A Pragmatic Approach for Machine Learning in D

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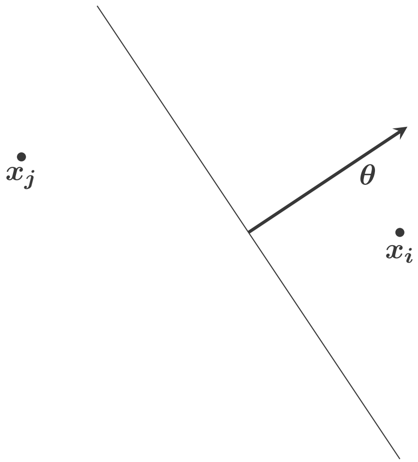
Logistic Regression


dS/dt = Γ g(N − N0)(1 − εS)S + N/τn − S/τp
S ≤ 1/ε

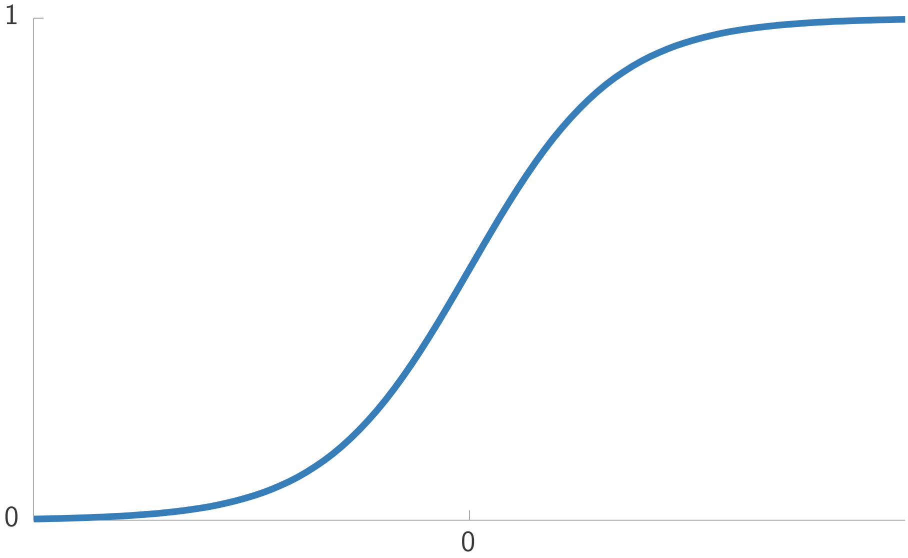
$$\boldsymbol{x_i}^\top \boldsymbol{\theta}$$


x_j
θ
x_i

Logistic Function

$$m(x) = \frac{1}{1 + \exp(-x)}$$

Logistic Function

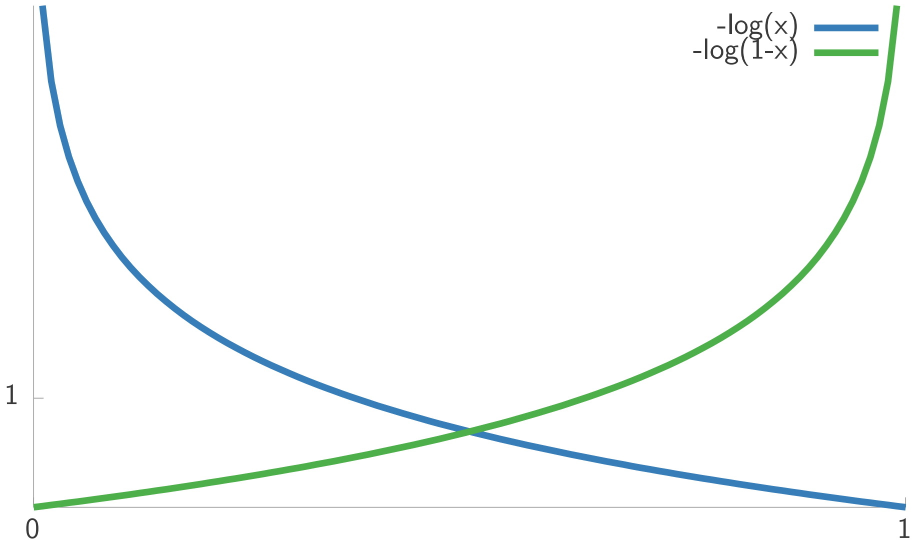


$$m(\boldsymbol{x_i}; \boldsymbol{\theta}) = \frac{1}{1 + \exp(-\boldsymbol{x_i}^\top \boldsymbol{\theta})}$$

Cross Entropy Loss

$$H(p, q) = -\sum_{x} p(x) \log q(x)$$

Cross Entropy Loss



Cross Entropy Loss

Let $y_i \in \{y_1, y_2\}$ the set of label classes.

$$
\begin{aligned}
-\sum_x p(x)\log q(x) &= -\sum_x \mathbb{1}_{x=y_i}\log q(x) \\
&= -\left(\mathbb{1}_{x=y_1}\log q(x) + \mathbb{1}_{x=y_2}\log(1-q(x))\right) \\
&= -\left(\mathbb{1}_{x=y_1}\log m(\boldsymbol{x_i};\boldsymbol{\theta}) + \mathbb{1}_{x=y_2}\log(1-m(\boldsymbol{x_i};\boldsymbol{\theta}))\right) \\
&= -\left(\mathbb{1}_{x=y_1}\log m(\boldsymbol{x_i};\boldsymbol{\theta}) + \mathbb{1}_{x=y_2}\log(m(-\boldsymbol{x_i};\boldsymbol{\theta}))\right) \\
&= -\log m(y_i\boldsymbol{x_i};\boldsymbol{\theta}) \text{ with setting } y_1 = 1 \text{ and } y_2 = -1 \\
&= -\log\left(\frac{1}{1+\exp(-y_i\boldsymbol{x_i}^\top\boldsymbol{\theta})}\right) \\
&= \log\left(1+\exp(-y_i\boldsymbol{x_i}^\top\boldsymbol{\theta})\right)
\end{aligned}
$$

$$\log\left(1 + \exp(-y_i\, \boldsymbol{x}_i^\top \boldsymbol{\theta})\right)$$

$$\sum_{i=1}^{m} \log\left(1 + \exp(-y_i \, \boldsymbol{x}_{\boldsymbol{i}}^{\top} \boldsymbol{\theta})\right)$$

$$\sum_{i=1}^{m} \left[\log\left(\mathbf{1} + \exp(-\boldsymbol{y} \odot \boldsymbol{X}\boldsymbol{\theta}) \right) \right]_i$$

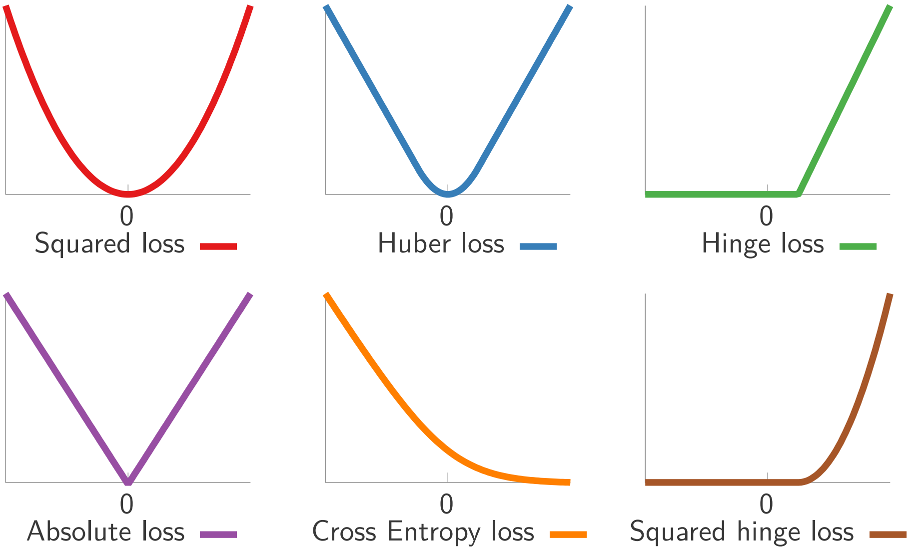
Data

- Numeric
- Scalars, vectors, matrices, ...
- Quality vs Quantity

Models

- Defines mapping between data and model parameters
- Classification and regression models
- Factorization methods
- Deep Neural Networks
- ...

Losses


0
Squared loss
0
Huber loss
0
Hinge loss
0
Absolute loss
0
Cross Entropy loss
0
Squared hinge loss

Model Parameters

- Updated by minimizing the modeled loss
- Distribute parameters for large models

Optimization

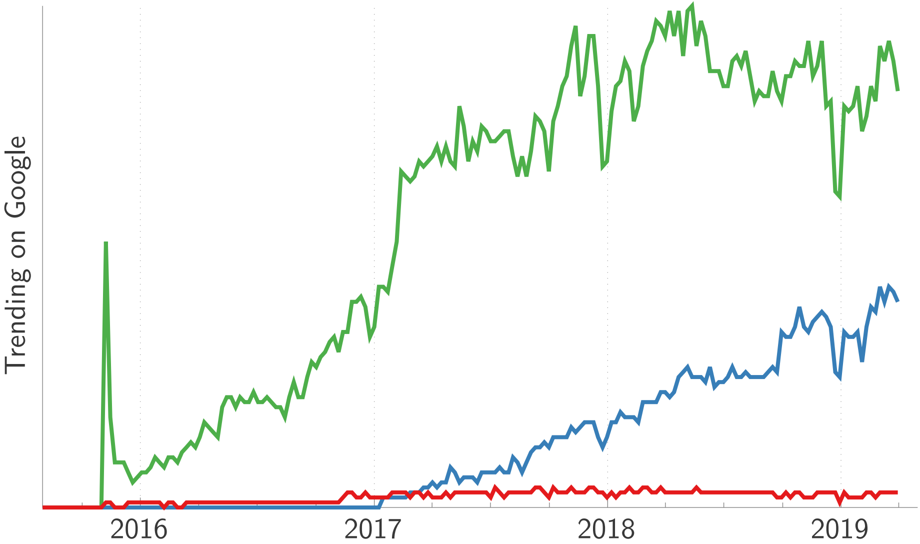
- (Stochastic) Gradient Descent Step

$$\boldsymbol{\theta}_{i+1} = \boldsymbol{\theta}_i - \alpha \boldsymbol{g}$$

- Variations for faster convergence
- Learning rate is important

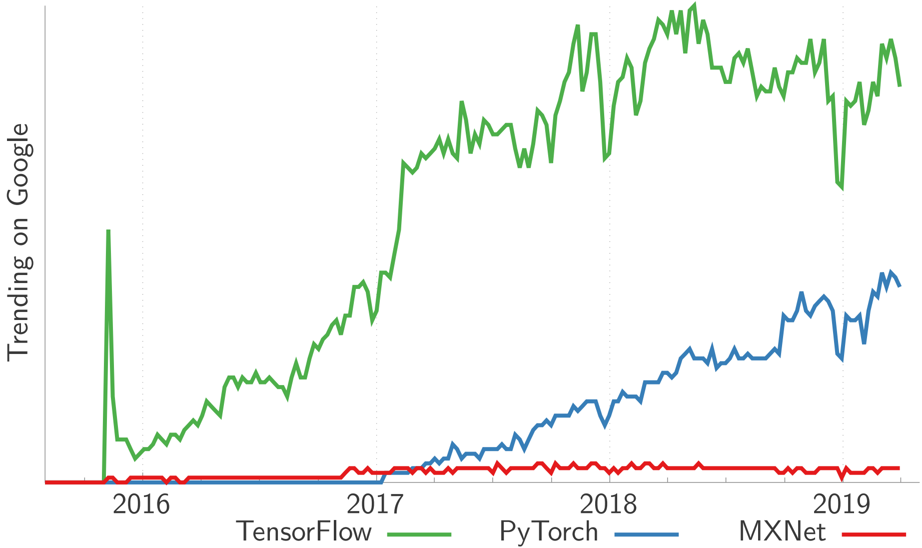
MXNet

- Mix symbolic and imperative programming
- Dependency scheduler
- Memory efficient and fast execution of symbolic graphs



Trending on Google
2016
2017
2018
2019

Why Not MXNet



Why MXNet

- Exposes C API to access all functionality (not only prediction)
- Both prototyping and production code in D
- Use your D language skills

MXNet Backend

- Basic Linear Algebra Subprograms (Intel MKL, Apple Accelerate, ATLAS, OpenBLAS)
- CUDA and cuDNN
- Open Neural Network Exchange

Symbolic vs Imperative

- Define symbolic network, bind values to it and execute it
- Imperative scheduled and evaluated as you go

MXNet API

- AtomicSymbol
- Symbol
- NDArray
- Executor
- Autograd
- Key-value store
- ...

Model and Loss

```
// creating the network
// data arguments
auto x_symbol = new Variable("X"); // feature matrix
scope(exit) x_symbol.freeHandle();
auto y_symbol = new Variable("y"); // label vector
scope(exit) y_symbol.freeHandle();

// network architecture and model parameters
auto w_symbol = new Variable("W");
scope(exit) w_symbol.freeHandle();
auto fc = new FullyConnected(x_symbol, num_classes, w_symbol);
scope(exit) fc.freeHandle();
auto softmax = new SoftmaxOutput(fc, y_symbol);
scope(exit) softmax.freeHandle();
```

Context and Data

```
// setup context where computations should happen
auto context = cpuContext();
// size of a training batch
auto batch_size = 100;
// data variable X
auto matrix_x = new NDArray!(float)(context, [batch_size,
    num_pixels]);
scope(exit) matrix_x.freeHandle();
// data variable y
auto vector_y = new NDArray!(float)(context, [batch_size]);
scope(exit) vector_y.freeHandle();
```

Initialize Model Parameters

```
// initialize parameter W to zero
auto matrix_w = new NDArray!(float)(context, [num_classes,
    num_pixels], 0f);
scope(exit) matrix_w.freeHandle();

// holds gradient w.r.t. W
auto gradient_w = new NDArray!(float)(context, matrix_w.shape()
    );
scope(exit) gradient_w.freeHandle();
```

Bind Executor

```
// verify that the all arguments are provided in proper order
assert(softmax.arguments == ["X", "W", "y"]);
// define the executor binding the model with data and model
    parameters
auto executor = new Executor!(float)(context, softmax,
    arguments, gradients, gradients_req_type, []);
scope(exit) executor.freeHandle();
```

Training in Batches

```
// set batch and ...
matrix_x.copyFrom(images_batch);
vector_y.copyFrom(labels_batch);

// make a forward and a backward pass
executor.forward();
executor.backward();
auto step_length = 5e-1f;
// and a gradient descent step
gradient_w *= step_length;
matrix_w -= gradient_w;
```

dmxnet

- Still in 0.x
- Targeted platform Linux
- Unit- and integration tested
- Documented

Demo

Outlook

- Cleanup D1 artifacts
- More examples to learn from
- Automatic generating of Symbols/NDArrays
- Tape-based gradient calculation
- Use uniform function call syntax

```
auto model = symbol("image").convolve()
                            .activate()
                            .pool()
                            .fullyConnected()
                            .softmax();
```

Conclusions

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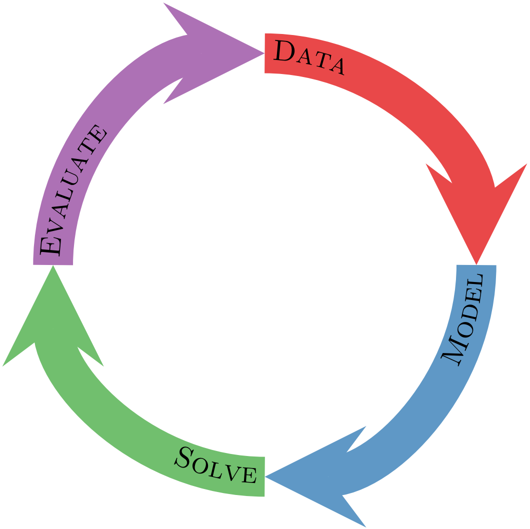
Appendix

Data Analysis Cycle



VGG19