Research Faculty Summit 2018

Systems | Fueling future disruptions
The Good, the Bad, and the Ugly of ML for Networked Systems

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(by courtesy) Stanford University
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Three uses of machine learning

- **Paradigm 1** [learn then deploy]:
  “ML produces an artifact. People deploy it in real life.”

- **Paradigm 2**: [deploy and learn]:
  “People deploy an artifact that learns in real life.”

- **Paradigm 3**: [learn from the machines]:
  “ML teaches us about our own thinking.”
My view

- **Paradigm 1** [learn then deploy]:
  Often harder than we expect.
  ("Past performance is no guarantee of future results.")

- **Paradigm 2**: [deploy and learn]:
  Worth researching, but hard because of the nature of networks.

- **Paradigm 3**: [learn from the machines]:
  Old-fashioned AI view—still valuable!
Paradigm 1: Sprout (NSDI 2013) in publication

Sprout, NSDI 2013 (figure 7)
Paradigm 1: Sprout in real life in America

Stanford Pantheon result (July 31, 2018, T-Mobile in California),
https://pantheon.stanford.edu/result/3455/
Paradigm 1: Sprout in real life in India

Stanford Pantheon result (August 1, 2018, Airtel in New Delhi),
https://pantheon.stanford.edu/result/3474/
Paradigm 1: Vivace (NSDI 2018) in publication

Throughput (Mbps)

Time (s)

Vivace, NSDI 2018 (figure 7)
Paradigm 1: Vivace in real life

Stanford Pantheon result (August 1, 2018, AWS Brazil-HostDime Colombia),
https://pantheon.stanford.edu/result/3470/
Paradigm 1: Pensieve (SIGCOMM 2017) in publication

Figure 11: Comparing Pensieve with existing ABR algorithms in the wild. Results are for the $QoE_{lin}$ metric and were collected on the Verizon LTE cellular network, a public WiFi network, and the wide area network between Shanghai and Boston. Bars list averages and error bars span ± one standard deviation from the average.

Pensieve, SIGCOMM 2017 (figure 11)
Paradigm 1: Pensieve in reproduction

Figure 1: Comparison of Pensieve with other ABR algorithms across 10 tests on real world networks

Stanford CS244 student project,
“BBR converges toward a fair share of the bottleneck bandwidth whether competing with other BBR flows or with loss-based congestion control. [...] Unmanaged router buffers exceeding several BDPs, however, cause long-lived loss-based competitors to bloat the queue and grab more than their fair share.”

https://queue.acm.org/detail.cfm?id=3022184
Paradigm 1: BBR in independent evaluation

Cubic vs BBR over a 12ms RTT 10G circuit

Geoff Huston, TCP and BBR, RIPE 76 (May 2018)
Why *not* use BBR?

- Because it *over achieves!*
- The classic question for many Internet technologies is scaling
  - “what if everyone does it?”
  - BBR is not a scalable approach
  - It works so well while it is used by just a few users, some of the time
  - But when it is active, BBR has the ability to slaughter concurrent loss-based flows
  - Which sends all the wrong signals to the TCP ecosystem
    - The loss-based flows convert to BBR to compete on equal terms
    - The network is then a BBR vs BBR environment, which is unstable

*Geoff Huston, TCP and BBR, RIPE 76 (May 2018)*

Is this BBR experiment a failure?

Is it just too ‘greedy’ and too ‘insensitive’ to other flows to be allowed out on the Internet to play?

- Many networks have been provisioned as a response to the aggregate behaviours of loss-based TCP congestion control
- BBR changes all those assumptions, and could potentially push many networks into sustained instability
- We cannot use the conventional network control mechanisms to regulate BBR flows
  - Selective packet drop just won’t create back pressure on the flow

Geoff Huston, TCP and BBR, RIPE 76 (May 2018)
Paradigm 1: BBR in independent evaluation

Where now?

BBR 2.0

– Alter BBR’s ‘sensitivity’ to loss rates, so that it does not persist with an internal bandwidth delay product (BDP) that exceeds the uncongested BDP.
  This measure would moderate BBR 1.0’s ability to operate for extended periods with very high loss levels.
– Improve the dynamic sharing fairness by moderating the Bandwidth Delay Product by using an estimated ‘fair’ proportion of the path BDP.
– Accommodate the signal distortion caused by ACK stretching middleware.
– Place an upper bound on the volume of in-flight data.
– Alter the +/- 25% probe factors dynamically (i.e. allow this to be less than 25% overload).

Geoff Huston, TCP and BBR, RIPE 76 (May 2018)
Proposal (2008): train a model to predict flu incidence from historical search engine queries. Then deploy the model to predict flu in advance of the government.
Late Edition

Today, dour sunbeams, high St. cloud, 43. Southwest, hillbeams, low 49. Windsouwest, chilly, a few scattered showers, some heavy ones, high 51. Weather map is on Page A23.

DEMOCRATS SEEK EMERGENCY HELP FOR AUTOMAKERS

CALL FOR AID PACKAGE

Leaders May Try to Use Lame-Duck Session to Press Bush

By DAVID M. HERSENMANN and CARL HILSE

WASHINGTON — Democratic Congressional leaders said Tuesday that they were ready to push emergency legislation to aid the imperiled auto industry when lawmakers return to Washington next week for the first time after the election, setting the stage for one last showdown with President Bush.

Next week, during the lame-dog session of Congress, we are determined to pass legislation that will save the jobs of millions of workers whose livelihoods are at stake, the majority leader, Harry Reid of Nevada, said in a statement.

His call for the session came shortly after the House speaker, Nancy Pelosi, and Congress and the administration "must take immediate action" to stave off a possible collapse of the American auto industry.

Ms. Pelosi stopped short of saying Congress would adopt legislation to provide emergency financial aid to the automakers, giving the Treasury Department the option of using money from the $700 billion bailout program instead.

But with the White House insisting that the bailout money be reserved for financial institutions, that option seemed unlikely, making a similar Democratic push in the lame-dog session all the more likely.

Buying Binge Slams to Halt

Crisis of Confidence For U.S. Consumers

Just as one crisis of confidence may be ending, another may be coming. The panic on Wall Street has eased in the last few weeks, and stocks have become somewhat more willing to make losses. But in those same few weeks, American households appear to have fallen into their own defensive, cautious mode. Suddenly, our consumer society is doing a lot less consuming. The numbers are pretty incredible. Sales of new vehicles have plunged 25 percent in the third quarter. Consumer spending appears likely to fall more than for the first time since 1990 and perhaps for the largest amount since 1981.

With Wall Street edging back from the brink, this crisis of consumer confidence hasn't become the No. 1 short-term issue for the economy. Nobody doubts that families need to start saving more than they saved over the last two decades. But if they change their behavior too quickly, it could be very painful.

Already, Circuit City has filed for bankruptcy, and General Motors has said that it is in danger of running out of cash. If the consumer slump continues, there is a potential for a dangerous feedback loop, in which spending cuts and layoffs reduce sales.

"It's a scary time," Liz Allen, 26, a nursing student in Atlanta, told one of The Times reporters who dined out across the country last weekend in a quest to ask people about the economy. "Worry costs the economy more. If people worry too much, they won't buy.

Keith Winstein

The 2012–2013 Divergence of Google Flu Trends

Nov. 11, 2008 announcement

Keith Winstein keithw@mit.edu MIT CSAIL
Google Flu Trends plot as of today

United States: Influenza-like illness (ILI) data provided publicly by the U.S. Centers for Disease Control.

(http://www.google.org/flutrends/about/how.html)
Most of plot is training data

United States Flu Activity
Influenza estimate

Google Flu Trends estimate
United States data

Training data

United States: Influenza-like illness (ILI) data provided publicly by the U.S. Centers for Disease Control.
Large divergence (3.7×) in New England (HHS region 1)
Paradigm 1: spam filtering

SpamAssassin (spam filtering engine):

- Anybody can propose a spam-filtering algorithm.
- Central party learns best weights based on predictive power of each algorithm.
- Weights are then deployed in the field.
Paradigm 1: spam filtering

- **2007**: a rule is added
- Rule: “Does the year match 200\(x\)?”
- Catches a lot of spam.
- Extremely low false-positive rate!
- *(but... big surprise on 1/1/2010)*
Learn-then-deploy is a challenging pattern, and empirically it’s easy to fool ourselves into premature declarations of success.
Paradigm 2: deploy **and** learn

- **Proposal:** Build systems that learn continuously, online.
- Directly observe operational figure-of-merit over time.
- React quickly to real-world changes.
Figure 6: Search Latency reduction for users in the QUIC experiment over an 18-month period. Numbered events are described in Section 5.2.

Real systems learn over time: baby robot, car, etc.
Challenges of *network* learning

But classical results indicate challenges to learning when

- ...information is distributed. Dec-POMDP is undecidable.

- ...compute and data are in different places.

- ...agents are adversarial (congestion control, routing, traffic engineering, security).

All of these scenarios are characteristic of *networks*.
THE IMPOSSIBILITY OF BAYESIAN GROUP DECISION MAKING WITH SEPARATE AGGREGATION OF BELIEFS AND VALUES

BY AANUND HYLLAND AND RICHARD ZECKHAUSER

Bayesian theory for rational individual decision making under uncertainty prescribes that the decision maker define independently a set of beliefs (probability assessments for the states of the world) and a system of values (utilities). The decision is then made by maximizing expected utility. We attempt to generalize the model to group decision making. It is assumed that the group's belief depends only on individual beliefs and the group's values only on individual values, that the belief aggregation procedure respects unanimity, and that the entire procedure guarantees Pareto optimality. We prove that only trivial (dictatorial) aggregation procedures for beliefs are possible.

1. INTRODUCTION

Many decisions made under uncertainty, indeed many important ones, are
What if the scenario is adversarial?

**Burr’s conjecture** *(Schapira and Weinstein, HotNets 2017)*

It is impossible for a decentralized congestion-control scheme *that greedily optimizes an objective function whose only input is the fate of its own traffic* to be globally asymptotically stable over a network with shared DropTail queues.
What if compute and data are separated?
What if compute and data are separated?

DNN layers

Training

NNFC

Device in the Field

Cloud Datacenter

DNNs are fine-tuned for each device; updates are delta compressed relative to DNN on each device.

Video frames selected for training are sent to the cloud.
What if compute and data are separated?

On-Device Compute (ms / frame)

Data Rate Across Split (bytes / frame)

DNN intermediates (FP32)

DNN in cloud

DNN on device

best prior approaches

useful trade-off region
The lesson? (paradigm 2)

Deploy-and-learn can be great, but **networked systems** present unique and interesting challenges worthy of research.
Independent of ML’s utility in deployment, machine learning can help us understand why systems ought to be the way they are.

**Human:** These are our requirements and objectives and design rules—what’s the best system?

**Machine:** How about this?

**Human:** That’s crazy! But, it does meet the requirements. Hmm...
The lesson? (paradigm 3)

- Teaching something is the best way to learn anything.
- The dumber the student, the better the teacher learns.
- Machines are very dumb. Therefore...

Teaching machines to learn to design systems is the best way for us to learn to design systems.
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  Old-fashioned AI view—still valuable!

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Slide palette info

The PowerPoint palette for this template has been built for you and is shown below. Avoid using too many colors in your presentation.

- **Accent colors 1-6** – (6 Theme Colors to the far right)

  - Use **Accent 1** as the main accent color.
  - Use **Accent 2** and **Accent 3** when additional colors are needed.
  - Use **Accent 4-6** sparingly – only when more colors are necessary.
Text with bullet points—adjusting list levels

• Main topic 1: size 28pt
  • Size 24pt for second level
    • Size 20pt for third level
    • Size 20pt for fourth level

Use the “Decrease List Level” and “Increase List Level” tools on the Home Menu to change text levels.

Try this:
1. Place your cursor in any row of text to the left that says “Size 20pt for subtopics”
2. Next click the Home tab, and then on the “Decrease List level” tool. Notice how the line moves up one level.
3. Now try placing your cursor in one of the “Main topic...” lines of text. Click the “Increase List Level” tool and see how the text is pushed in one level

Use these 2 tools to adjust your text levels as you work
Headline goes here

- Click to add text
  - Click to add text
    - Click to add text
Headline goes here

Click to add text
  Click to add text
    Click to add text
  Click to add text
Headline goes here

- Click to add text
  - Click to add text
    - Click to add text
Headline goes here
Transition or demo slide option 1

Subhead can go here
Transition or demo slide option 2

Subhead can go here
Transition or demo slide option 3

Subhead can go here
Thank you!