Deep Learning for Programming

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Or Thoughts ... From an Old Guy
Or Thoughts … From an Old Guy

⇦ ME

(before shaving and haircut)
Outline

Context

Old ML and Stats versus New ML

A Catalogue of Deep Learning Ideas

Conclusion
Context

from MIT Technology Review

Karen Hao, 03/11/2020
Information Retrieval: Images

image search gives
Information Retrieval becomes ML

Information Retrieval (IR): from a single query (image, text), retrieve “best” matching documents. e.g. text/image search engine
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- this is like learning from just one example!
- called zero/one-shot learning in Deep Neural Networks, especially for images
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- state-of-the-art in text IR is hybrid IR and transformer-based language models!
  - see SIGIR 2018 tutorial by Xu, He and Li
  - see QGenHyb by Ma, Korotkov, Yang, Hall, McDonald, EACL 2021
  - to my knowledge IR techniques and earlier one-shot researchers did not intersect!
Deep Learning successes:
- machine translation, speech understanding
- bio-informatics (e.g., 3-D protein folding)
- object/person tracking in video

representation learning!
Context, cont.

- Deep Learning successes:
  - machine translation, speech understanding
  - bio-informatics (e.g., 3-D protein folding)
  - object/person tracking in video

- Machine Learning in the guise of Deep Learning is now happening at a world-wind pace:
  - a phase shift happening a few years ago,
  - huge teams making rapid advances,
  - results/methods already outdated and superceded at their point of publication,
Context, cont.

- Deep Learning successes:
  - machine translation, speech understanding
  - bio-informatics (e.g., 3-D protein folding)
  - object/person tracking in video
- Machine Learning in the guise of Deep Learning is now happening at a world-wind pace:
  - a phase shift happening a few years ago,
  - huge teams making rapid advances,
  - results/methods already outdated and superceded at their point of publication,
- How can we employ these techniques in traditional computer science?
Software Systems adding AI/ML

- source data needs quality management, versioning, etc. ⇐ the biggest problem
- AI systems components entangled in complex ways
- ML knowledge required of developers to harness the ML tools
- whole new testing and development frameworks needed
- explainability, fairness, transparency, fault tolerance, ...
Software Systems adding AI/ML

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30 years ago a similar problem in AI was faced when integrating/developing expert systems with traditional software:

- machine learning was proposed as the solution!
- even then the problem of data quality management was recognised
**AI/ML Dev. Tasks**

**TABLE II**  
The top-ranked challenges and personal experience with AI. Respondents were grouped into three buckets (low, medium, high) based on the 33rd and 67th percentile of the number of years of AI experience they personally had (N=308). The column *Frequency* shows the increase/decrease of the frequency in the medium and high buckets compared to the low buckets. The column *Rank* shows the ranking of the challenges within each experience bucket, with 1 being the most frequent challenge.

<table>
<thead>
<tr>
<th>Challenge</th>
<th>Frequency</th>
<th>Rank</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Data Availability, Collection, Cleaning, and Management</td>
<td>-2%</td>
<td>60%</td>
<td>-</td>
<td></td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Education and Training</td>
<td>-69%</td>
<td>-78%</td>
<td>-</td>
<td></td>
<td>-</td>
<td></td>
<td>-</td>
</tr>
<tr>
<td>Hardware Resources</td>
<td>-32%</td>
<td>13%</td>
<td>-</td>
<td></td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>End-to-end pipeline support</td>
<td>65%</td>
<td>41%</td>
<td>-</td>
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<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Collaborator and working culture</td>
<td>19%</td>
<td>69%</td>
<td>-</td>
<td></td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Specification</td>
<td>2%</td>
<td>50%</td>
<td>-</td>
<td></td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Integrating AI into larger systems</td>
<td>-49%</td>
<td>-62%</td>
<td>-</td>
<td></td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Education: Guidance and Mentoring</td>
<td>-83%</td>
<td>-81%</td>
<td>-</td>
<td></td>
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<td>-</td>
<td>-</td>
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<tr>
<td>AI Tools</td>
<td>144%</td>
<td>193%</td>
<td>-</td>
<td></td>
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<td></td>
<td>-</td>
</tr>
<tr>
<td>Scale</td>
<td>154%</td>
<td>210%</td>
<td>-</td>
<td></td>
<td>-</td>
<td></td>
<td>-</td>
</tr>
<tr>
<td>Model Evolution, Evaluation, and Deployment</td>
<td>137%</td>
<td>276%</td>
<td>-</td>
<td></td>
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</tr>
</tbody>
</table>
AI/ML Dev. Pipeline

Fig. 1. The nine stages of the machine learning workflow. Some stages are data-oriented (e.g., collection, cleaning, and labeling) and others are model-oriented (e.g., model requirements, feature engineering, training, evaluation, deployment, and monitoring). There are many feedback loops in the workflow. The larger feedback arrows denote that model evaluation and monitoring may loop back to any of the previous stages. The smaller feedback arrow illustrates that model training may loop back to feature engineering (e.g., in representation learning).

different to traditional agile or other!
AI/ML Dev. Pipeline

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different to traditional agile or other!
near identical to the data science dev. pipeline from 2013
and they’ve had huge trouble integrating into the career/HR environment
Programming Languages for AI/ML

- support for building & testing ML models

- libraries for:
  - streaming data
  - hyper-parameter optimisation
  - probability components
  - matrices and tensors
  - auto-differentiation
  - model components (convolutions, transformers, etc.)

- probabilistic programming
AI/ML for Programming Languages

- debugging, testing and code reviews
- comments checking and generation
- code search and matching
- auto-generating software
- smart compilation
- auto-generating distributed and/or low-level code
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Old ML and Stats versus New ML

Old ML

Deep ML Reminders

New (Deep) ML

A Catalogue of Deep Learning Ideas

Conclusion
What did We Learn from Old ML?

▷ how to do exponential family, linear and partitioning models well
  
  e.g., XGBoost, online LDA, Gaussian mixtures, logistic regression
  
  ▷ how to augment them with fancy mathematical tricks
    
    e.g., kernels, non-parametric Bayesian
    
    i.e., infinite vectors
  
  i.e., cases where learning admits computational simplifications
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- models as first-class objects
  - e.g., Bayesian & Markov networks, neural networks
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  - models as first-class objects
    - e.g., Bayesian & Markov networks, neural networks
- statistical ML theory
  - e.g., bias-variance tradeoff, variational methods, ensembles
  - e.g., Bayesian MCMC as “gold standard” learning
What did We Learn, cont.?

- **cost functions** (using statistical ML theory)

  e.g., regularisation, metrics and divergences,

  i.e., the theory of objective functions for deep NNs
What did We Learn, cont.?

- **cost functions** (using statistical ML theory)
  - e.g., regularisation, metrics and divergences,
  - i.e., the theory of objective functions for deep NNs
- **paradigms**
  - e.g., online learning, active learning, transfer learning
- **learning on networks**
  - deterministic networks
  - probabilistic networks
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A Non-trivial Network

see playground.tensorflow.org
Deep Representations

Observation: different layers of the network “learn” alternative representations.

from https://thedatoscientist.com/what-deep-learning-is-and-isnt/
Deep Architectures

Complex systems are built from neural modules.

from “Memory-Based Network for Scene Graph with Unbalanced Relations”, MM'20, Wang et al.
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How Does Deep Learning Innovate?

- Model/Spec driven black-box algorithms ease the workload of developers.
  - machine learning without statistics!

- Porting down to GPUs or multi-core allows real speed.

- Learning representations and discovering higher order concepts.
  - convolutions, structures, sequences, ...

- High capacity makes them very flexible in fitting and does implicit parallel search.

- Self-supervision, i.e., pre-training networks with fabricated but useful tasks.

- Allows "modelling in the large":
  - multi-task learning, imitation learning, meta-learning.
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  - multi-task learning, imitation learning, meta-learning
  - components like convolutions, structures, sequences, ...
Why is Deep Neural Nets Successful?

from Stanford Uni. NLP course, CS224N/Ling284 2020
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Ensembling

Data Augmentation

Self-Supervision

Probabilistic Programming

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**Ensembling**

▶ Have set of \((x, y)\) data Data and network parameters \(\theta \in \Theta\).

▶ The **Bayesian posterior**, predicting \(y\) given new test point \(x\):

\[
\int_{\theta \in \Theta} p(y | x, \theta) \cdot p(\theta | \text{Data}) \, d\theta
\]

prediction using parameters \(\theta\)  posterior on parameters \(\theta\)

▶ The gold standard algorithm is **complex MCMC**

▶ The **simple ensemble** says to train a small set of “good but different” models \(\hat{\Theta}\) and pool them together

\[
\frac{1}{|\hat{\Theta}|} \sum_{\theta \in \hat{\Theta}} p(y | x, \theta)
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  \]

- First did as a student’s masters project at University of Sydney in 1988.
The (Frequentist) Laws of Learning

- The First Law of Learning for model family $H$ (Geman & Geman, 1992)

$$\text{Mean-Squared-Error}(H) = \text{Bias}(H)^2 + \text{Variance}(H) + \text{IrreducibleError}$$
The (Frequentist) Laws of Learning

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- The Second Law of Learning for ensemble $\mathcal{H}$ of models (Uedo & Nakano, 1996):

  $$\text{Mean-Squared-Error}(\mathcal{H}) = \overline{\text{Bias}(\mathcal{H})^2} + \frac{1}{|\mathcal{H}|} \overline{\text{Variance}(\mathcal{H})} + \text{IrreducibleError}$$
  $$+ \left(1 - \frac{1}{|\mathcal{H}|}\right) \text{Covariance}(\mathcal{H})$$
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  \]
  \[+ \left(1 - \frac{1}{|\mathcal{H}|}\right) \text{Covariance}(\mathcal{H})\]

- Therefore:
  - elements of the ensemble should have lower bias and variance
  - elements of the ensemble should be de-correlated
Understanding the Second Law

- estimating $\int_{\theta \in \Theta} p(y | x, \theta) \cdot p(\theta | \text{Data}) \, d\theta$
- the random points clump “statistically”
- the quasi-random points are de-correlated with little clumping
  - e.g., determinantal point processes
    - (like some adversarial training)
  - e.g., Stein variational gradient descent
Understanding the Second Law

- estimating $\int_{\theta \in \Theta} p(y \mid x, \theta) \cdot p(\theta \mid \text{Data}) \, d\theta$
- the random points clump “statistically”
- the quasi-random points are de-correlated with little clumping
  - e.g., determinantal point processes
    (like some adversarial training)
  - e.g., Stein variational gradient descent
- ensemble $\sum_{\theta \in \hat{\Theta}} p(y \mid x, \theta)$ works better using quasi-random points
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Data Augmentation

IDEA: classified data is hard to get, so let's generate new data!
Data Augmentation: MNIST

- technique first used in Zipcode recognition for the US Post
- images can be rotated, shifted, thinned, etc.
Data Augmentation: Theory

- We need to identify an invariant in our data we want to hold.
  
  e.g. For text, we could replace synonyms, back-translate, etc.

- We need an algorithm to apply changes to the data reflecting the invariant.

- Probabilistic model, for the augmentation distribution $\text{Aug}$

  \[
  p(y_i | x_i, \theta) = \int_{x'} p(y_i | x'_i, \theta) p(x' | x_i, \text{Aug}) \, dx'
  \]

  standard data likelihood

  augmented data likelihood
Data Augmentation: Theory

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  $$
  p(y_i | x_i, \theta)
  $$
  standard data likelihood

  $$
  p(y_i | x_i, \theta, \text{Aug}) = \int_{x'} p(y_i | x'_i, \theta)p(x'|x_i, \text{Aug}) \, dx'
  $$
  augmented data likelihood

- Developed as vicinal risk minimisation by Chapelle et al. 2001.
Data Augmentation: Implementation

- Probabilistic model, for the augmentation distribution Aug

\[
p(y_i \mid x_i, \theta, \text{Aug}) = \int_{x'_i} p(y_i \mid x'_i, \theta) p(x'_i \mid x_i, \text{Aug}) \, dx' \quad \text{augmented data likelihood}
\]

\[
\approx \sum_{x'_i \in E(x_i)} p(y_i \mid x'_i, \theta) \quad \text{ensembled approximation}
\]

using **ensemble of augmentations** \( E(x_i) \) generated with \( p(x'_i \mid x_i, \text{Aug}) \)

- At learning time we train stochastically with one or more augmentations.

- At inference time we should also do augmentations.
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Encoding, Decoding and Embeddings

Our operational framework: every piece of input structure has two embeddings, contextual and non-contextual.

from “Representation Learning on Graphs: Methods and Applications”, Hamilton, Ying and Leskovec, 2017
Self-supervision

- to do pre-training, we need a task for learning
- embedding methods (CBOW, Word2Vec, etc.) are an early precursor
- pre-training should build lower-level features useful for subsequent target classes
Self-supervision

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- embedding methods (CBOW, Word2Vec, etc.) are an early precursor
- pre-training should build lower-level features useful for subsequent target classes

Self-supervision: an artificial task created for the purposes of learning a network useful as a pre-trained network.

- called “self” supervised since the task is created automatically
Self-supervision: an artificial task created for pre-training network.

- examples for **image recognition**:
  - color a B/W image
  - fill-in missing patches ("image in-painting")
  - object classification from very broad image class

- examples for **text classification**:
  - predict missing words
  - forwards and backwards order
Self-supervision: an artificial task created for pre-training network.

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- examples for **text classification**:
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- generally, the self-supervision task should be (1) richer and more refined than or (2) similar to subsequent target tasks
A pseudo-likelihood (Besag 1975) is an approximation to the joint probability distribution of a collection of random variables using univariate conditionals:

\[
p(X|M, \Theta) = \prod_{i=1}^{l} p(x_i | x_1, \ldots, x_{i-1}, M, \Theta) \quad \text{(product rule of probability)}
\]

\[
= p(x_1 | M, \Theta)p(x_2 | x_1, M, \Theta) \cdots \underbrace{p(x_l | x_1, \ldots, x_{l-1}, M, \Theta)}_{\text{repeat this term}}
\]

\[
\tilde{p}(X|M, \Theta) \equiv \prod_{i=1}^{l} p(x_i | X_{-i}, M, \Theta) \quad \text{where } X_{-i} = X \setminus \{x_i\}
\]

Each term is a single prediction.
Pseudo-likelihood, cont.

\[ \tilde{p}(X|M, \Theta) \equiv \prod_{i=1}^{l} p(x_i | X_{-i}, M, \Theta) \quad \text{where } X_{-i} = X \setminus \{x_i\} \]

- it is easily computed because the individual conditionals can usually be easily marginalised.
- maximising pseudo-likelihood is known to be consistent with maximising likelihood in the limit of infinite data.
- Pseudo-likelihood can be viewed as a simplified theoretical view of self-supervision.
- But an alternative view is of representation learning.
Self-supervision with Natural Language

- pseudo-likelihood training on

\[
PLL(W; \theta) = \sum_{t=1}^{W} \log p(w_t | W_{-t}, \theta)
\]

- may add other prediction objectives about sentence ordering, etc.

- when the model is multi-layer transformers, is the basis of the biggest revolution in NLP history (BERT, XLNET, ...)

figure from Salazar, Liang et al., ACL 2020
techniques similar to word embeddings have been developed for graphs
nodes in graphs also have extensive side information
  “hospital patient” node in a graph may have their socio-economic data attached
pseudo-likelihood style self-supervision applies equally as well
Summary

- Arbitrary graph structures with embedded text can be modelled using this framework.
- Self-supervision works but:
  - pays to be clever about the pseudo-likelihood prediction tasks
- These self-supervision encoder-decoder networks form ideal pre-trained networks for subsequent prediction tasks.
  - can be done for written code and comments
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Bayes infer. Using Gibbs Sampling

BUGS, Spiegelhalter, Thomas, Best, Gilks, 1996

Modelling language:

model{
  # model priors
  beta0 ~ dnorm(0, 0.001)
  eta1 ~ dnorm(0, 0.001)
  tau ~ dgamma(0.1, 0.1)
  sigma <- 1/sqrt(tau)
  # data model, linear regression
  for( i in 1:n) {
    mu[i] <- beta0 + beta1*x[i]
    y[i] ~ dnorm(mu[i] , tau)
  }
}
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Modelling language:

```r
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        y[i] ~ dnorm(mu[i] , tau)
    }
}
```

- Simple Bayesian linear regression using Gaussian model \( \vec{x} = \beta_0 + \beta_1 \vec{y} \).
- All constants, parameters and data are defined in the language.
Probabilistic Programming

- used to define probability models for automatic algorithm generation
- provide statistical constructs that users can directly call and use
- predominantly declarative - focus on what needs to be done over how
- can provide support for a plethora of operations
  - Gibbs, Hamiltonian Monte Carlo and other Gibbs
  - variational algorithms
  - black-box optimisation

this section largely drawn from PhD thesis of Dr. Sachith Seneviratne
Probabilistic Programming: Examples

**BUGS** uses a directed acyclic graph (DAG) to represent a model (1995)

**AutoBayes** uses Schema to compose models (1998)

**Stan** uses Hamiltonian Monte Carlo and targets continuous sampling (2012)

**Edward** CPU/GPU support with various inference schemes (2016)

**Google TensorFlow Probability** scale performance across CPUs, GPUs, and TPU, within **TensorFlow**
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Initially developed independently of Deep Learning, but has similar goals, and similar techniques, and there is now convergence.
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Example Uses

- **Model/Spec driven** black-box algorithms ease the workload of developers.
  - machine learning without statistics!
- **Porting down** to GPUs or multi-core allows real speed.
- **Learning representations** and discovering higher order concepts.
  - convolutions, structures, sequences, ...
  - **high capacity** makes them very flexible in fitting and does implicit parallel search
- **self-supervision**
  - i.e., pre-training networks with fabricated but useful tasks
- Allows “modelling in the large”:
  - multi-task learning, imitation learning, meta-learning
  - components like convolutions, structures, sequences, ...
Code is Different to Natural Language

- NLP is “natural” and extremely hard to parse, with new or erroneous tokens appearing
  - majority of deep nets treat it like a sequence, not a structure
- code is easy to parse with precise structures, except for
  - the language buried in comments,
  - and variable names
- we even have auxiliary information like modification time, author, etc.

code has rich structures and auxiliary information as well as embedded text
Pre-training for Code

- use graphs to represent structure of code, model with graph NNs
- harness standard language models for the comments
- harness standard tokenisation models for variable names (WordPiece, etc.)
- develop clever self-supervision tasks:
  - predict comments
  - predict control flow
  - predict expressions
Variants in Probabilistic Programming

Sachith Seneviratne’s PhD thesis, 2020

- high level code generated from models
- variant algorithms (part Gibbs, part variational, different probability formulations)
- variant implementations (different parts in multi-core, GPU)
- automated testing harness to “race” techniques
Variants in Probabilistic Programming

Sachith Seneviratne’s PhD thesis, 2020

- high level code generated from models
- variant algorithms (part Gibbs, part variational, different probability formulations)
- variant implementations (different parts in multi-core, GPU)
- automated testing harness to “race” techniques

Needs the code generation and automated testing infrastructure to make work.
Another Application

TODAY’S HIGHLIGHTS

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My guess is the number will become half after 10 years

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The 3 Worst Pieces of Programming Advice I’ve Ever Heard
3. Build as quickly as possible

Generating clickbait for developers
Another Application

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