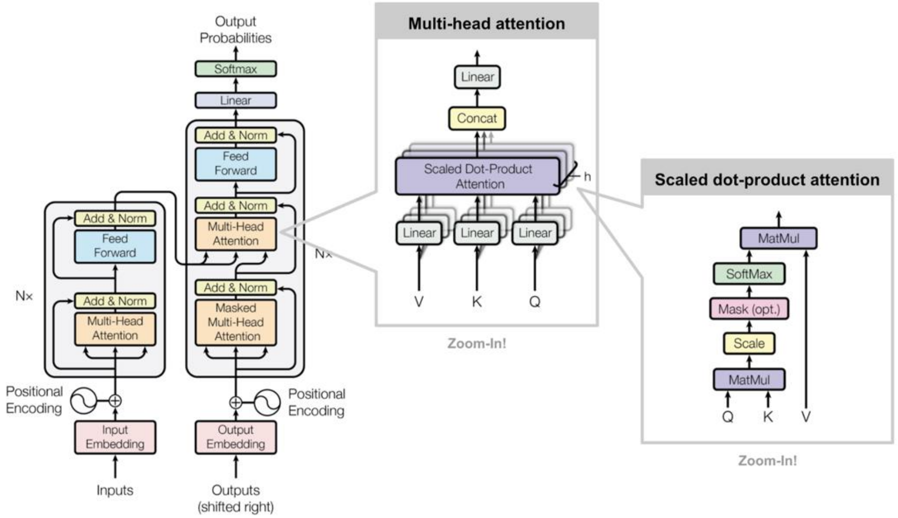


Convolutional networks



Transformers

Components of a ML solution (roughly)

- Loss
- Experience
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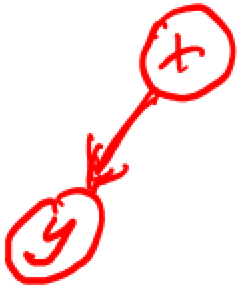
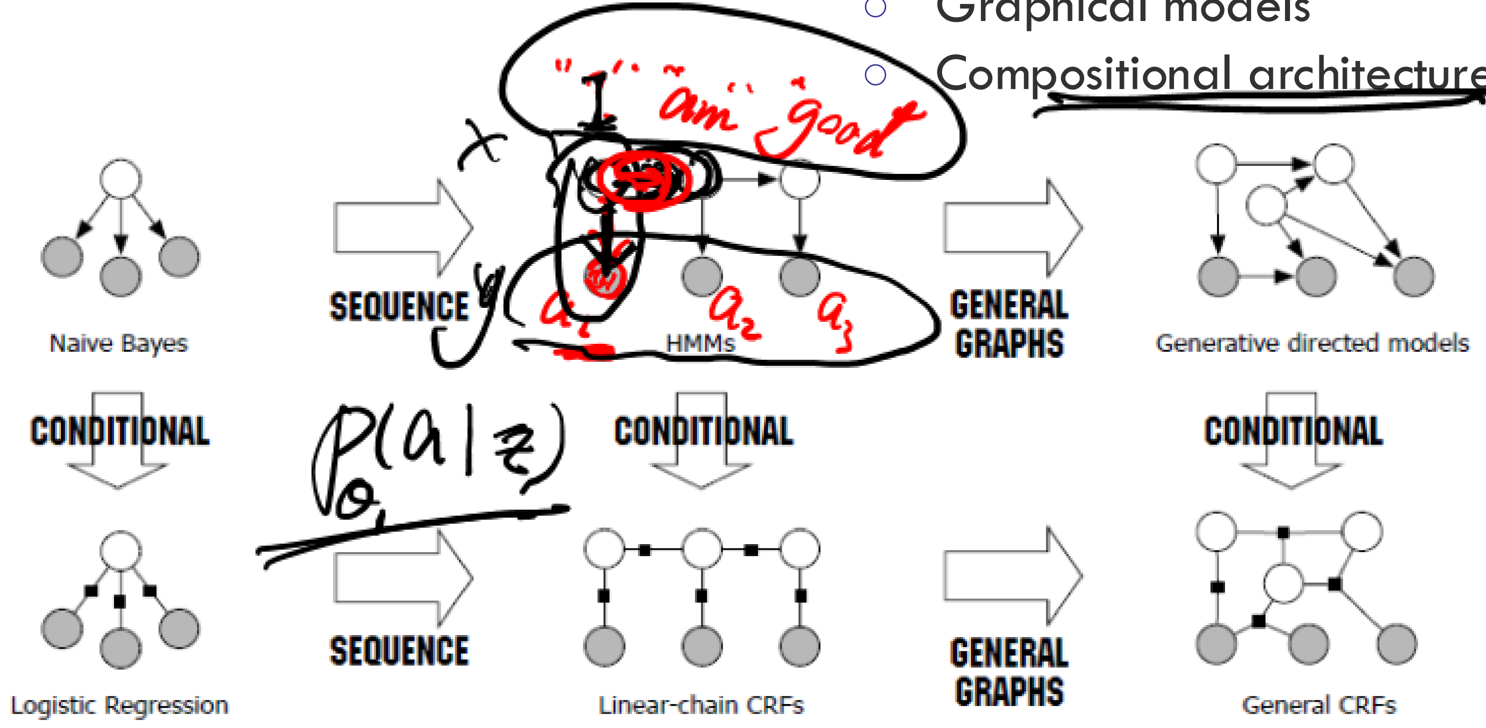




Components of a ML solution (roughly)

- Loss
- Experience
- Optimization solver
- Model architecture

This course discusses a *little* about optimization

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

Optimization solver | Loss | Model architecture | Experience

Assuming you know basic procedures:

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

ADAM

Muon

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)

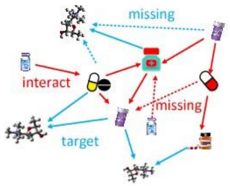
- (1) How can we make more efficient use of data?
  - Clean but small-size, Noisy, Out-of-domain

- (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)

x y (x, y)

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

"variational free energy"

- Algorithms

hinton

  - **Supervised learning:** MLE, maximum entropy principle
  - **Unsupervised learning:** EM, variational inference, VAEs

Diffusion

  - **Self-supervised learning:** successful instances, e.g., BERT, GPTs, contrastive learning, applications to downstream tasks

2018

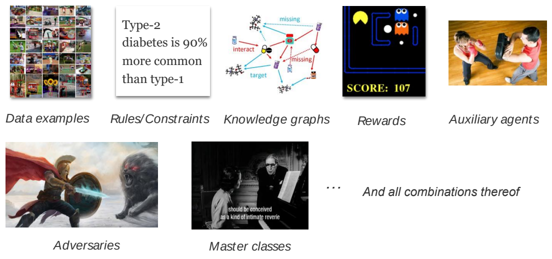
Semi-supervised

  - **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 2013
    - 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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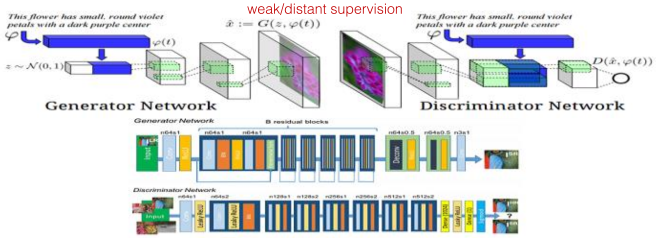

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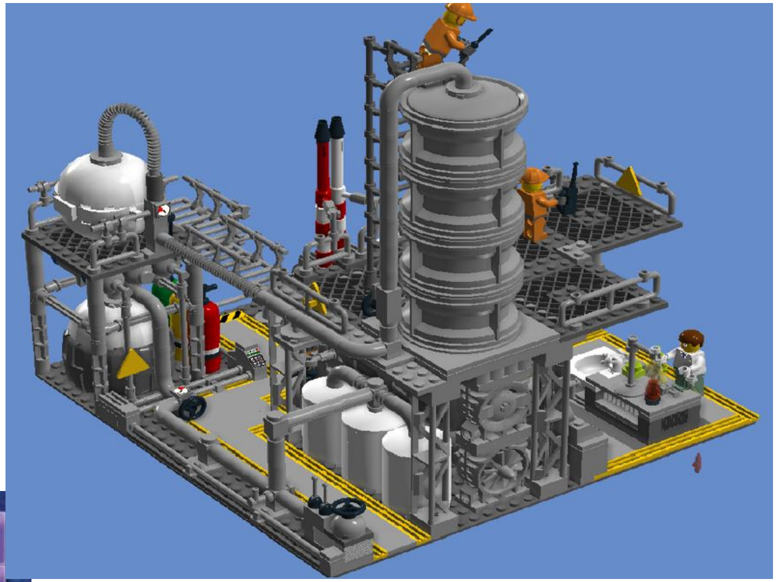

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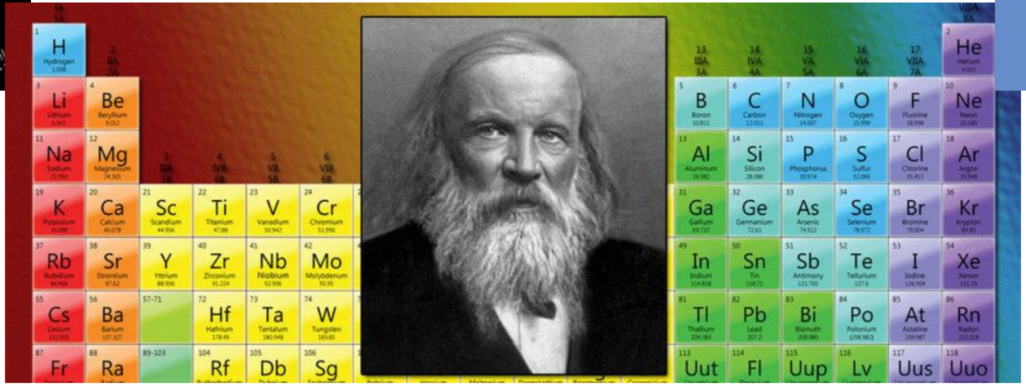
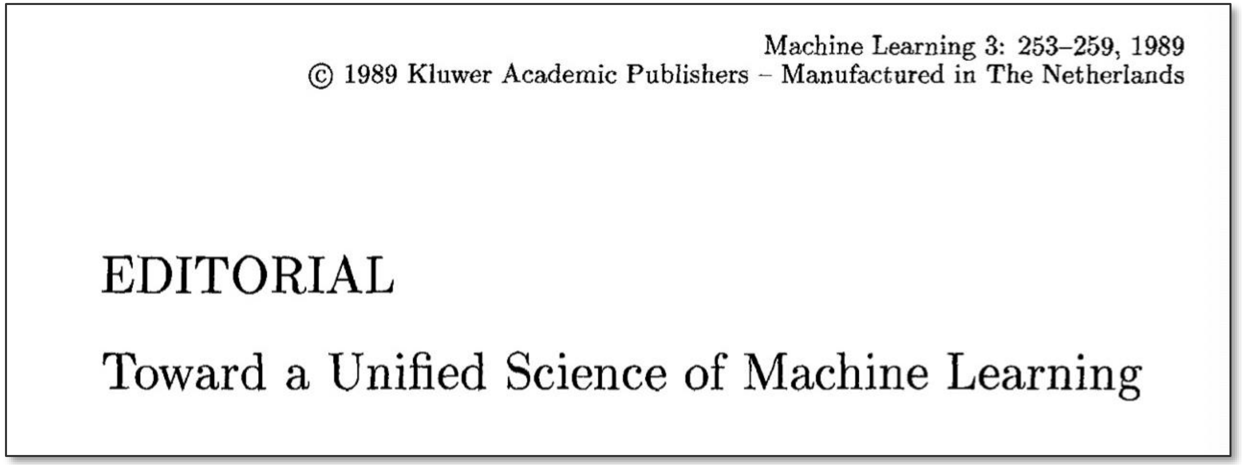


Quest for more standardized, unified ML principles

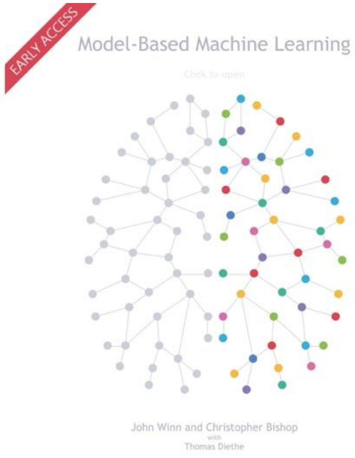


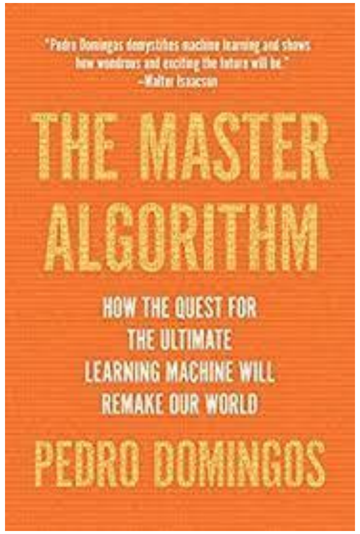
Machine Learning 3: 253–259, 1989

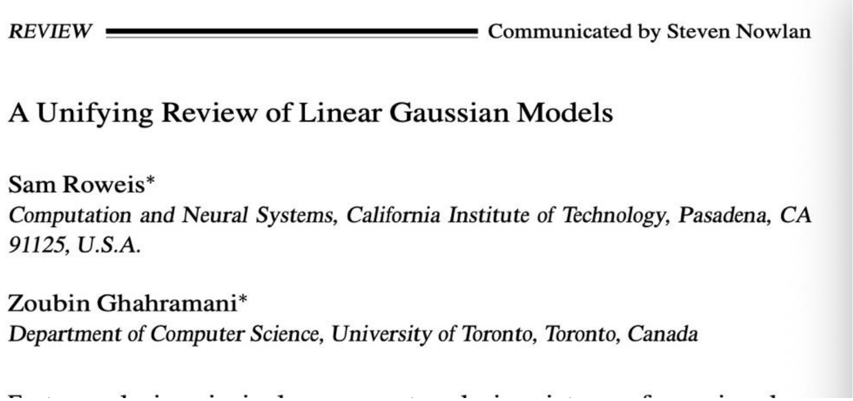
EDITORIAL

Toward a Unified Science of Machine Learning

[P. Langley, 1989]







REVIEW Communicated by Steven Nowlan

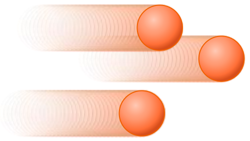
A Unifying Review of Linear Gaussian Models

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

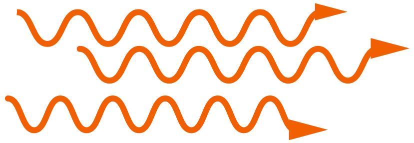
Zoubin Ghahramani*
Department of Computer Science, University of Toronto, Toronto, Canada

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
$P=\mu\left(\gamma\frac{dy}{dt}-\beta\frac{dz}{dt}\right)-\frac{dF}{dt}-\frac{d\Psi}{dz}$ $Q=\mu\left(\alpha\frac{dz}{dt}-\gamma\frac{dx}{dt}\right)-\frac{dG}{dt}-\frac{d\Psi}{dy}$ $R=\mu\left(\beta\frac{dx}{dt}-\alpha\frac{dy}{dt}\right)-\frac{dH}{dt}-\frac{d\Psi}{dz}$	(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

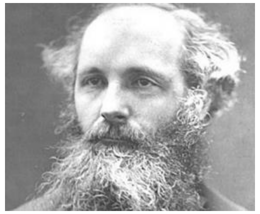
Maxwell’s Eqns simplified w/ rotational symmetry

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

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

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

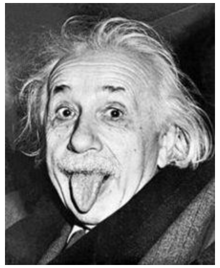
$$\nabla\times\mathbf{H}=\frac{\partial\mathbf{D}}{\partial t}+\mathbf{J}$$



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

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

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

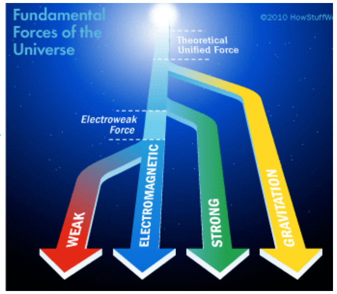


Standard Model w/ Yang-Mills theory and US(3) symmetry

$$\mathcal{L}_{\mathrm{gf}}=-\frac{1}{2}\mathrm{Tr}(F^2)$$

$$=-\frac{1}{4}F^{a\mu\nu}F^{a}_{\mu\nu}$$

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

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

Uncertainty

Divergence

Experience

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

Will discuss in later in the class

Questions?