Learning with Limited Supervision

Stefano Ermon
Stanford University
Recent Progress in AI

- Labeled data
- High capacity models
- Hardware
Labeling bottleneck

The New New Oil

Credit: Chris Re

Physical Sciences

Development
Age of Big Unlabeled Digital Data

Images

Satellites

Video

Text

Pedro Domingos @pmddomingos · Aug 30
The 3 key problems in AI, per @EricHorvitz:
1. Commonsense reasoning
2. Unsupervised learning
3. Integration
(See facebook.com/RSLNmag/videos...)

6 95 192
Probabilistic Generative Modeling

$p(\cdot)$ is high

$p(\cdot)$ is low

Learn $p(x)$

Images without labels

Samples $\sim p(x)$

Nips-17
Applications

1 2 3

A
B
C

Low res
High res

NIPS-16, ICML-17, UAI-17, NIPS-17, ICLR, work under review
Latent Variable Model

Latent factors of variation (disentangled)

\[ p_\theta(x, z) = p(z)p_\theta(x|z) \]

Hou el al.
Deep Generative Models

Choose parameters to maximize the (log) likelihood of the data:

\[ \max_{\theta} \log p_{\theta}(x) = \max_{\theta} \log \sum_z p_{\theta}(x, z) \]

\[ p_{\theta}(x, z) = p(z)p_{\theta}(x|z) \]

Intractable

AISTATS-16
AAAI-16
ICML-16, NIPS-16
AISTATS-18
Generative Adversarial Networks
Latent Variable Models

\[ p_\theta(x, z) = p(z)p_\theta(x|z) \]
Reinforcement Learning

- Goal: Learn policies
- High-dimensional, raw observations

RL needs cost signal
Imitation Learning

Input: demonstrations provided by *an expert*

\[ \{(s_0^i, a_0^i, s_1^i, a_1^i, \ldots)\}_{i=1}^n \sim \pi_E \]

Goal: find policy that *generates* a similar behavior
Imitation Learning

Several existing approaches:

• Behavioral cloning
• Inverse reinforcement learning
• Apprenticeship learning

Our approach: a generative \textbf{latent} variable model
Generative Adversarial Imitation Learning

Ho and Ermon, *Generative Adversarial Imitation Learning* (NIPS-16)
How to optimize the objective

• Previous Apprenticeship learning work:
  • Full dynamics model
  • Small environment
  • Repeated RL

• We propose: gradient descent over policy parameters (and discriminator)

• Trust region policy optimization

Results

Input: driving demonstrations (Torcs)

Output policy:

From raw visual inputs

Results
Latent structure in demonstrations

Human model

Latent variables $z$  Policy  Environment  Observed Behavior

Semantically meaningful latent structure?
InfoGAIL

Latent structure

- Add Smiling
- Remove Smiling
- Add Eyeglass
- Remove Eyeglass

Maximize mutual information

Latent variables $z$

Policy

Environment

Observed data

Observed Behavior

Infer structure
InfoGAIL Example

Pass left (z=0)?
Pass right (z=1)?

Environment

Observed Behavior

Pass left (z=0)
Pass right (z=1)
Migrations and Climate Change: Ethiopia data

08/20/2011 GPS traces

- Camp
- Water point
- Trajectories (color varies by household)
Supervised Learning - Discriminative

INPUTS 5 0 "X"

OUTPUTS ? ?

Discriminative model
Unsupervised Learning - Generative

Outputs

\[ z_1 \rightarrow 5 \rightarrow 0 \rightarrow z_2 \rightarrow 4 \rightarrow z_K \rightarrow 1 \]

Generative model
Semi Supervised Learning – Attempt 1

**Issue:** The two components are independent of each other! Can be optimized separately.
Semi Supervised Learning

Idea: couple any discriminative model and generative one through a shared latent space

Deep Hybrid Models: Bridging Discriminative and Generative Approaches (UAI-17)
Results on Semi supervised learning

<table>
<thead>
<tr>
<th>Method</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>VAE (Kingma et al., 2014)</td>
<td>3.33 ± 0.14%</td>
</tr>
<tr>
<td>SDGM (Maaløe et al., 2016)</td>
<td>1.91 ± 0.10%</td>
</tr>
<tr>
<td>Ladder Network (Rasmus et al.)</td>
<td>1.06 ± 0.37%</td>
</tr>
<tr>
<td>ADGM (Maaløe et al., 2016)</td>
<td>0.96 ± 0.02%</td>
</tr>
<tr>
<td>Improved GAN (Salimans et al., 2016)</td>
<td>0.93 ± 0.07%</td>
</tr>
<tr>
<td>Implicit DHM (ours)</td>
<td>0.91 ± 0.06%</td>
</tr>
</tbody>
</table>

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<thead>
<tr>
<th>Method</th>
<th>Accuracy</th>
</tr>
</thead>
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<tr>
<td>VAE (Kingma et al., 2014)</td>
<td>36.02 ± 0.10%</td>
</tr>
<tr>
<td>SDGM (Maaløe et al., 2016)</td>
<td>16.61 ± 0.24%</td>
</tr>
<tr>
<td>Improved GAN (Maaløe et al., 2016)</td>
<td>8.11 ± 1.3%</td>
</tr>
<tr>
<td>ALI (Dumoulin et al., 2016)</td>
<td>7.42 ± 0.65%</td>
</tr>
<tr>
<td>II-model (Laine &amp; Aila, 2016)</td>
<td>5.45 ± 0.25%</td>
</tr>
<tr>
<td>Implicit DHM (ours)</td>
<td>4.45 ± 0.35%</td>
</tr>
</tbody>
</table>

MNIST (100 labels)  
SVHN (1000 labels)
Latent Variable Models

\[
p_\theta(x, z) = p(z)p_\theta(x|z)
\]
Learning to track an object, without labels
Outputs have to form a parabola
90.1% correlation with the true height, without labels (supervised network gives 94.5%)

Learns a good mapping, up to an additive constant
95.4 % correlation with the true position
Peach “implies” Mario

Supervising Neural Networks with Physics and other Domain Knowledge

Best Paper Award AAAI-17

Need to specify the constraints manually and explicitly
Adversarial constraint learning

Physics simulator **implicitly** defines the constraints

Ren et al, in submission
Motion Capture
A WORLD THAT COUNTS

Data for tracking development goals

Source: United Nations Statistics Division
Input: Satellite Images

Output: Poverty Measures

Uganda
Tanzania
Malawi
Deep Gaussian Process model

**Idea:** combine GP with CNN

Gaussian process layer

Location 1  ...  Location n

Enforces spatial correlation
This imaging technique could make it easier to find aid to reach the people who need it the most.

How satellite images are helping find the world’s hidden poor
Images from space hold a secret to helping some of the world’s poorest people

WFP
wfp.org

DEPARTMENT OF STATE
UNITED STATES OF AMERICA

SCIENTIFIC AMERICAN
10 IDEAS
THAT WILL CHANGE THE WORLD

- DISEASE FACTORIES
- BIRTH OF OUR SOLAR SYSTEM
- EVOLUTION OF MYTHS
- THE TUNDRA THAWS

ANTIBIOTICS FROM SCRATCH
SOFTWARE THAT CAN READ
ROBOT IN A PILL
BLOOD TESTS AS CHEAP AS PAPER

- A BATTERY THAT EATS CARBON
- CLOTHES THAT COOL
- PREDICTING POVERTY
- THE (UNHACKABLE) QUANTUM INTERNET
- SUPERMATERIALS FROM SUPERATOMS
- A SHIELD AGAINST VIRUSES
Deep Gaussian Process

Input: 
Remote Sensing Data

Output: 
Food Security Measures
Estimated Soybean Production

WORLD BANK BIG DATA INNOVATION CHALLENGE

STANFORD SUSTAIN

Combining satellite imagery and machine learning to predict crop yield

Challenge: Food security
Team: Jiexuan You, Xiaocheng Li, Stefano Ermon

Understanding worldwide crop yield is central to addressing food security challenges and reducing the impacts of climate change. We introduce a scalable, accurate, and inexpensive method to predict crop yield using publicly available remote sensing data and machine learning. Our deep learning approach can predict crop yield with high spatial resolution (county-level) several months before harvest, using only globally available covariates. We believe our solution can potentially help making informed planting decisions, setting appropriate food reserve level, identifying low-yield regions and improving risk management of crop-related derivatives.

#BIGDATAINNOVATE
<table>
<thead>
<tr>
<th>Year</th>
<th>Ours (Jul.)</th>
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<tbody>
<tr>
<td>2009</td>
<td>-4.26</td>
</tr>
<tr>
<td>2010</td>
<td>-7.02</td>
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<td>7.22</td>
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<td>2012</td>
<td>11.3</td>
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<td>2013</td>
<td>-1.47</td>
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<tr>
<td>2014</td>
<td>3.53</td>
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<tr>
<td>2015</td>
<td>-4.77</td>
</tr>
<tr>
<td>Absolute Mean</td>
<td>5.65</td>
</tr>
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</table>
AI for sustainable energy research

1. Domain Knowledge
2. Experiment Design
3. High throughput experiments
4. Data analysis
Chemical map of a Nickel battery electrodes

Pixel(r) XANES

Pixel(b) XANES

Known Standards

NiO

Machine Learning

+ Physics

3D structure

Tomo scan, one chemical map per angle

1 Billion voxel XANES in 10 hours

Scientific Reports, 2016
AAAI-15
Bayesian Optimization of a 2km, $400m machine

Online optimization of quadrupole magnets

Live run at SLAC
- 4x better than human operators
- 2x better than gradient descent

McIntire, Ratner, Ermon. “Sparse Gaussian Processes for Bayesian Optimization”, UAI-16
Bayesian Protein Optimization

GFP variant fluorescence

expected improvement
optimization

SKGEE ...
encoder
amino acid
sequence

FN

continuous representation
of GFP variants

GP
decoder

SKGEE ...

amino acid
sequence

A

Joint training: predicted fluorescence

B

main functional complex

n=189
mutations per sequence

latent dimension 2

latent dimension 1
Acknowledgments