Introduction to Machine Learning feat. TensorFlow

Peter Goldsborough

July 11, 2016

Table of Catents

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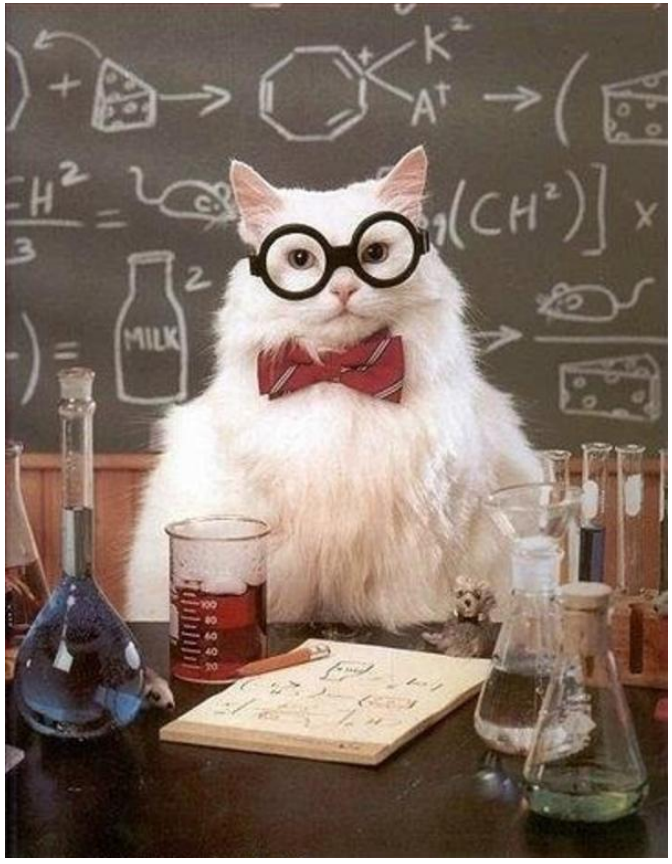

Theory

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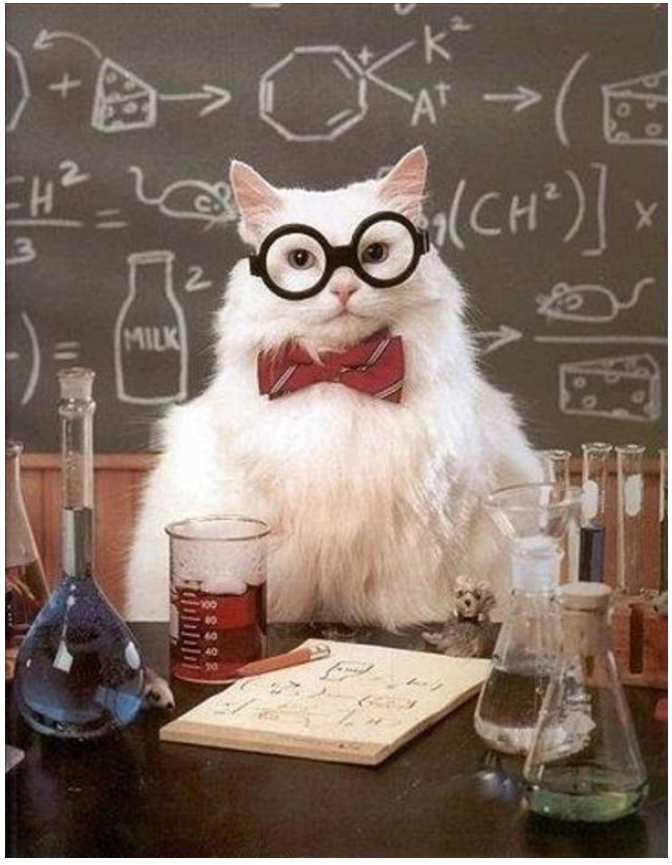

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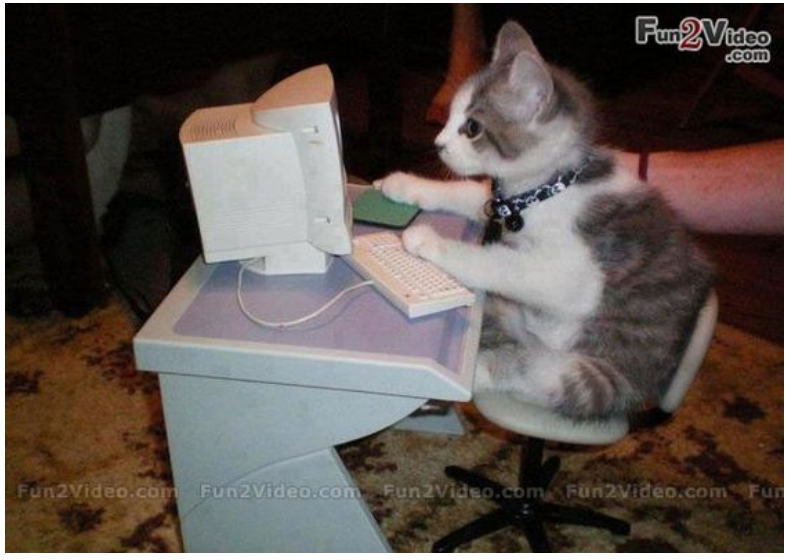

Practice

Background

Background

- CS Student @ TUM

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- Google & Bloomberg Intern

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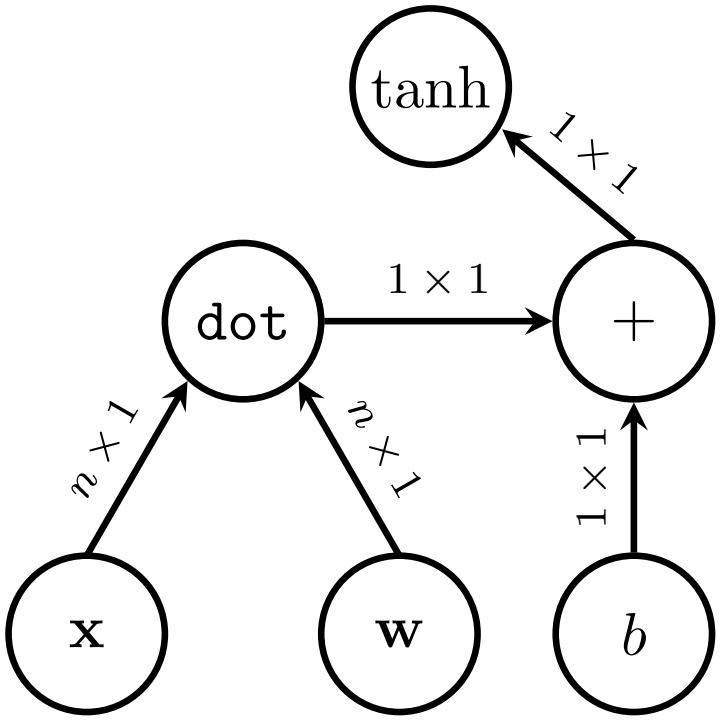
Seminar Topic: *Deep Learning With TensorFlow*

`github.com/peter-can-write/tensorflow-paper`

`github.com/peter-can-talk/python-meetup-munich-2016`

Computational Paradigms

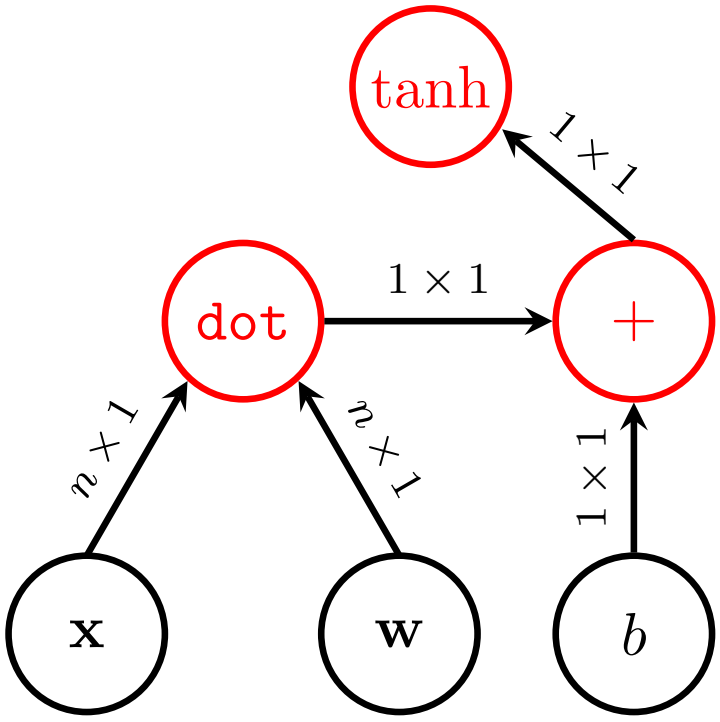
Computational Paradigms



$$\hat{y} = \tanh(\mathbf{x}^\top \mathbf{w} + b)$$

Computational Graphs

Computational Paradigms



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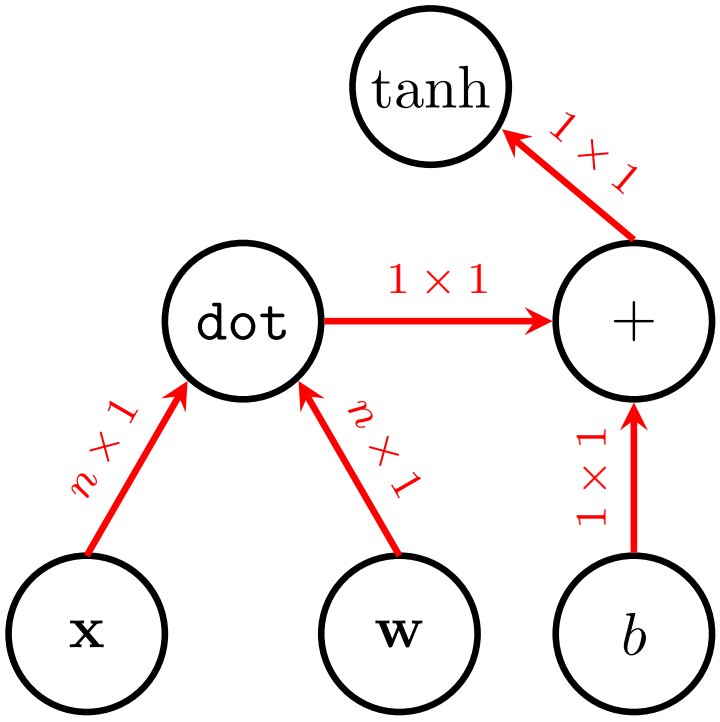
Computational Graphs

1. Operations

Computational Paradigms



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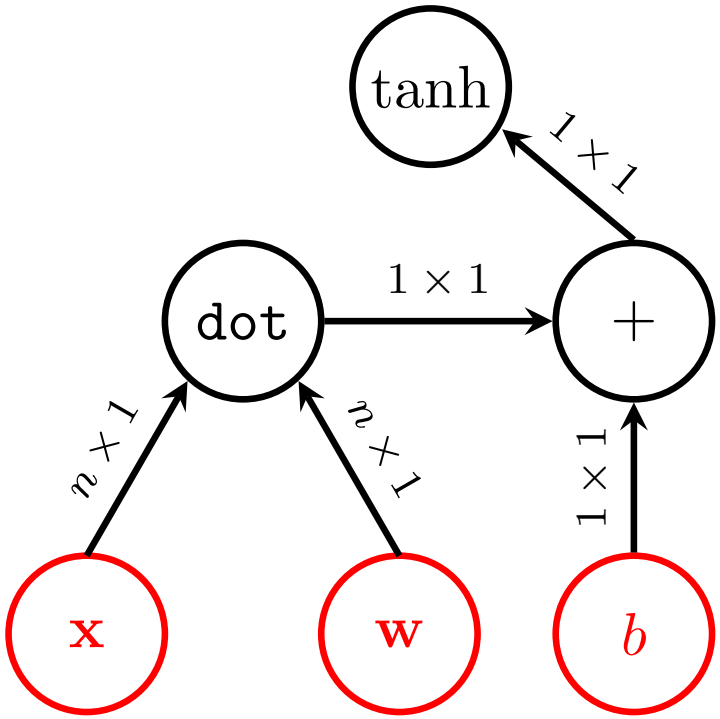
Computational Graphs

1. Operations
2. Tensors

Computational Paradigms

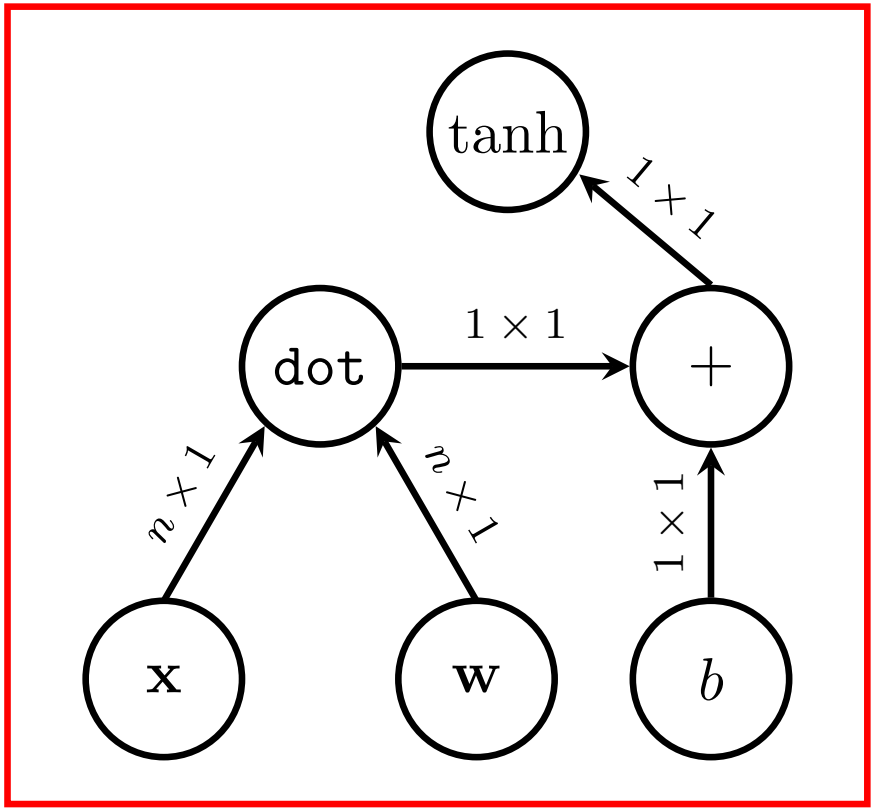


$$\hat{y} = \tanh(\mathbf{x}^\top \mathbf{w} + b)$$

Computational Graphs

1. Operations
2. Tensors
3. Variables

Computational Paradigms



$$\hat{y} = \texttt{session.run}(\tanh(\mathbf{x}^\top \mathbf{w} + b))$$

Computational Graphs

1. Operations
2. Tensors
3. Variables
4. Sessions

Execution Model

Execution Model

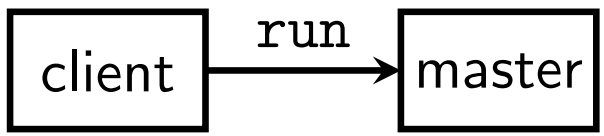
Actors

Execution Model

Actors

1. Client

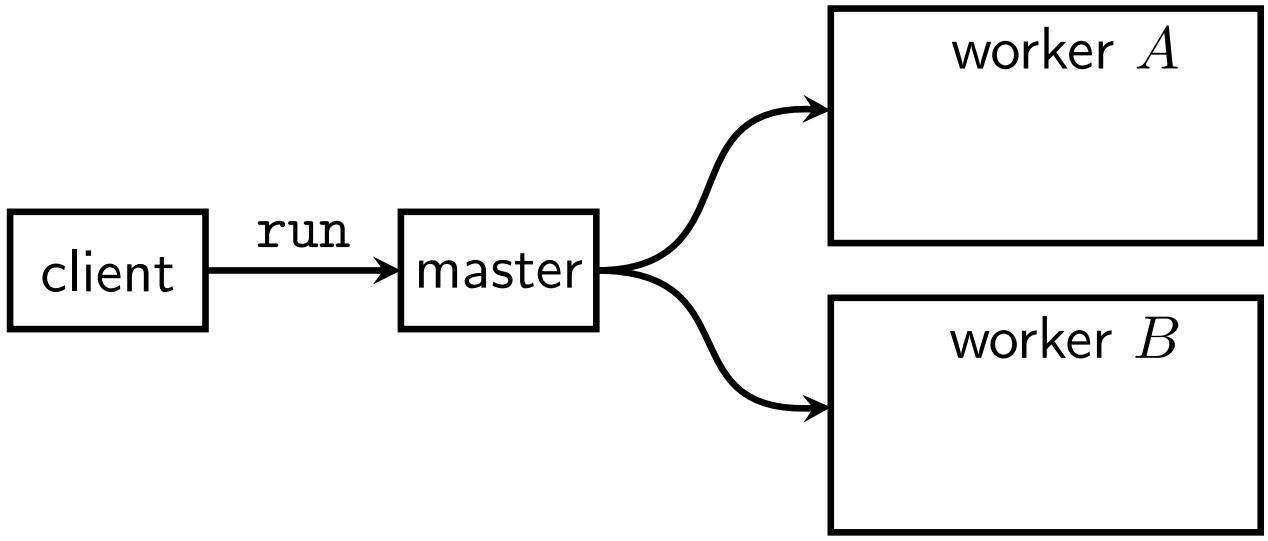
Execution Model



Actors

1. Client
2. Master

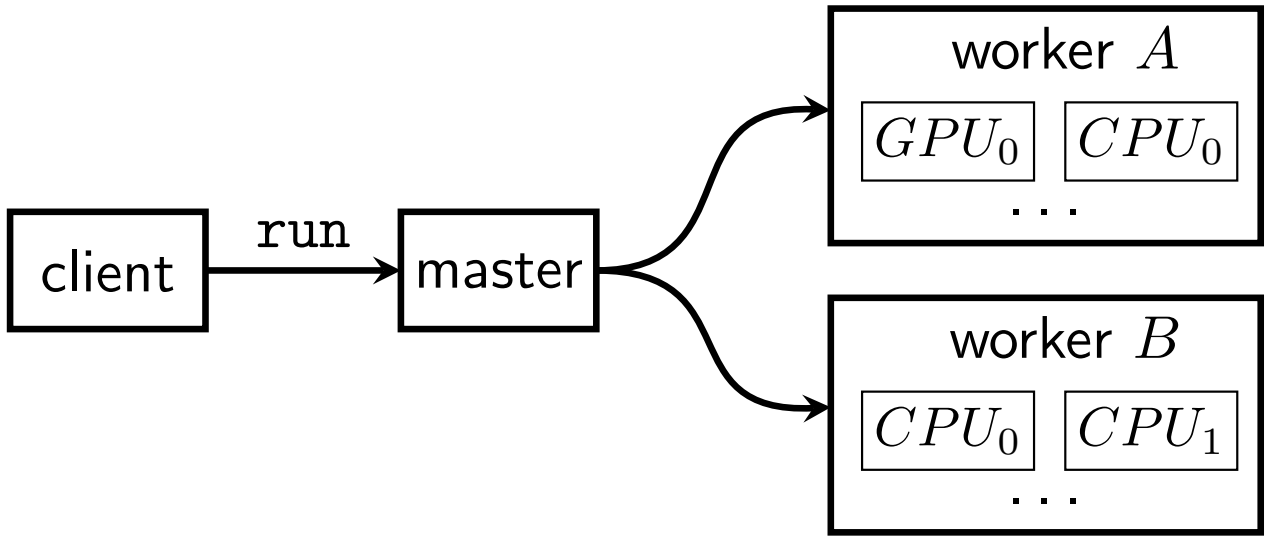
Execution Model



Actors

1. Client
2. Master
3. Workers

Execution Model



Actors

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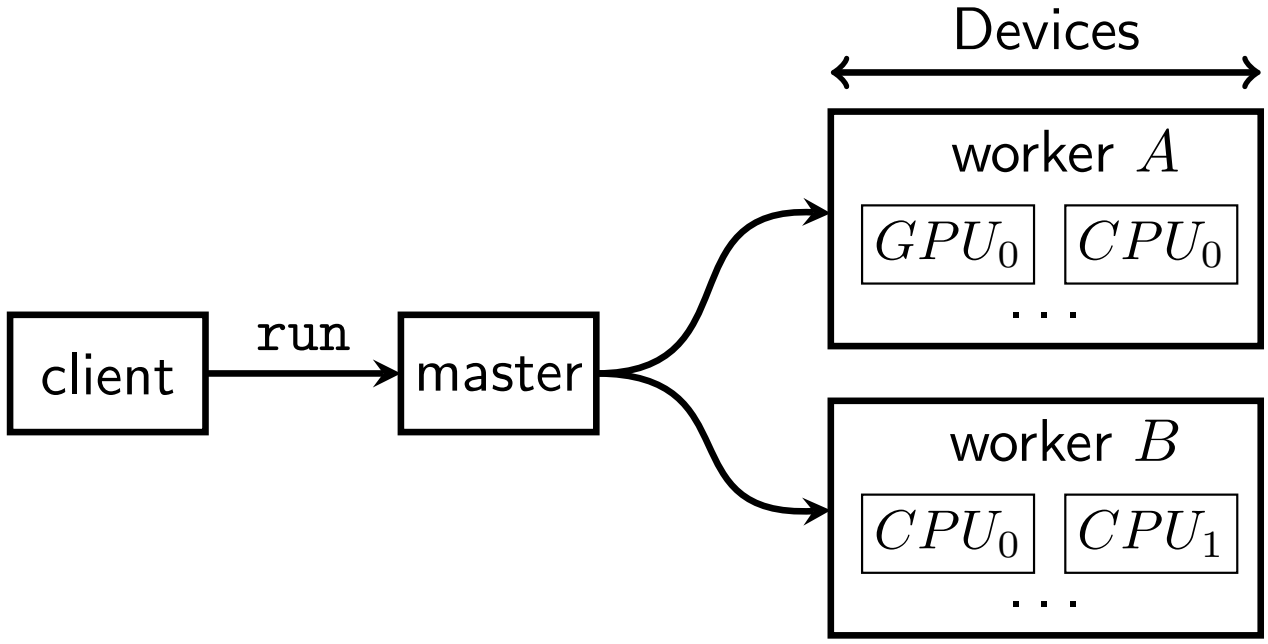
Execution Model



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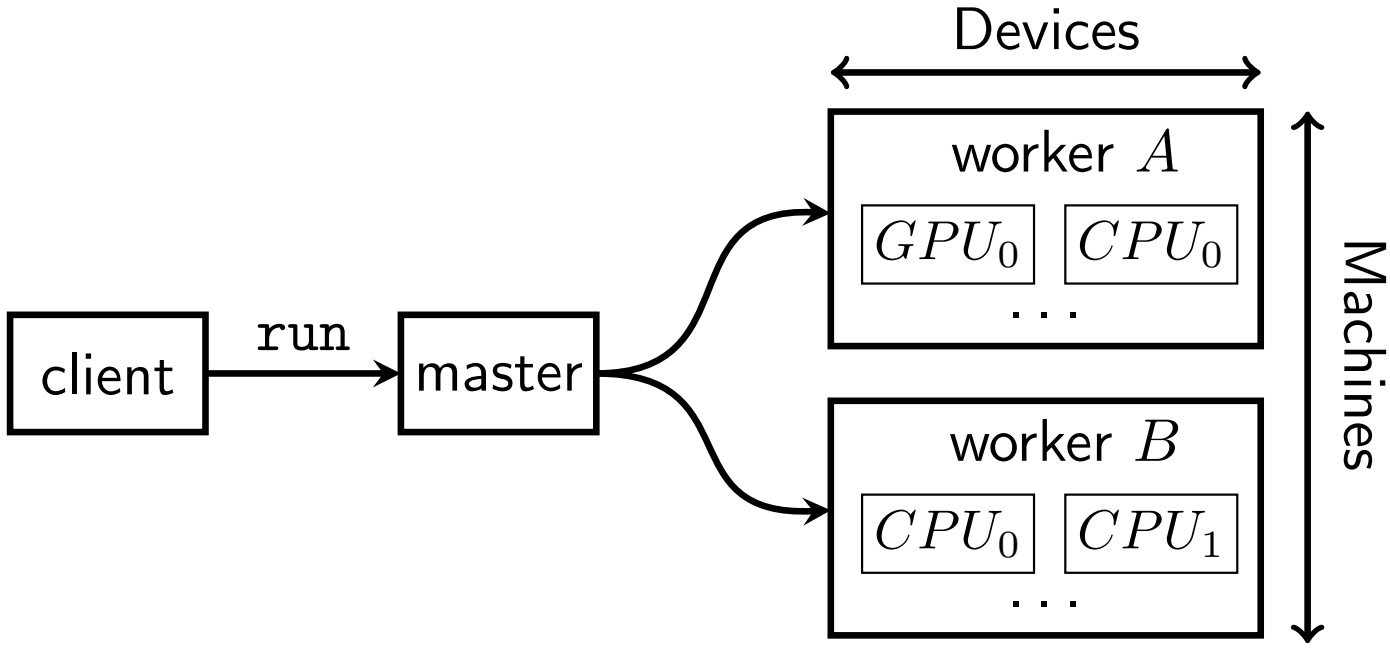

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Back Propagation

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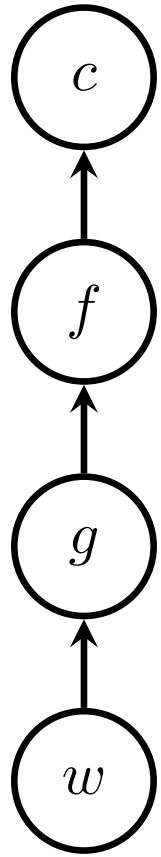

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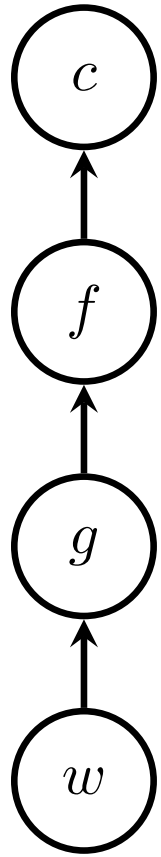
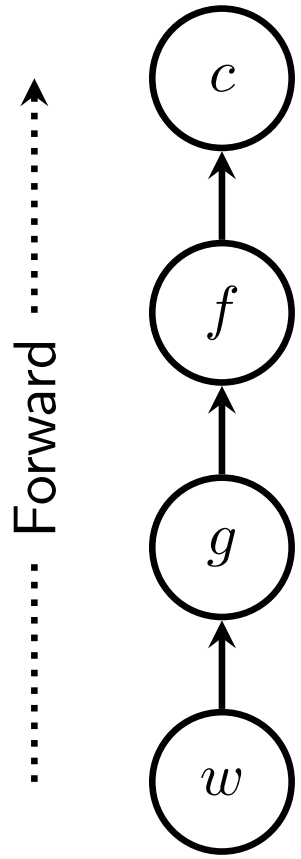


Symbol to Number Differentiation

Back Propagation

$$c = (f \circ g)(w)$$



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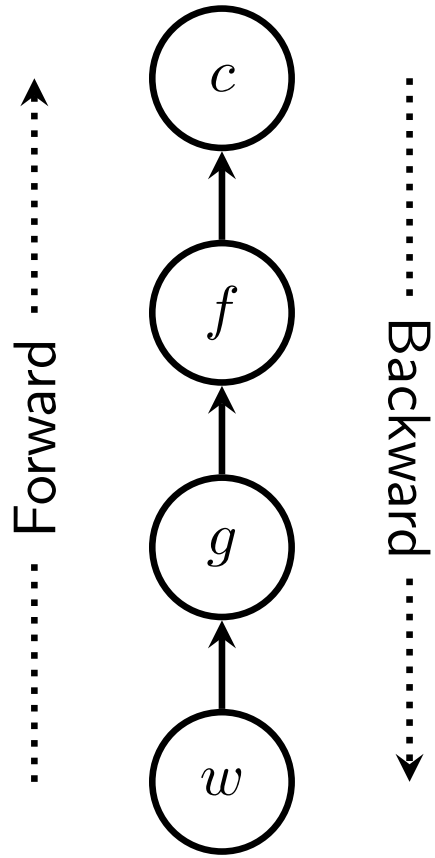

$$\frac{\mathrm{d}c}{\mathrm{d}w} = f'(g(w)) \cdot g'(w)$$

Symbol to Number Differentiation

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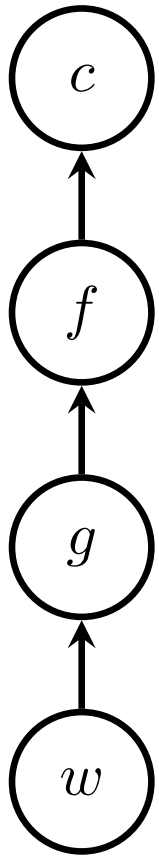

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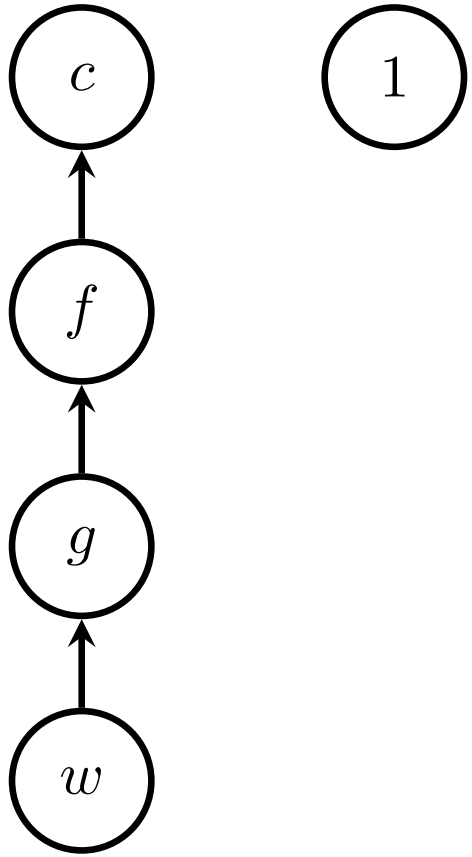

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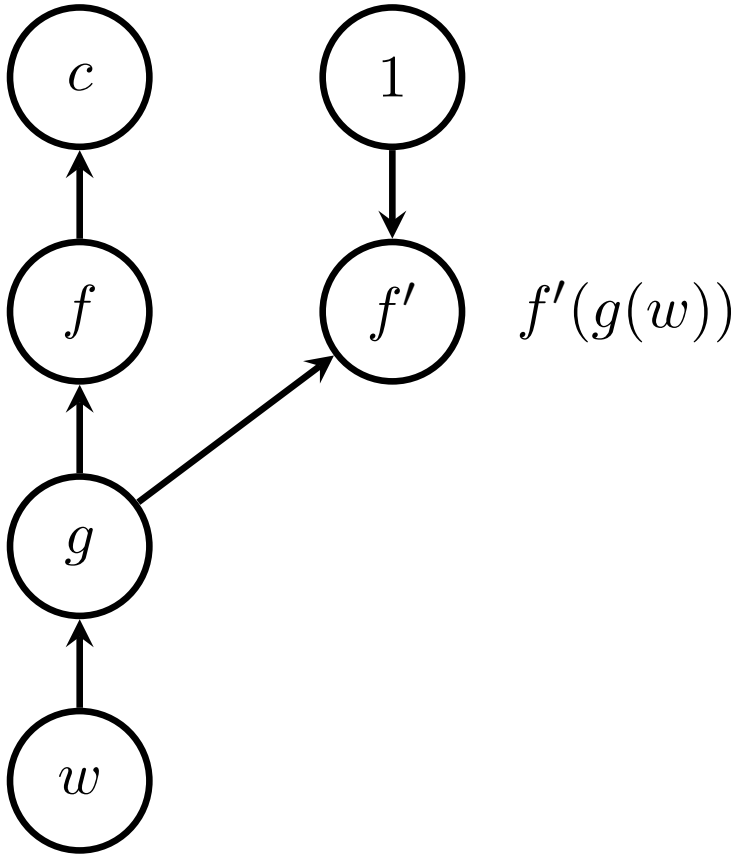

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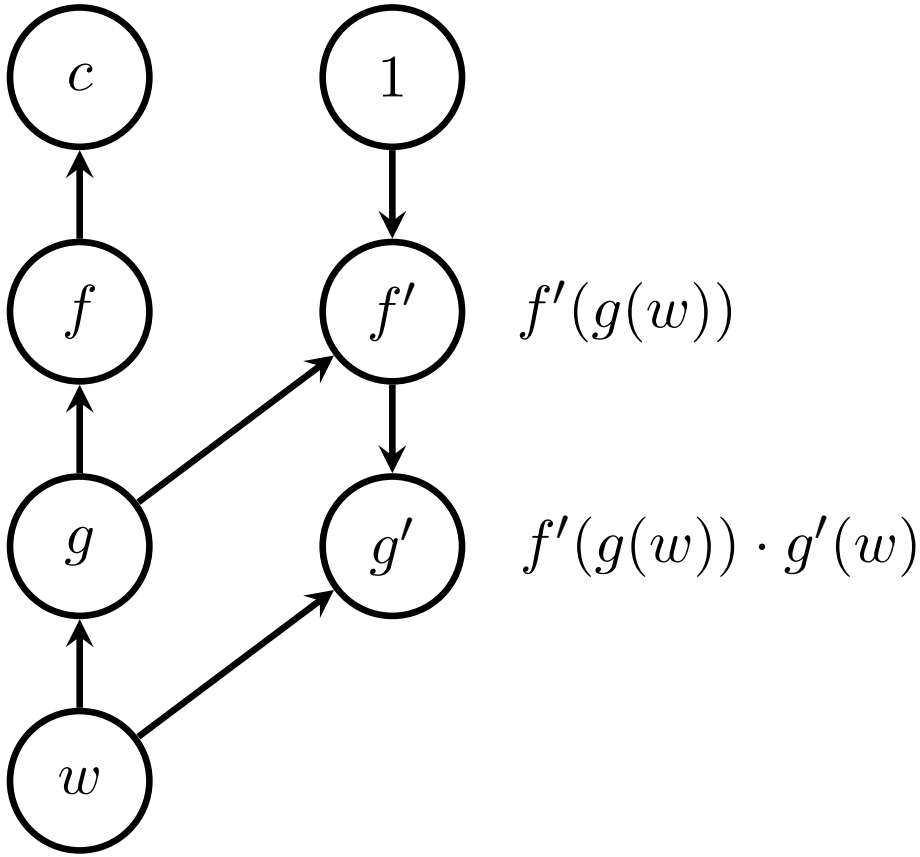

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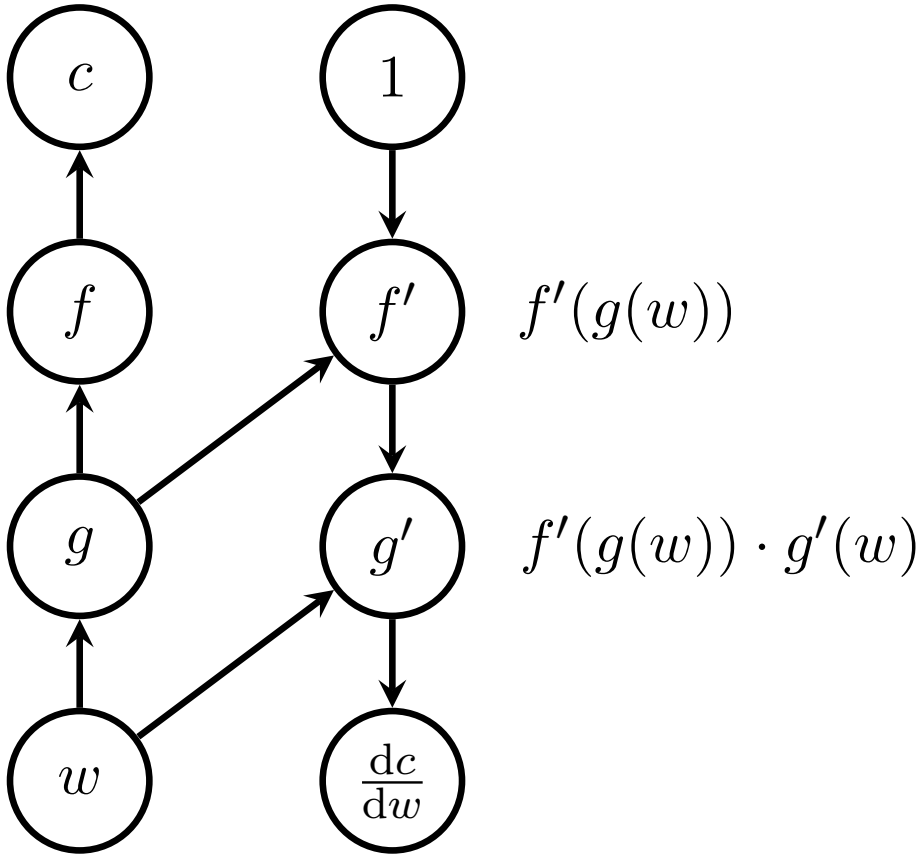

Symbol to Symbol Differentiation

Visualization Tools

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- Deep Neural Networks have the tendency of being . . . deep

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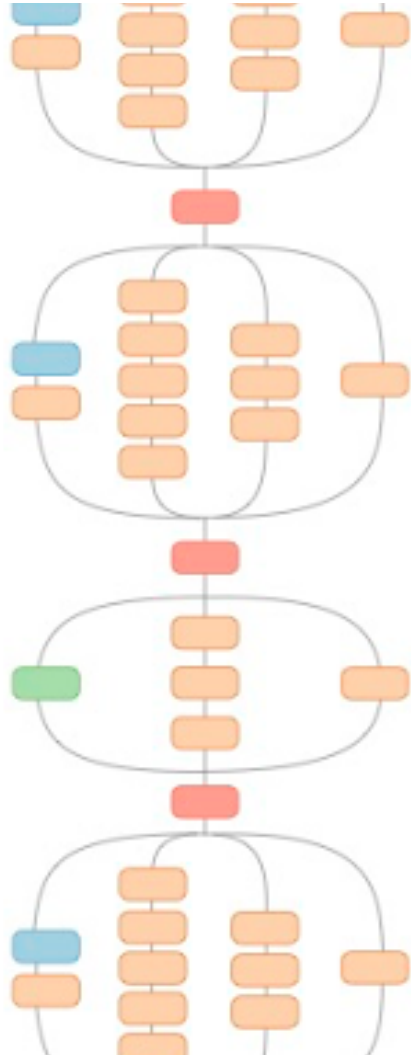
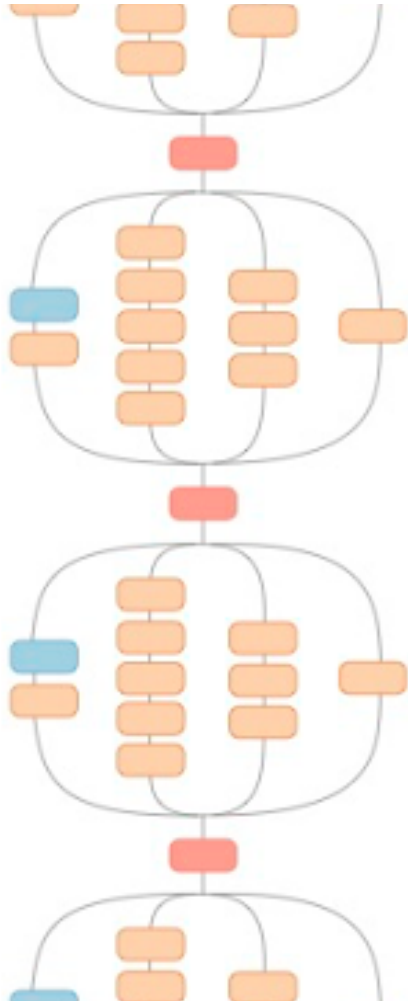
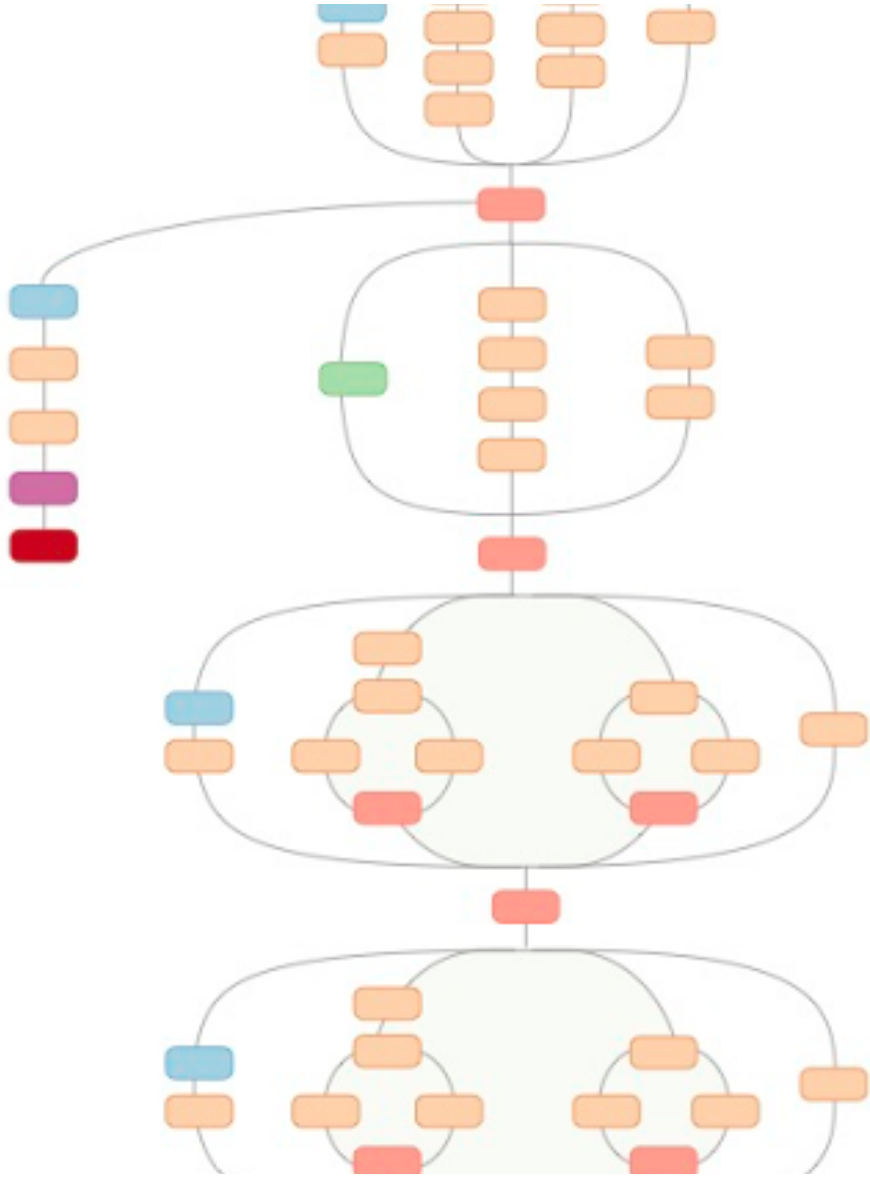
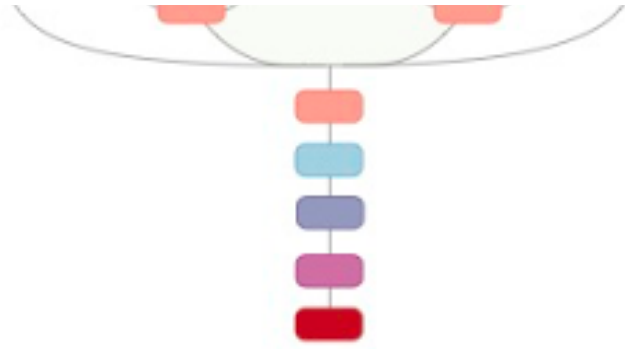
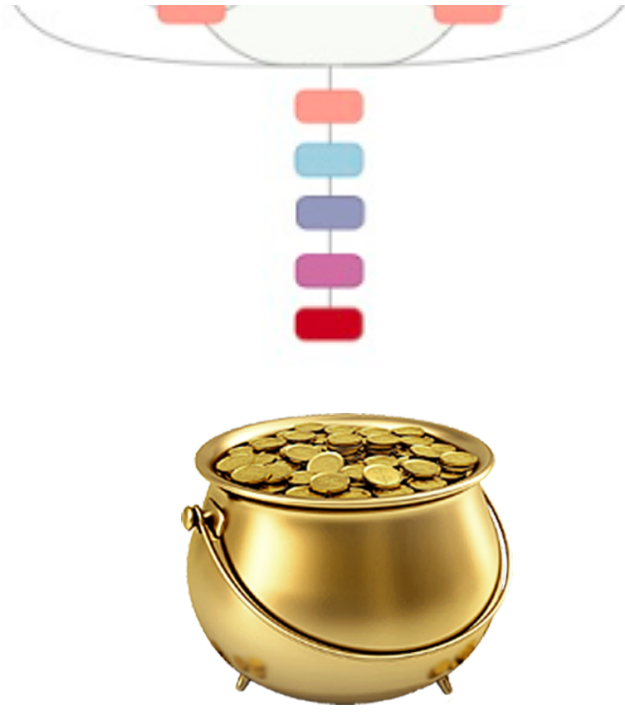








Source: http://googleresearch.blogspot.de/2016/03/train-your-own-image-classifier-with.html



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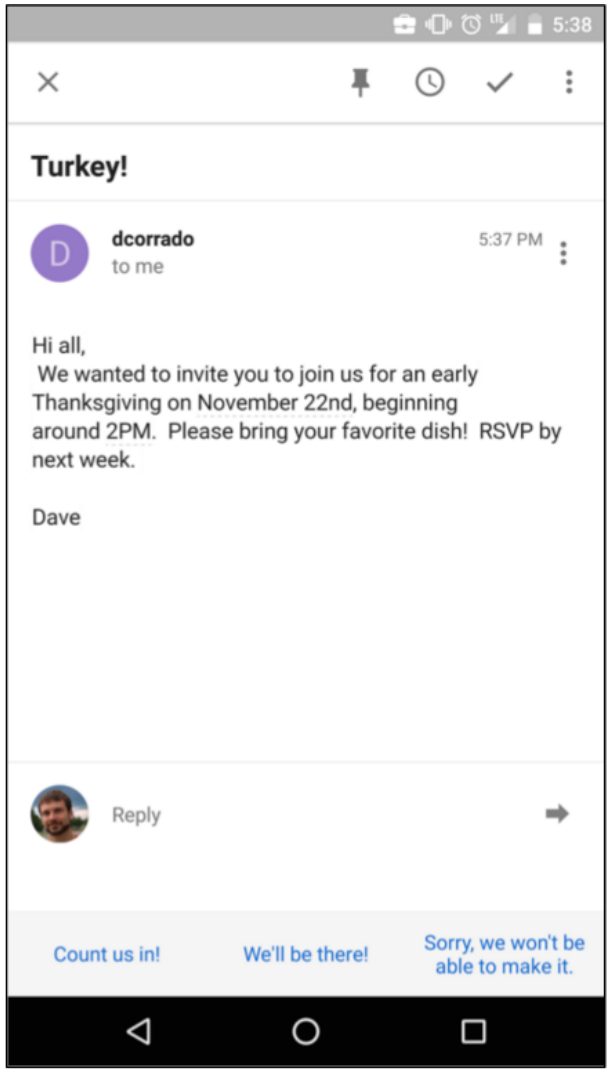
TensorBoard to the Rescue

Use Cases

Source: http://googleresearch.blogspot.de/2015/11/computer-respond-to-this-email.html

Use Cases

- Smart email replies in Google *Inbox*



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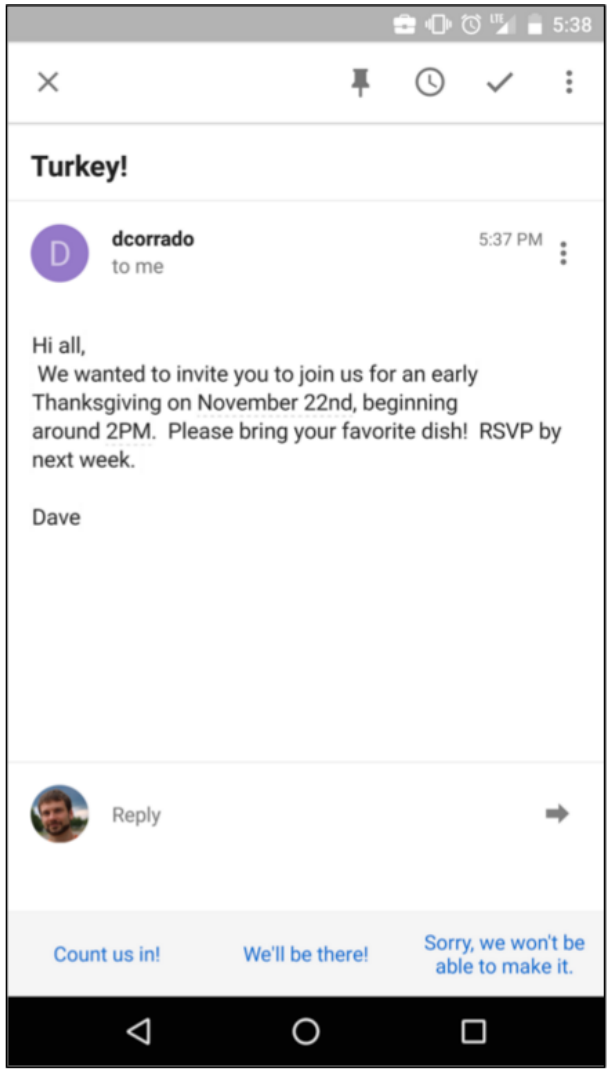
Use Cases

- Smart email replies in Google *Inbox*
- Emails mapped to "thought vectors"



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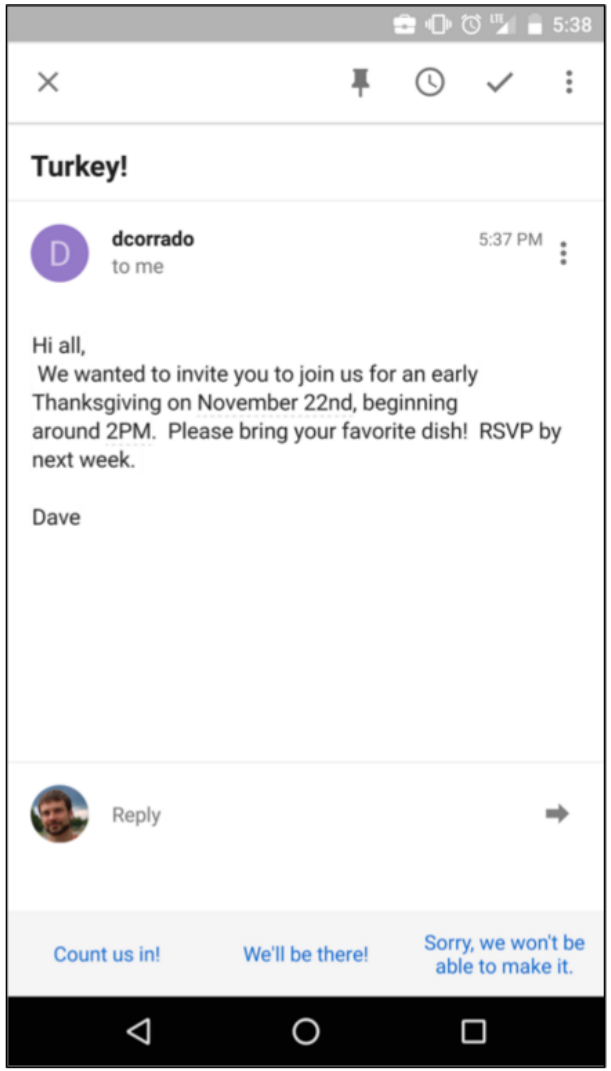
Use Cases

- Smart email replies in Google *Inbox*
- Emails mapped to "thought vectors"
- LSTMs synthesize valid replies



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  - Ability to run on many GPUs.

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Walkthrough

References


Andrej Karpathy, *The unreasonable effectiveness of recurrent neural networks*, May 21 2015 (accessed Jul 10, 2016), http://karpathy.github.io/2015/05/21/rnn-effectiveness/.