

# Assigning Responsibility for Deteriorations in Video Quality

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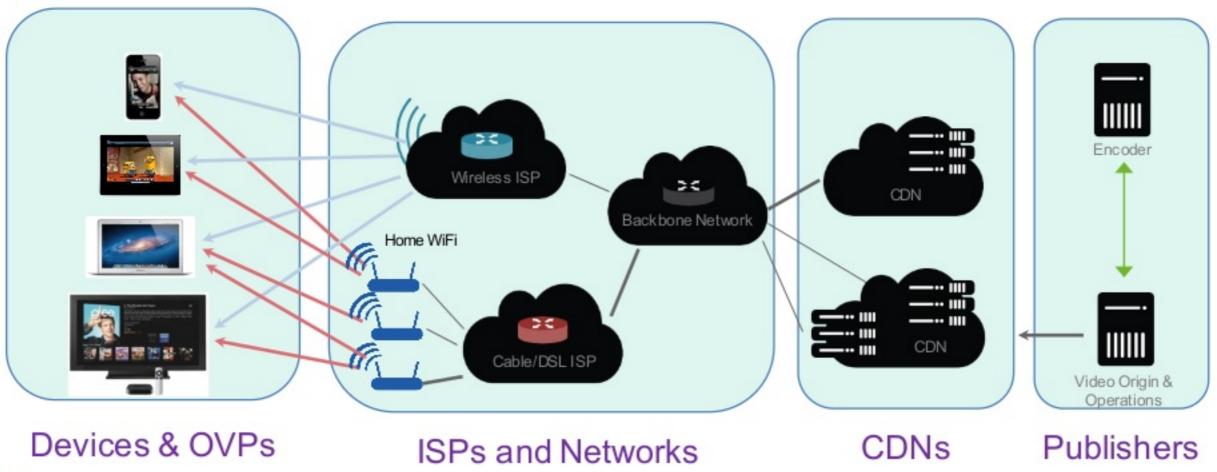
# CONVIVA®

...is a video experience management platform that maximizes viewer engagement.

We provide quality metrics that give a comprehensive view into online video businesses.

#### Internet Video Streaming is Hard

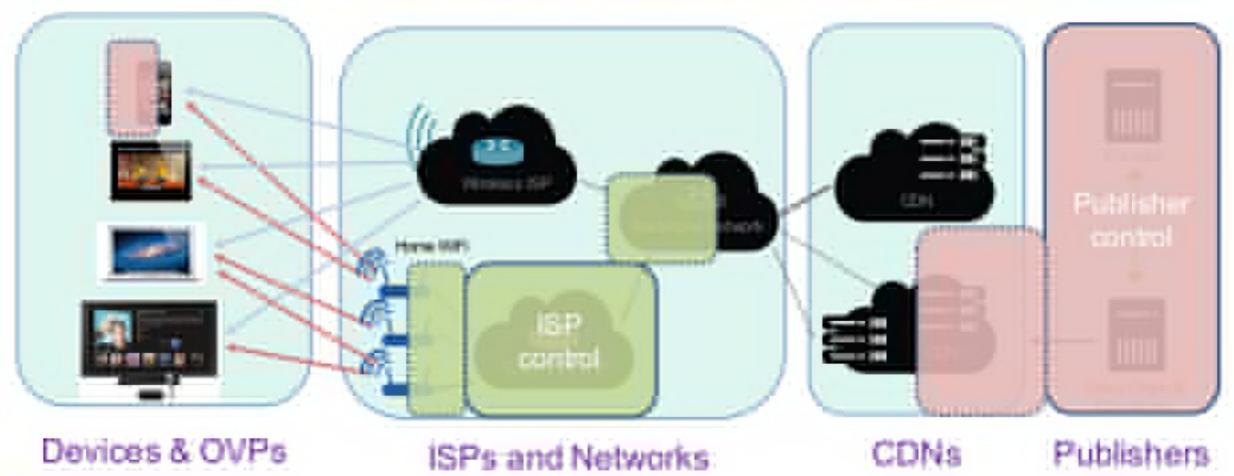
Many parties, many paths, but no E2E owner





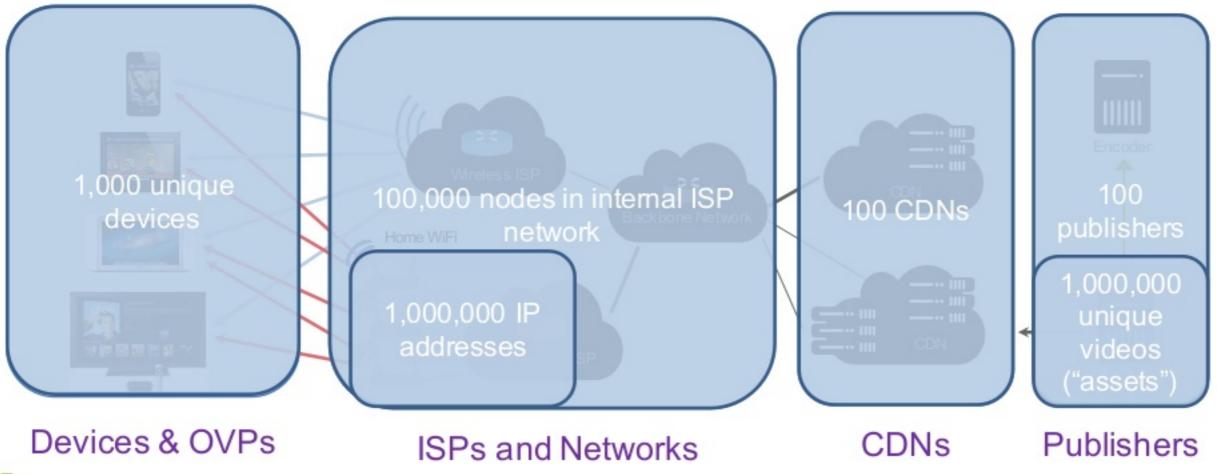
#### Internet Video Streaming is Hard

Many parties, many paths, but no E2E owner





#### The ecosystem is big.



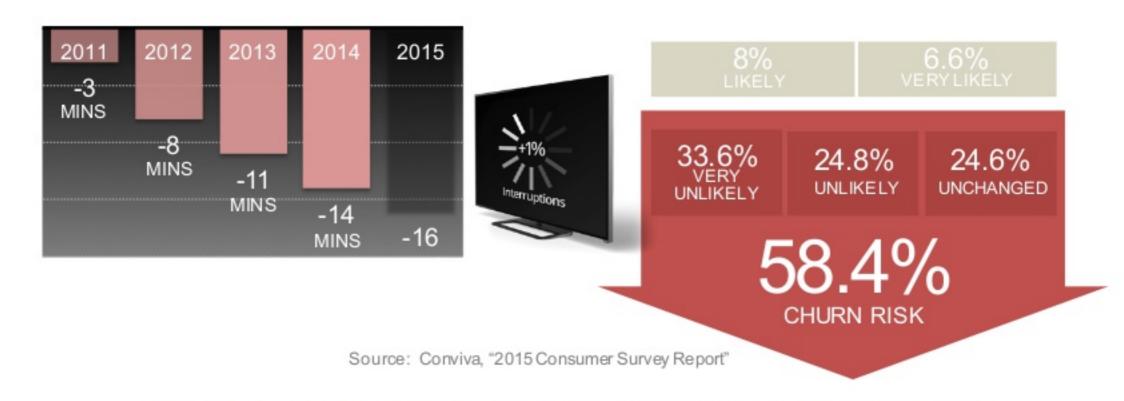


...in 10,000,000 video sessions from one week, at one US ISP

#### QoE is Critical to Engagement

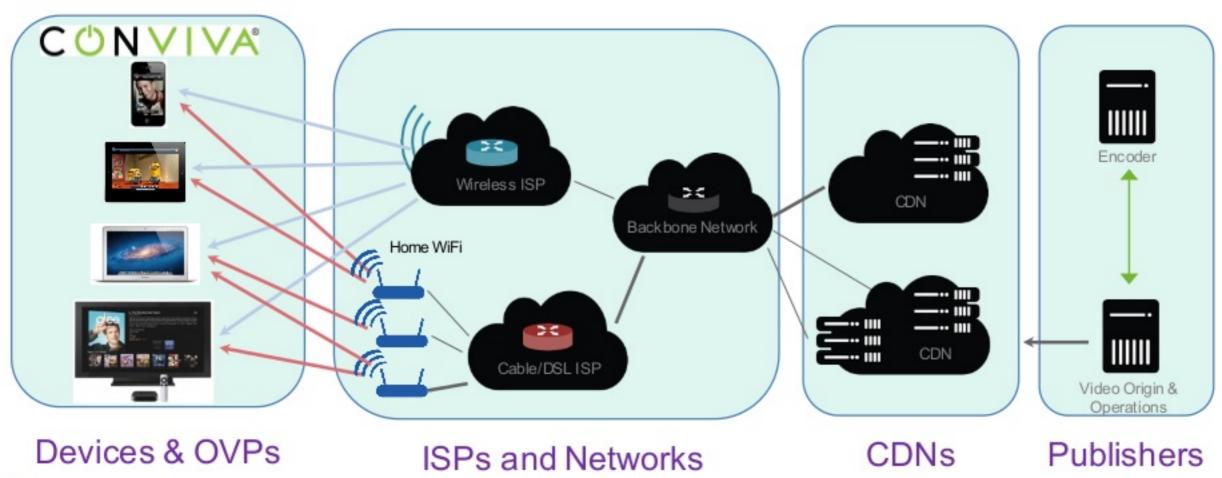
#### For both video and advertisement businesses

HOW LIKELY ARE YOU TO WATCH FROM THAT SAME PROVIDER AGAIN?



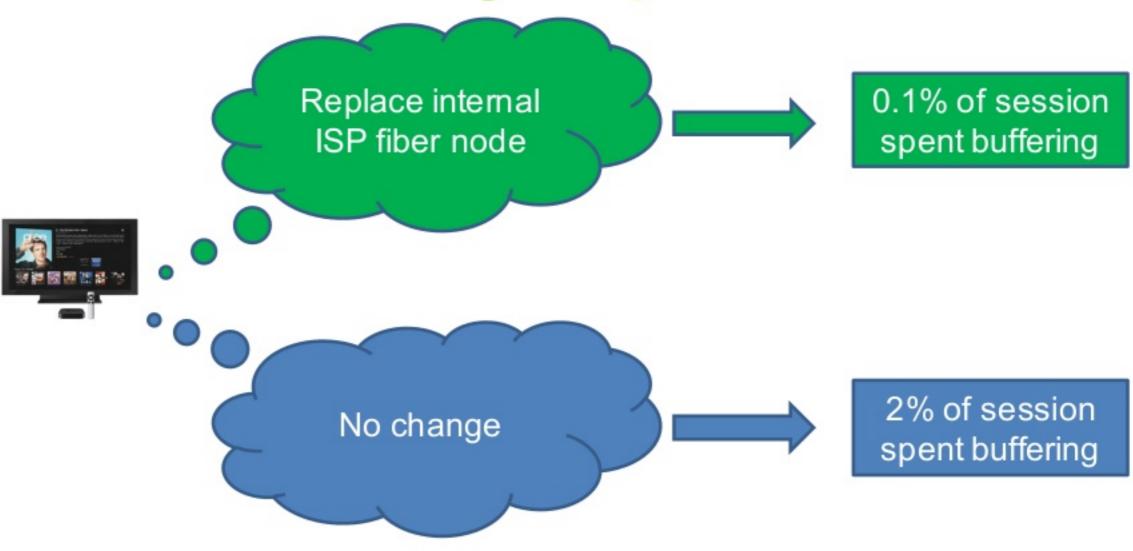


Viewers are expecting TV-like quality (or better)





# **Quality impact**





### **Quality impact**

Quality impact of this fiber node on this session

2% of session spent buffering

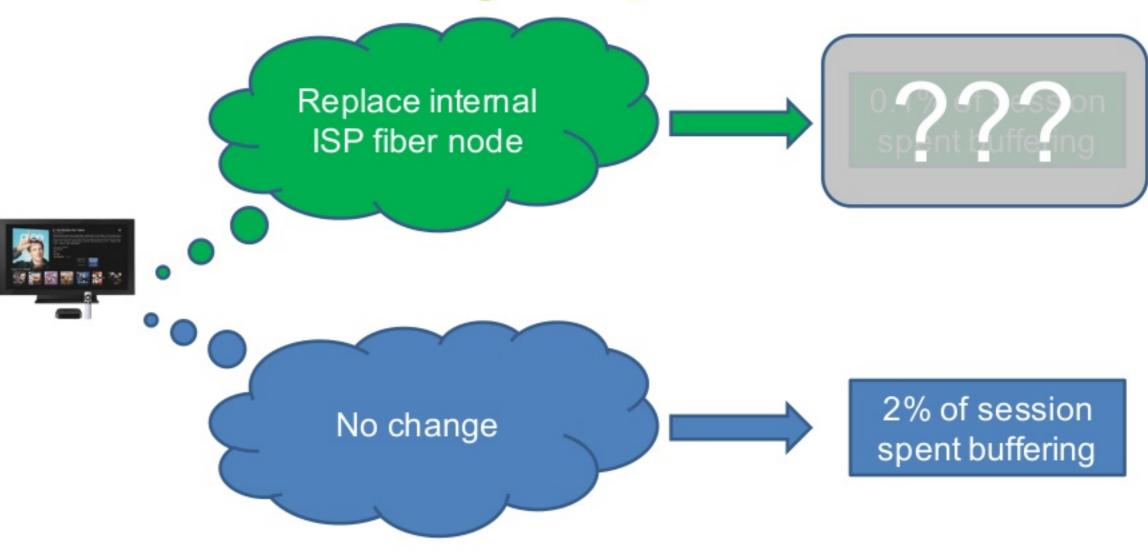
0.1% of session spent buffering

Quality impact of this fiber node

Quality impact of this fiber node on session 1 of n

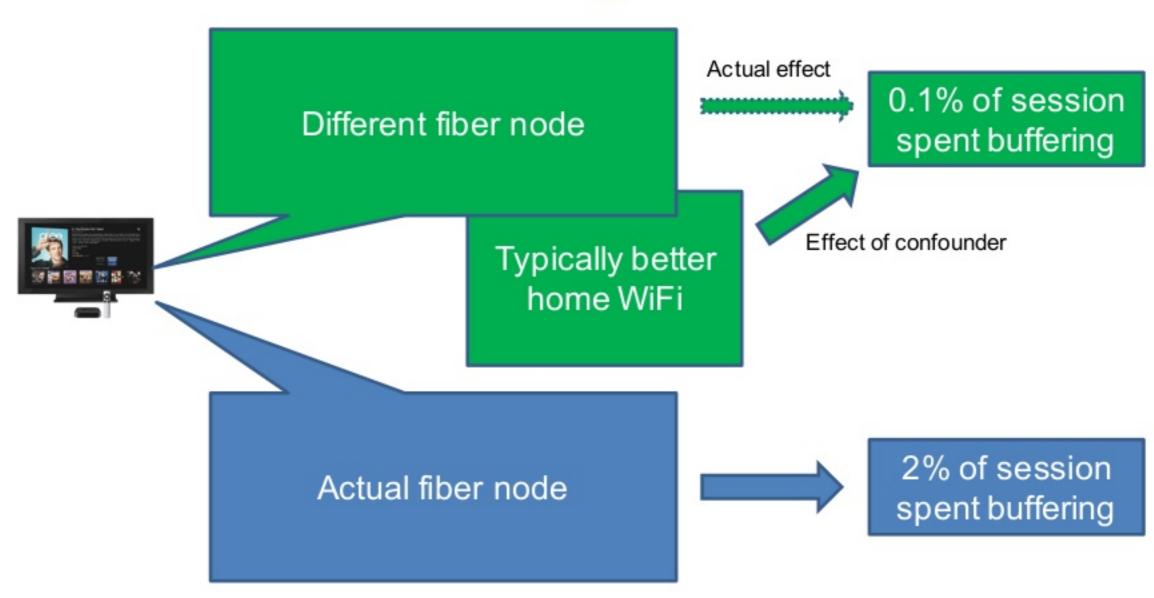


# **Quality impact**





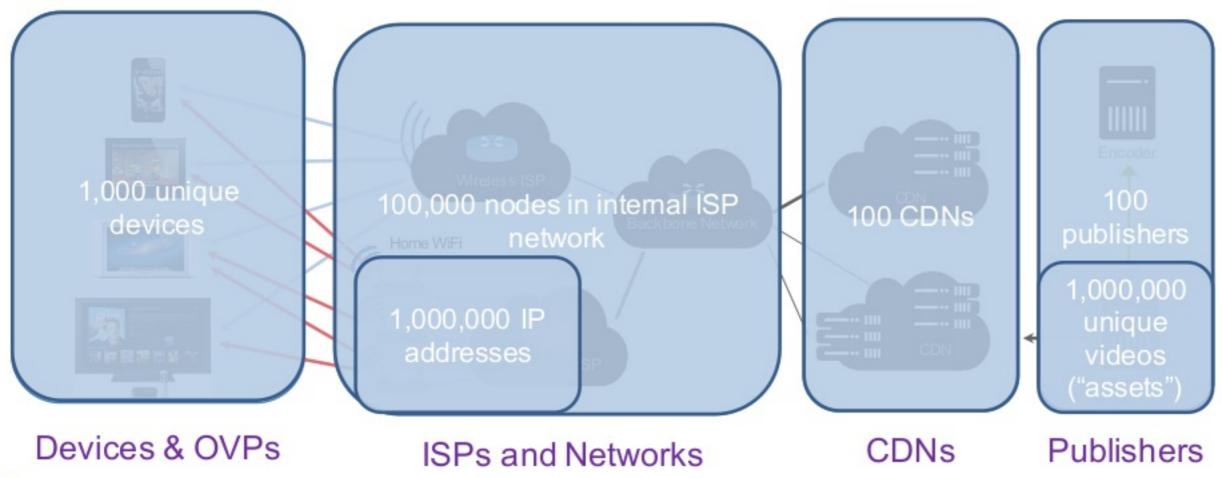
### Confounding factors





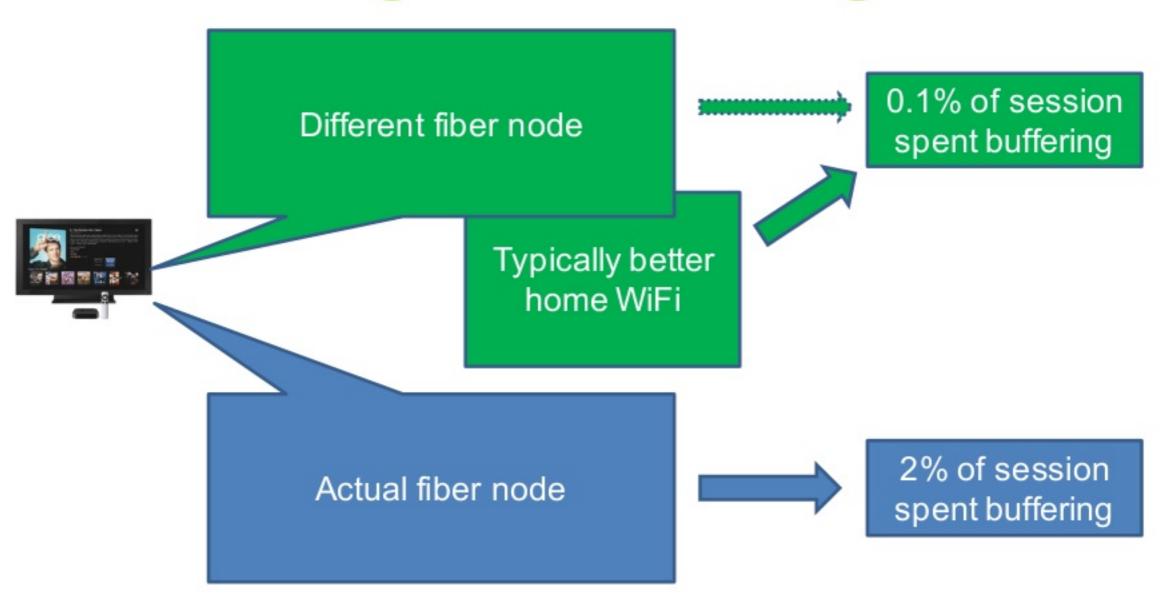
#### Many potentially-important factors

...and confounding factors!



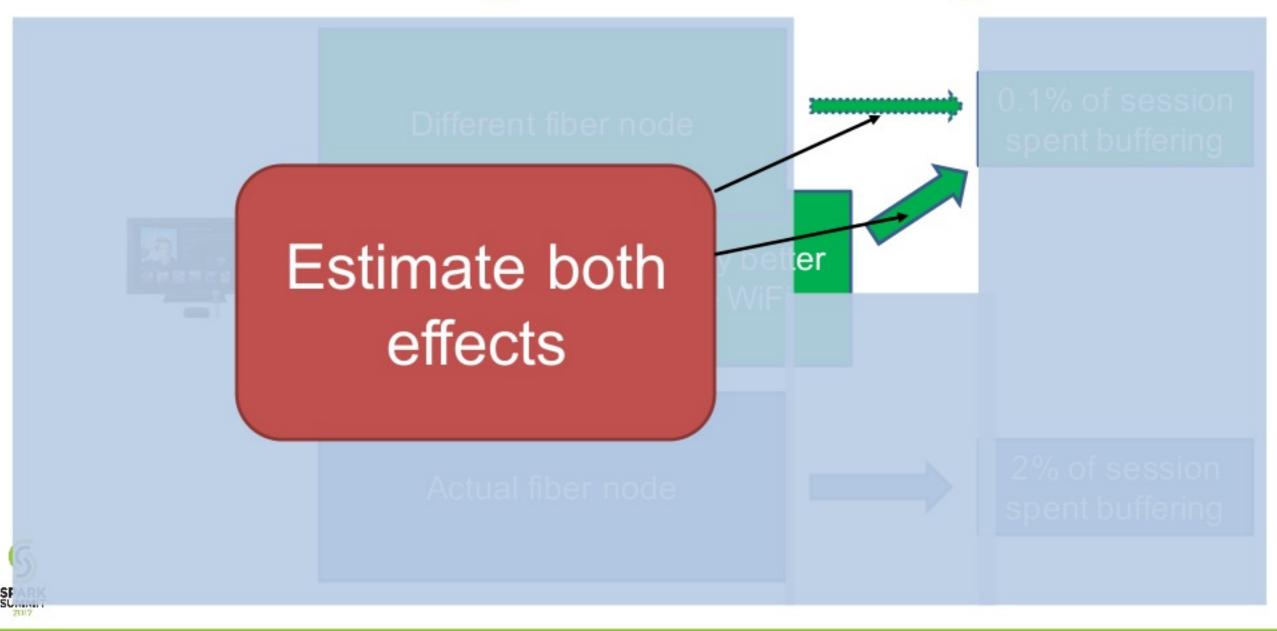


# Fixing confounding

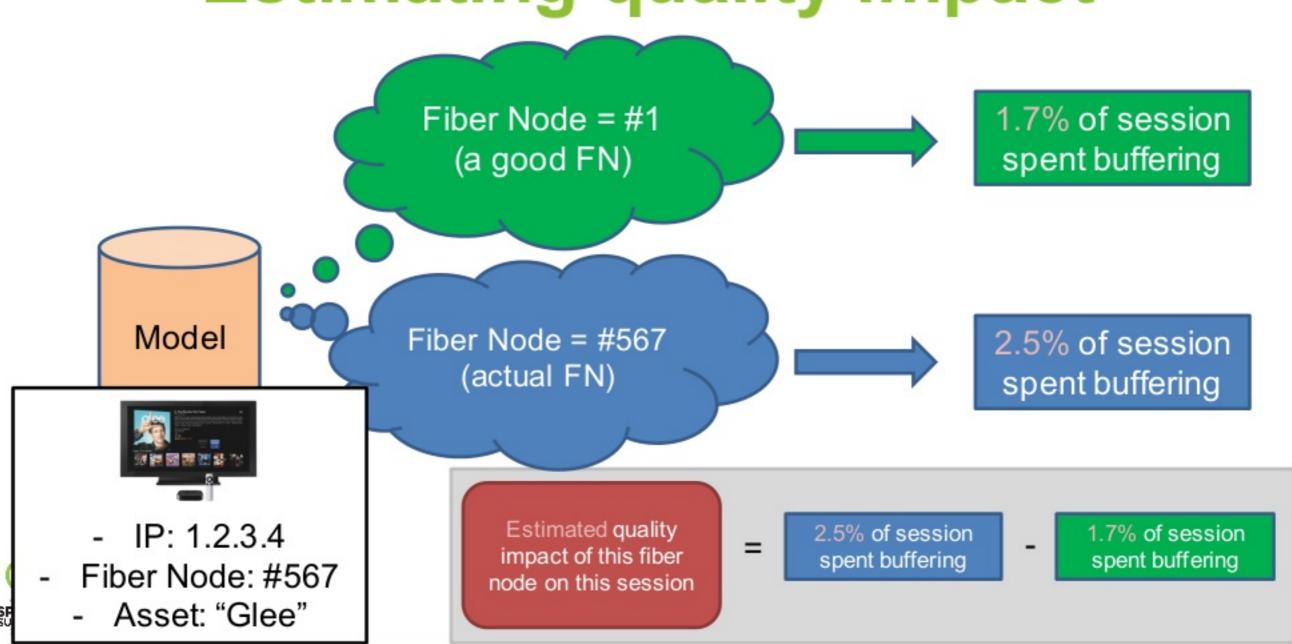




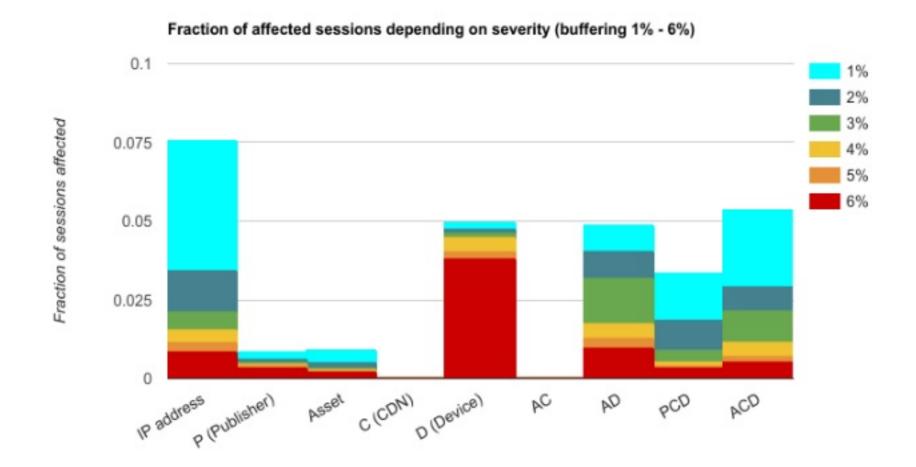
# Fixing confounding



#### Estimating quality impact



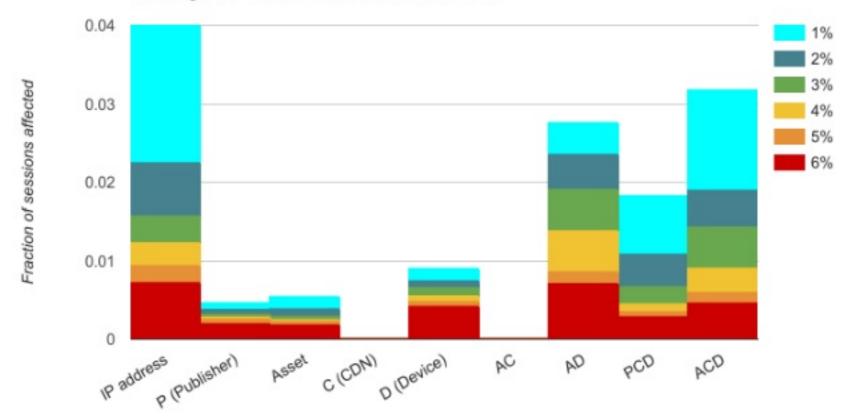
#### Devices produce short buffering





### Devices produce short buffering

Fraction of affected sessions depending on severity (buffering 1% - 6%). Only buffering time > half-second is accounted for here.

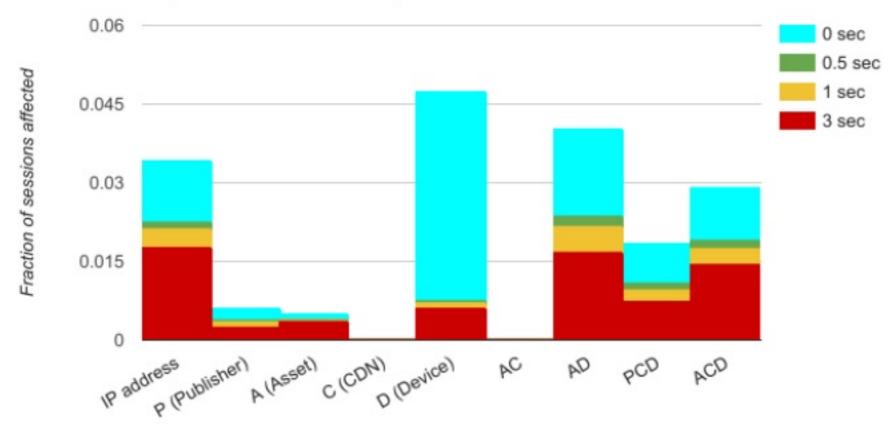




# Device-level issues are responsible for most short buffering episodes

Fraction of affected sessions depending on min buffering (0 - 3 sec).

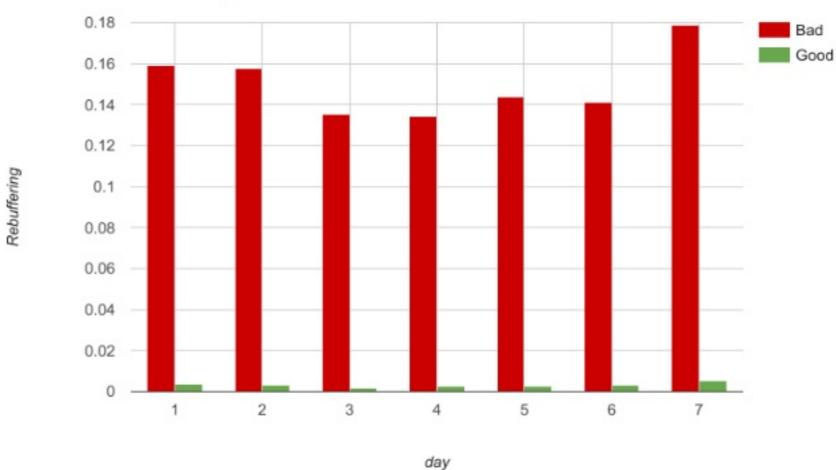
Only sessions with rebuffering ratio >= 2% are accounted for here.





#### Good and bad IP addresses

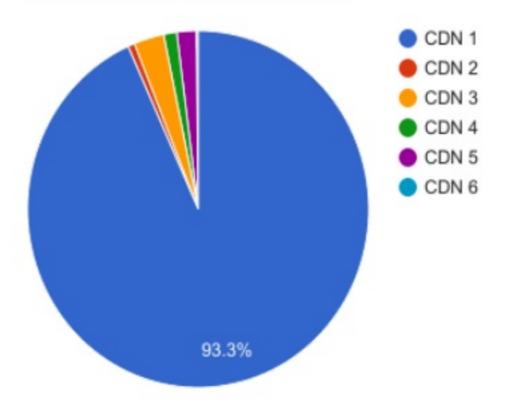
#### Rebuffering of model-classified Good and Bad IP Addresses





### From worst PCD, typical week:

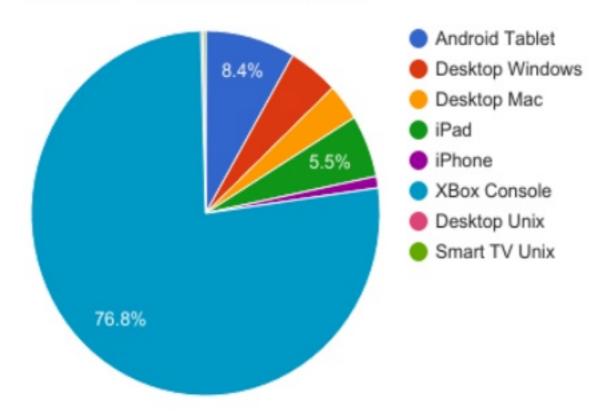
#### Number of sessions affected





### From worst PCD, typical week:

#### Number of sessions affected





#### Worst assets, typical week:

Only 6 really bad assets responsible for strong deterioration of their sessions regardless of other factors.

Of these, 4 are sport programs and 2 are obscure regularly scheduled foreign programs.



#### Modeling video quality



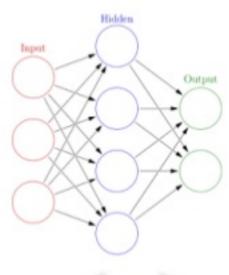






boosted trees

Today's results







#### Model for rebuffering ratio

#### Response: Rebuffering ratio (R)

(buffering time / (buffering time + playing time))

#### Categorical features:

IP address (I)

Fiber Node (N)

Service Group (S)

Publisher (P)

Asset (A)

CDN(C)

Device (D)

Live / VoD

#### More features:

Time, day of week, asset length.



#### Time or no time?

Time is strongest or one of strongest features.

Big game, popular show – many sessions suffer, regardless of IP and device or even CDN.

Time makes model more precise.

But: time steals effect from big nodes such as Asset and Publisher.

Similar question: Bitrate or no bitrate?



#### Model versions, practical issues

Preference: Spark cluster of 10-30 nodes, each node 4-8 cores and 30GB memory. Hopefully 1-3 hours to process 1-3 weeks of data of big ISP, whole US.

Nodes as embedded features. Boosted trees on Spark. Whole US. Learn from 1-3 weeks, apply to last week.

Nodes as one-hot encoding. Random forest on Spark. Each geographical area is processed separately.



#### Model versions, practical issues

Nodes as a trainable embedding first layer. Neural network on single Spark node with Tensorflow. Each geographical area separately.

Embedding size is same for all kinds of nodes.

Embedding size is ~ log of node's dictionary size.

One or two hidden layers above the embedding layer.

Adagrad or any other Ada-like optimizer performs better than no-Ada.

Slow improvements beyond fast mediocre accuracy.



### Finding a "good" node

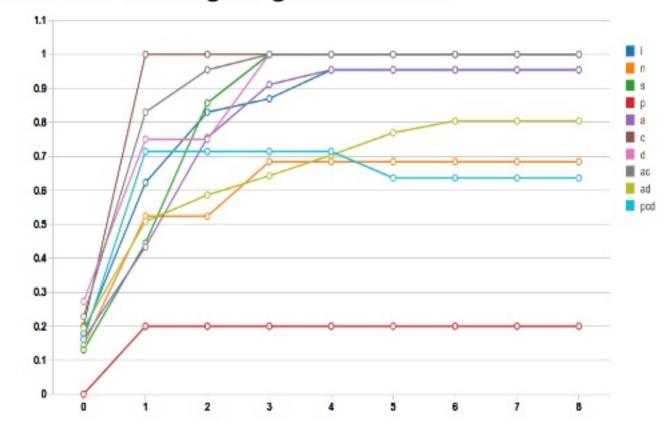
Effect of a node = Model( real features ) - Model( features with good node )

In case of trainable embedding – iterative finding of good nodes:

good = nodes with lowest avg label while set of good nodes is changing: for each session:

Effect = Model(real) - Model(good) good = nodes with lowest avg effect

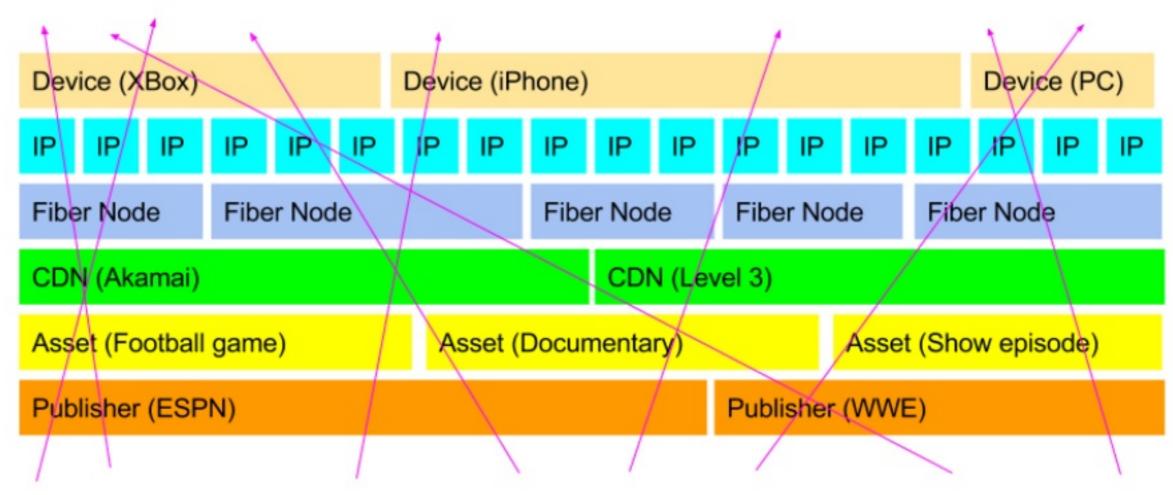
Overlap of set of good nodes with the set from previous iteration typically stabilizes in 2-3 iterations.





#### Sessions are affected by ...

Video sessions. Each has buffering >=0, from all involved nodes.





If effect is linear, this would be like ART in 3D tomography

# Thanks to Spark and Databricks for making it easy for us





#### Thank You.

Contact information: ovasilyev@conviva.com hmilner@conviva.com

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