Machine Learning and AI

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60s: Intelligence from Logic

- Herbert Simon and Allen Newell:
  - Logic Theorist
  - General Problem Solver: Heuristic Search
  - Physical Symbol System Hypothesis
70s: Neural Networks
Search and Massive Parallelism
1997: DeepBlue

IBM

Kasparov
2011: IBM Watson/ Knowledge is Power!
2010: CNN and Deep Learning

Convolutional Neural Nets CNN
Features at Different Levels

- Vision
- Speech
- Understanding
Next: Reinforcement Learning

DQN
DeepMind: End to End
AlphaGo: Generality in AI
CMU Never Ending Learning Machine

NELL KB assertions vs. time

periodic human supervision begins

Jan 2010  March  July  Oct

.90  .75  .71  .87
Biased Data → Big Data
Transfer Learning

Oquab, Bottou, Laptev, Sivic: Learning and Transferring Mid-Level Image Representations using Convolutional Neural Networks. CVPR 2014.
Transfer Learning: text to images

The apple is the pomaceous fruit of the apple tree, species Malus domestica in the rose family Rosaceae ...

Banana is the common name for a type of fruit and also the herbaceous plants of the genus Musa which produce this commonly eaten fruit ...
Large-Scale Recommendation Engines

Over 100 Billion Features

\[ x = (1, 0, 0, 0, 1, \ldots, 1, 0, \ldots, 0, 1, 0, 0) \]

- User Demographic
- User Relevance to Target
- Recent User Behavior

Human Managed Vs. Automatically Generated and Maintained
Discriminative → Generative Models
Figure 1: Examples of free-form, open-ended questions collected for images via Amazon Mechanical Turk. Note that common-sense knowledge is needed along with a visual understanding of
Single Sample Learning: Bayesian Program Learning

A

i) primitives

ii) sub-parts

iii) parts

iv) object template

B

procedure GENERATETYPE

\[ \kappa \leftarrow P(\kappa) \]  \hspace{1cm} \triangleright \text{Sample number of parts}

\[ \text{for } i = 1 \ldots \kappa \text{ do} \]

\[ n_i \leftarrow P(n_i|\kappa) \]  \hspace{1cm} \triangleright \text{Sample number of sub-parts}

\[ \text{for } j = 1 \ldots n_i \text{ do} \]

\[ s_{ij} \leftarrow P(s_{ij}|s_{i(j-1)}) \]  \hspace{1cm} \triangleright \text{Sample sub-part sequence}

\text{end for}

\[ R_i \leftarrow P(R_i|S_1,...,S_{i-1}) \]  \hspace{1cm} \triangleright \text{Sample relation}

\text{end for}

\[ \psi \leftarrow \{\kappa,R,S\} \]

return @GENERATETOKEN(\psi) \hspace{1cm} \triangleright \text{Return program}

Science December 2015
Robots: What Amazon Teaches US
Finance + AI

Millions of Users, Credit ratings +61.7%
Partially Observable Markov Decision Models (training 6 years data; test: 2 years data)

Models

Trend

Result

股票历史趋势

预测：涨

预测：跌

不可预测

预测正确（盈利）

预测错误（损失）
Case Study: Shenzhen/Shanghai Market, POMDP Model

- 模型预测单只股票下一交易日的涨跌 (红线-模型相对收益，黄线-股票实际价格)
  - 红点 – （平空仓，并且）开多仓
  - 绿点 – （平多仓，并且）开空仓
  - 蓝点 – （平仓）空仓
NLP Dialog Agent (based on Data >> 10k dialogs)
**Dynamic Memory Network by MetaMind**

**Story**
- wolves are afraid of mice.
- sheep are afraid of mice.
- winona is a sheep.
- mice are afraid of cats.
- cats are afraid of wolves.
- jessica is a mouse.
- emily is a cat.
- gertrude is a wolf.

**Question**
- what is winona afraid of?

**Answer:** mouse

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**Episode 1**
- 0.00: wolves are afraid of mice
- 0.00: sheep are afraid of mice
- 0.99: winona is a sheep
- 0.00: mice are afraid of cats
- 0.00: cats are afraid of wolves
- 0.00: jessica is a mouse
- 0.00: emily is a cat
- 0.01: gertrude is a wolf

**Episode 2**
- 0.00: wolves are afraid of mice
- 1.00: sheep are afraid of mice
- 0.00: winona is a sheep
- 0.00: mice are afraid of cats
- 0.00: cats are afraid of wolves
- 0.00: jessica is a mouse
- 0.00: emily is a cat
- 0.00: gertrude is a wolf
Genotype and Phenotype

Input: Very high dimension and low sample size labeled data \((N \approx 2000, D \approx 240K)\)

Task: Train an accurate phenotype predictor using genetic data.

Accelerate Hybridization Breeding

E.g. Facilitate understanding biology process

Genetic markers

Setaria italica

Complex phenotype

Machine Learning

Environment

markers underlying specific phenotype.
Conclusions

• Current AI technology:
  – Deep Learning: Needs BIG DATA
    • Samples must be sufficient to ensure convergence
  – Need to find complimentary points of Man and Machine
    • AMAZON example

• Future
  – Transfer Learning, One-Example Learning
  – Reinforcement Learning (complete feedback loop)