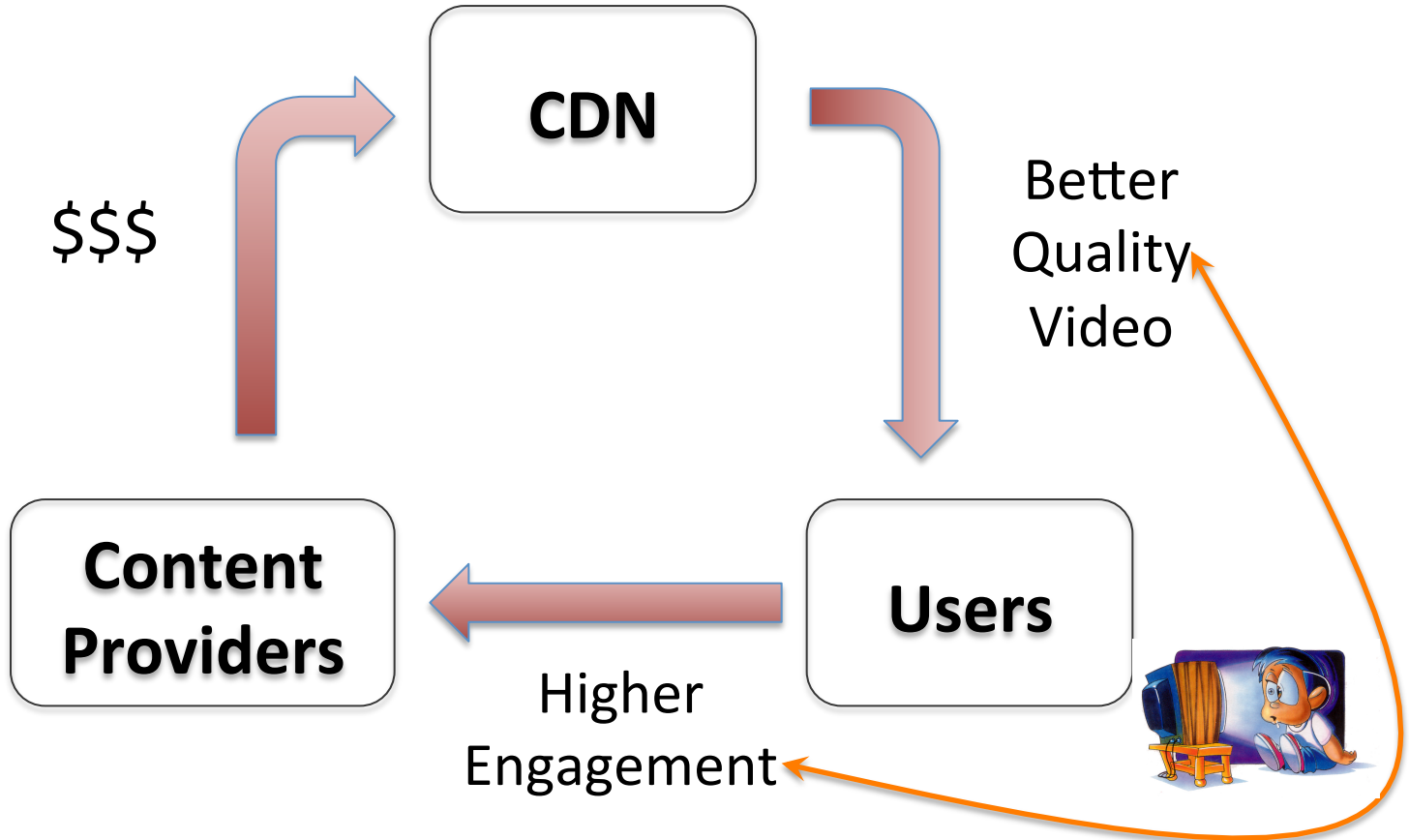# Developing a Predictive Model for Internet Video Quality-of-Experience

Athula Balachandran, Vyas Sekar,
Aditya Akella, Srinivasan Seshan,
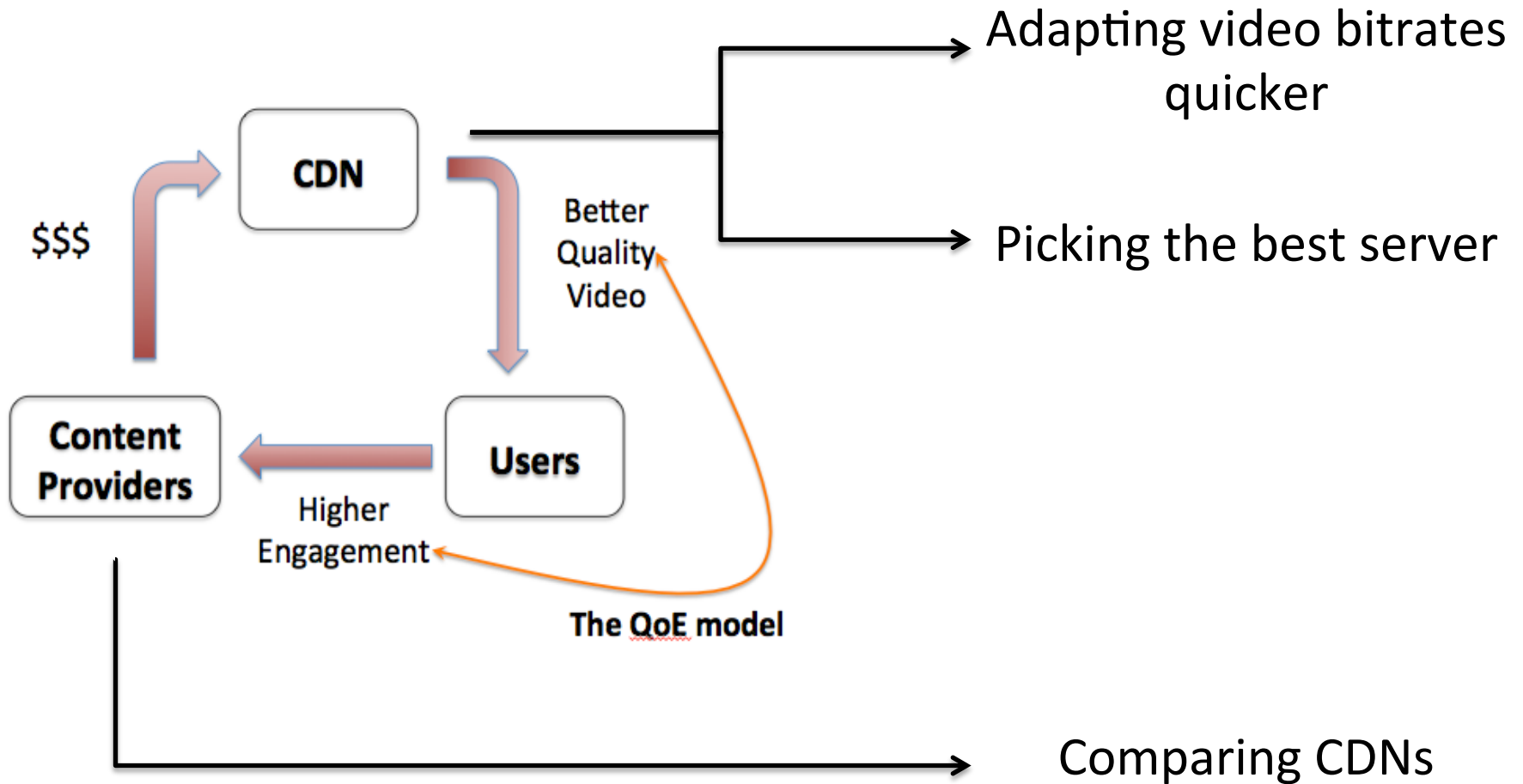Ion Stoica, Hui Zhang

QoE → $$$

The QoE model
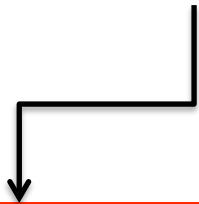
Diagram courtesy: Prof. Ramesh Sitaraman, IMC 2012

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Why do we need a QoE model?

Adapting video bitrates quicker

Picking the best server

Comparing CDNs

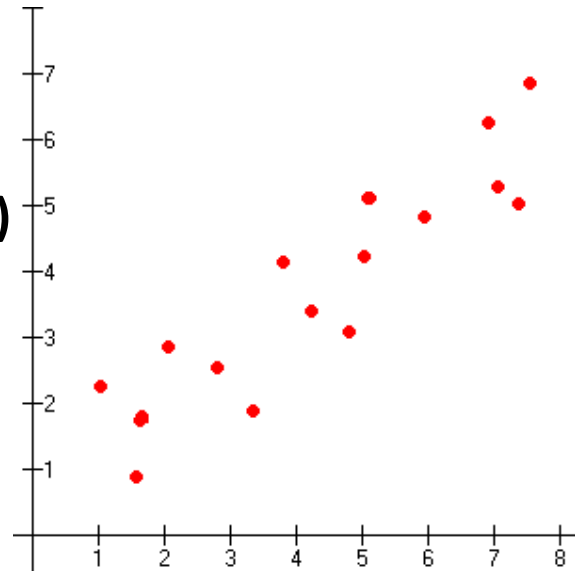# Traditional Video Quality Metrics

**Subjective Scores
(e.g., Mean Opinion Score)**

User studies not representative of "in-the-wild" experience
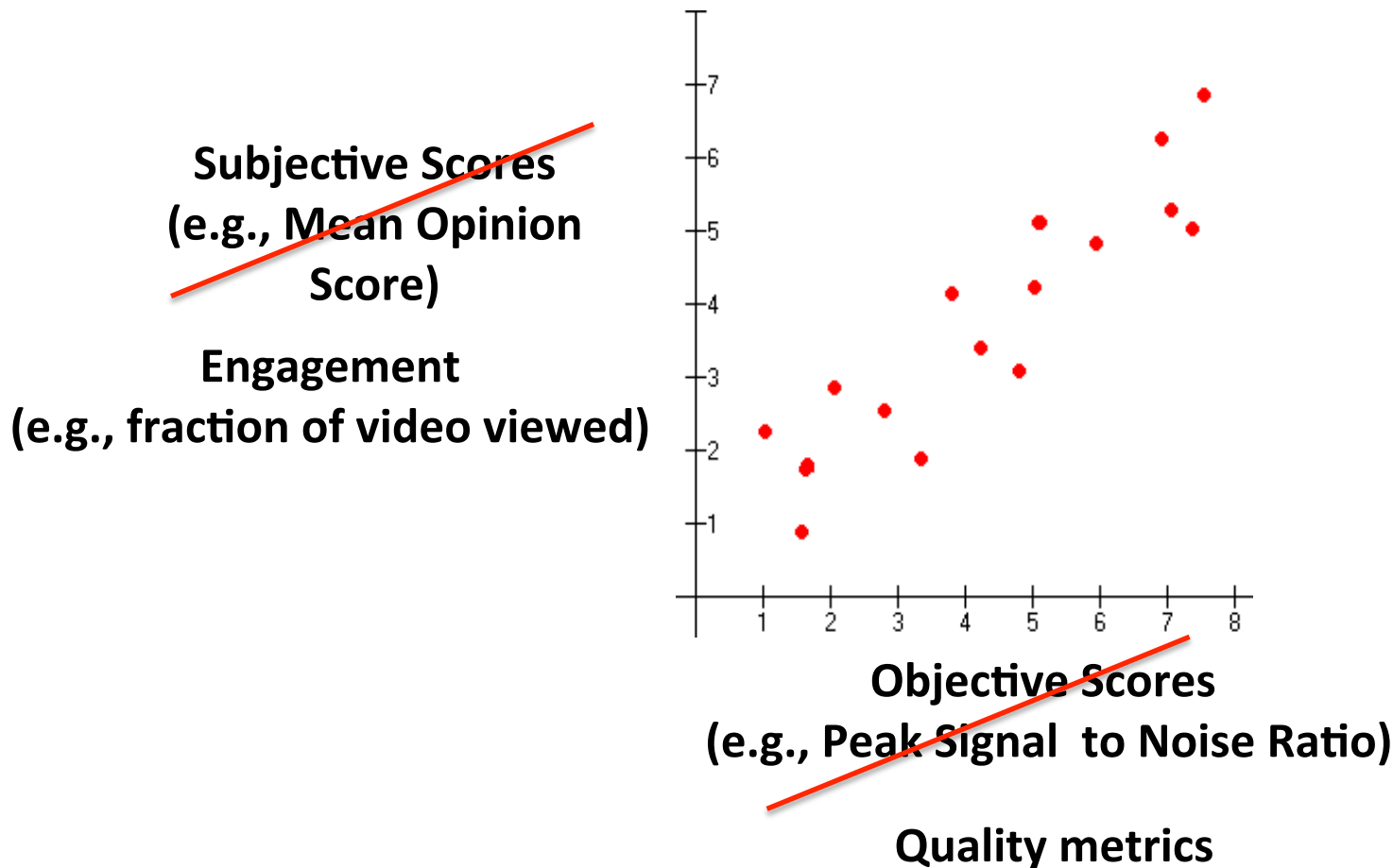
**Objective Scores
(e.g., Peak Signal to Noise Ratio)**

Does not capture new effects (e.g., buffering, switching bitrates)

Internet Video is a new ball game

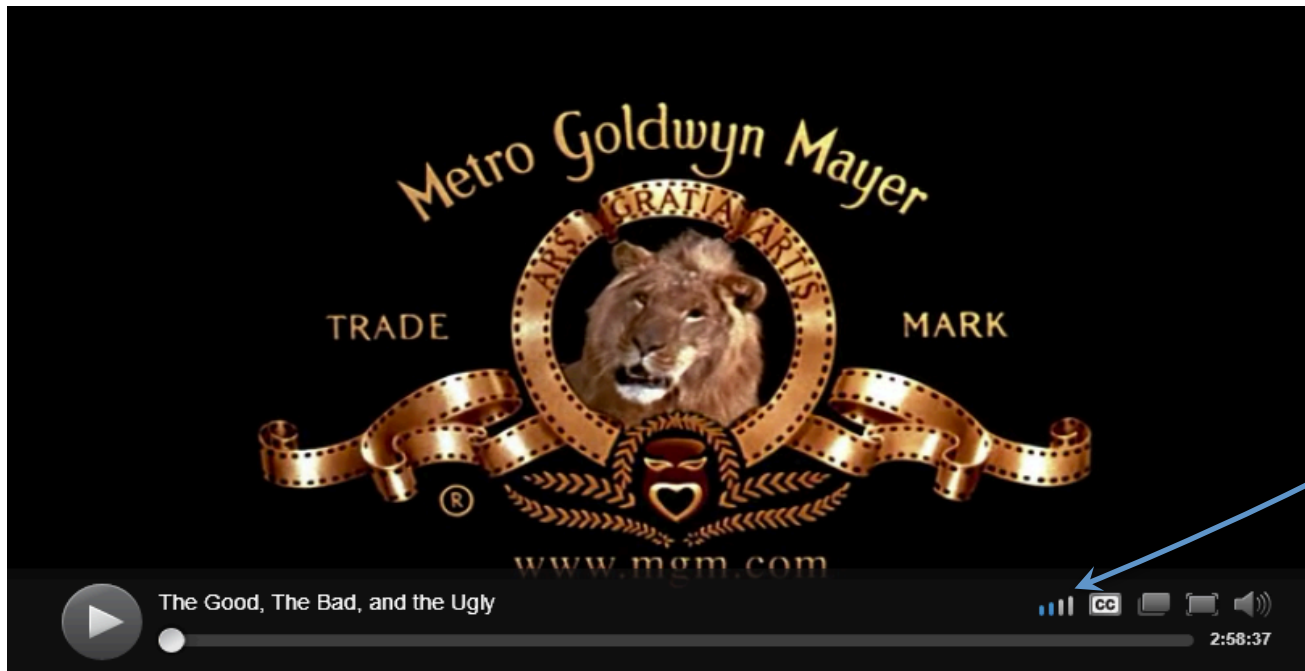**Subjective Scores (e.g., Mean Opinion Score)**

Engagement (e.g., fraction of video viewed)

Objective Scores (e.g., Peak Signal to Noise Ratio)

Quality metrics

Commonly used Quality Metrics

Join Time

Buffering ratio

Rate of buffering

Rate of switching

Average Bitrate

The Good, The Bad, and the Ugly

2:58:37

Which metric should we use?

Subjective Scores
(e.g., Mean Opinion Score)
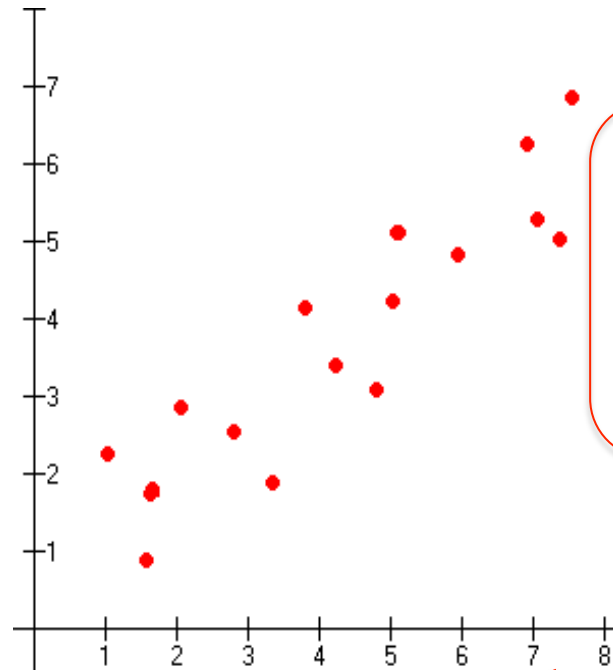
Engagement
(e.g., fraction of video viewed)

Today: Qualitative Single-metric

Objective Scores
(e.g., Peak Signal to Noise Ratio)

Quality metrics
Buffering Ratio, Average bitrate?

Unified and Quantitative QoE Model

**Subjective Scores
(e.g., Mean Opinion
Score)**

**Engagement
(e.g., fraction of video viewed)**

**Objective Scores
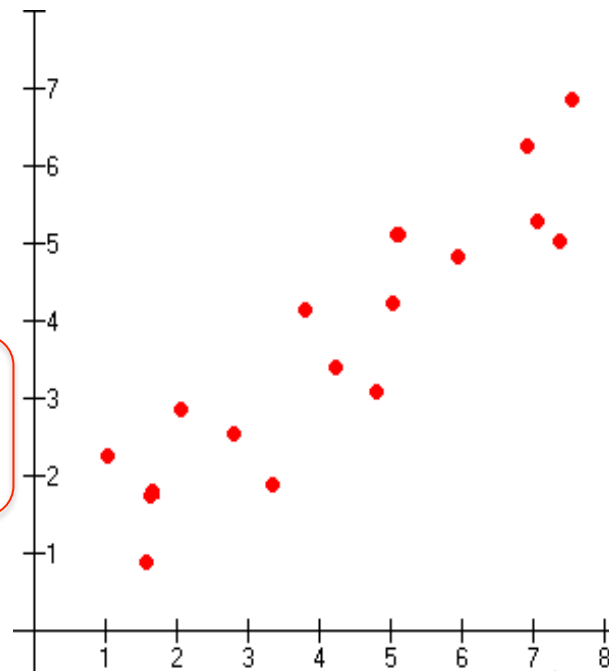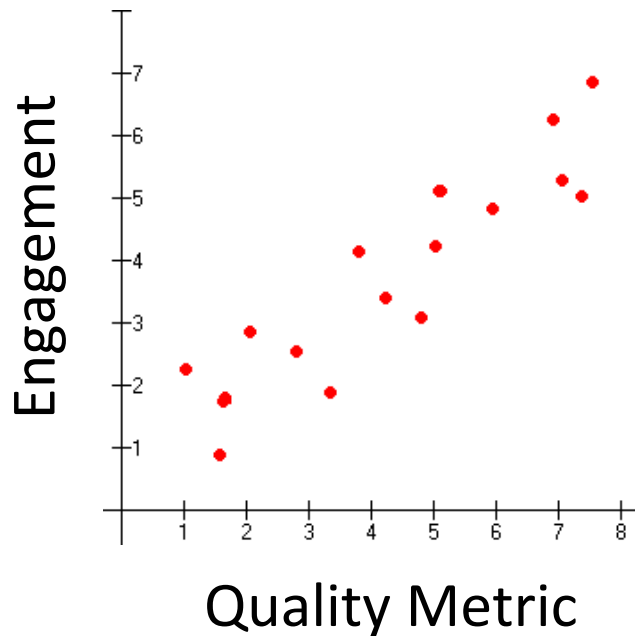(e.g., Peak Signal to Noise Ratio)**

**Quality metrics
Buffering Ratio, Average bitrate?**

*f (*Buffering Ratio, Average bitrate,…)

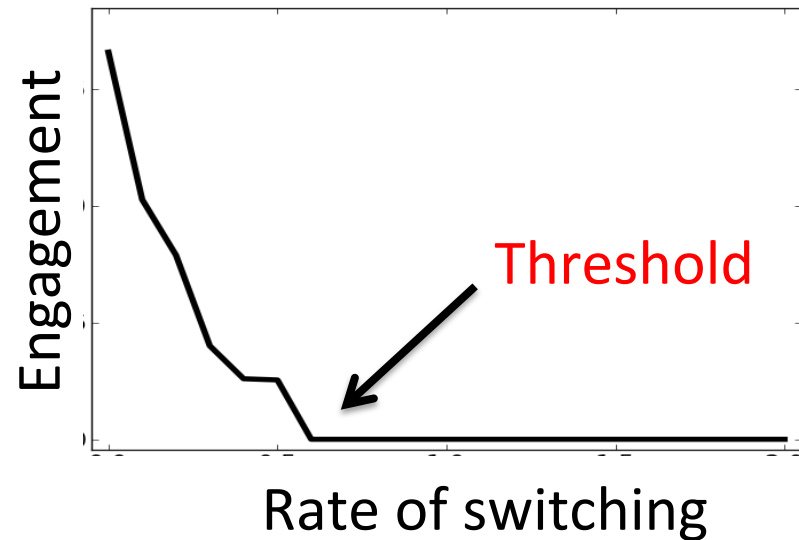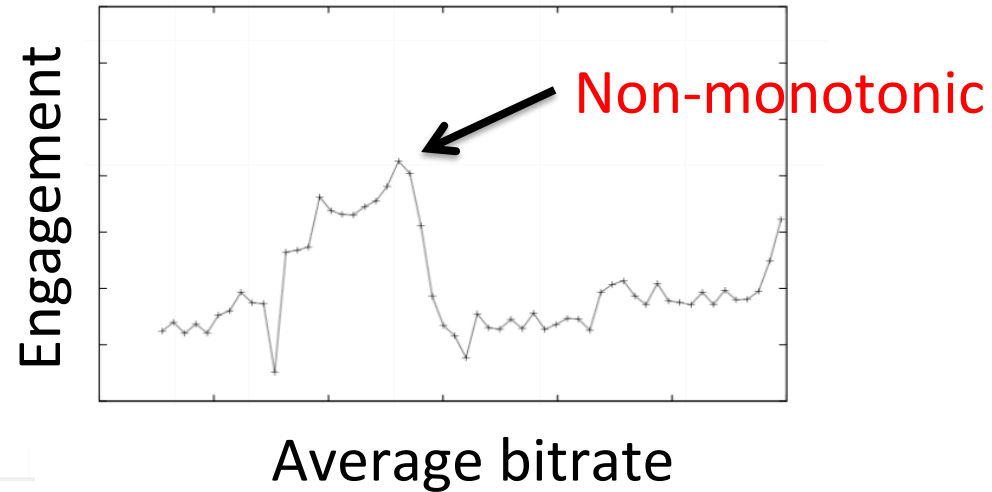# Outline

- **What makes this hard?**

- Our approach
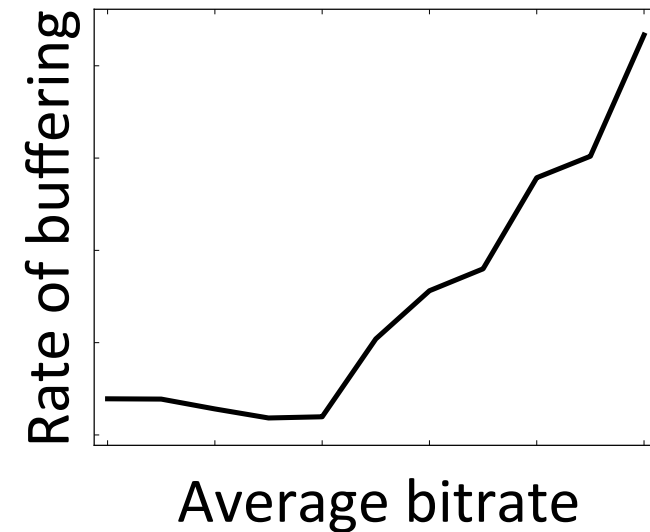
- Conclusion

Complex Engagement-to-metric Relationships

Engagement vs Quality Metric

Ideal Scenario

Non-monotonic

Average bitrate

Threshold

Rate of switching

[Dobrian et al. Sigcomm 2011]

Complex Metric Interdependencies
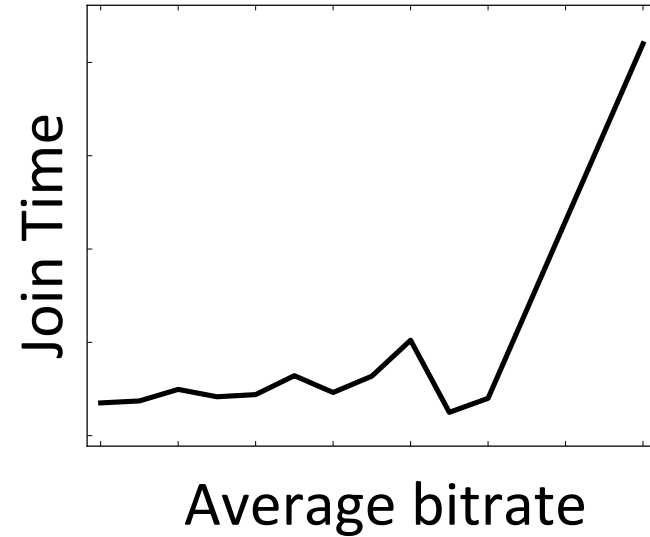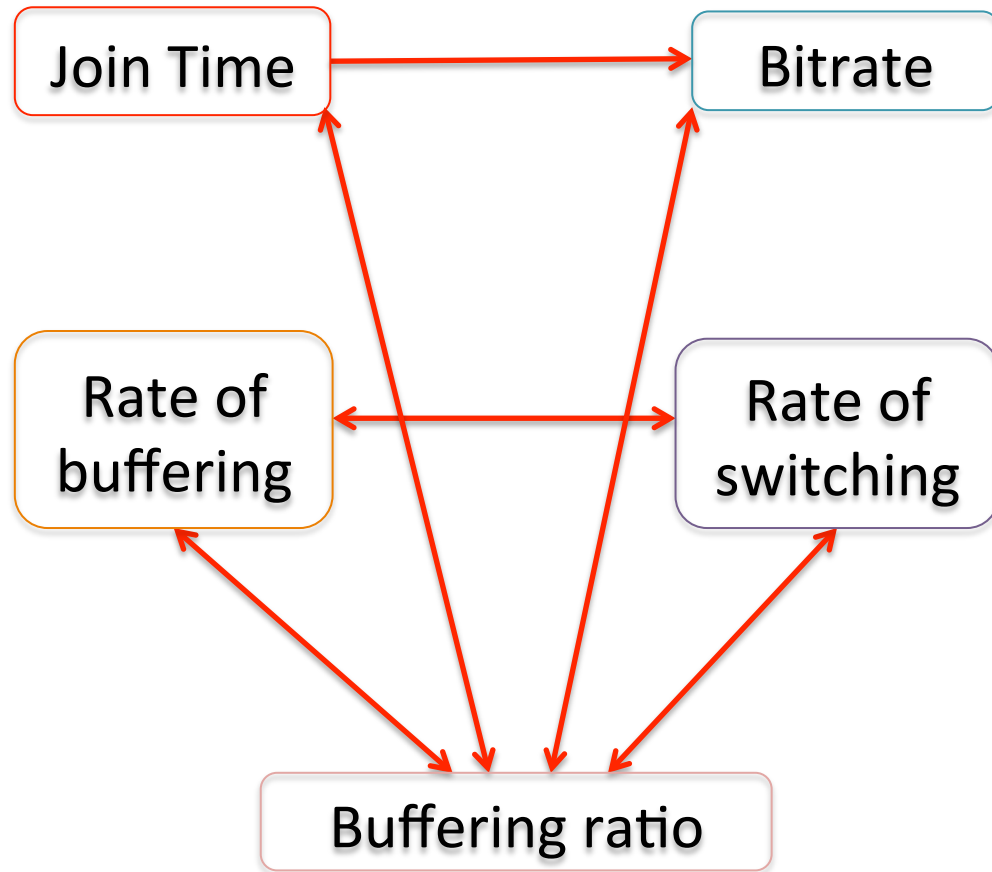
Confounding Factors

Type of Video → Live
Type of Video → VOD

Confounding Factors can affect:
1) Engagement

CDF (% of users)

Engagement
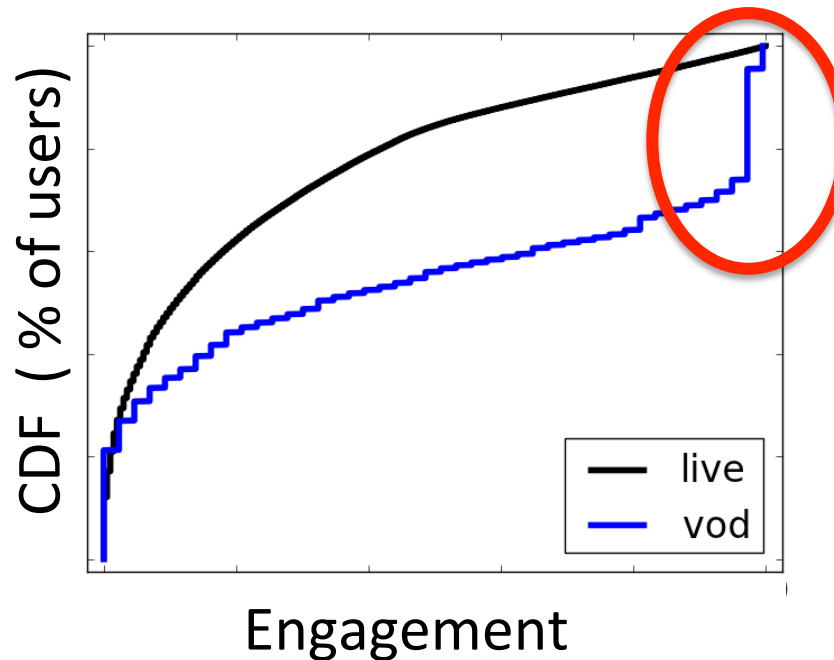
live
vod

Live and Video on Demand (VOD) sessions have different viewing patterns.

Confounding Factors

Type of Video → Live
Type of Video → VOD

Confounding Factors can affect:
1) Engagement
2) Quality Metrics
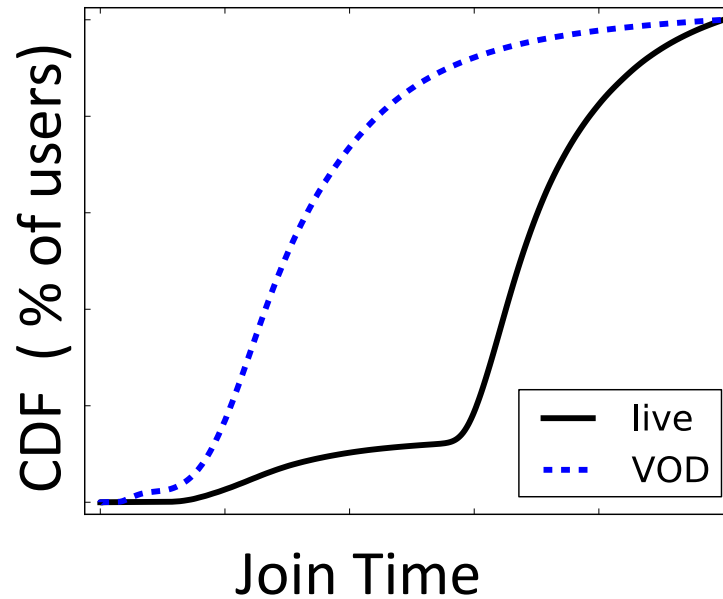
Live and Video on Demand (VOD) sessions had different join time distribution.

Confounding Factors

Type of Video

Connectivity → DSL/Cable
→ Wireless (3G/4G)
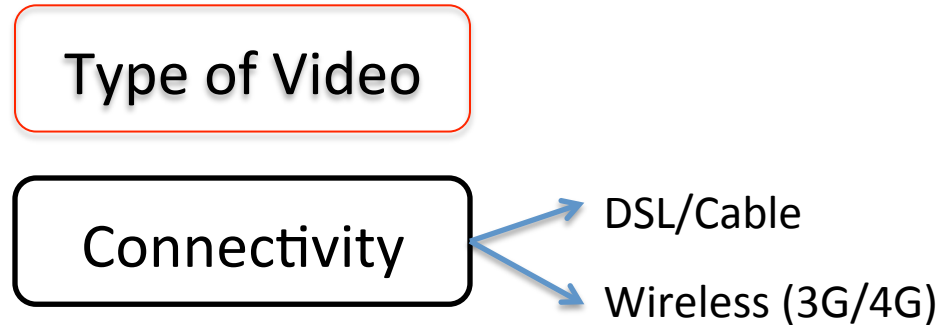
Confounding Factors can affect:
1) Engagement
2) Quality Metrics
3) Quality Metric → Engagement

Legend:
— DSL/Cable providers
···· Wireless providers

Y-axis: Engagement
X-axis: Rate of buffering
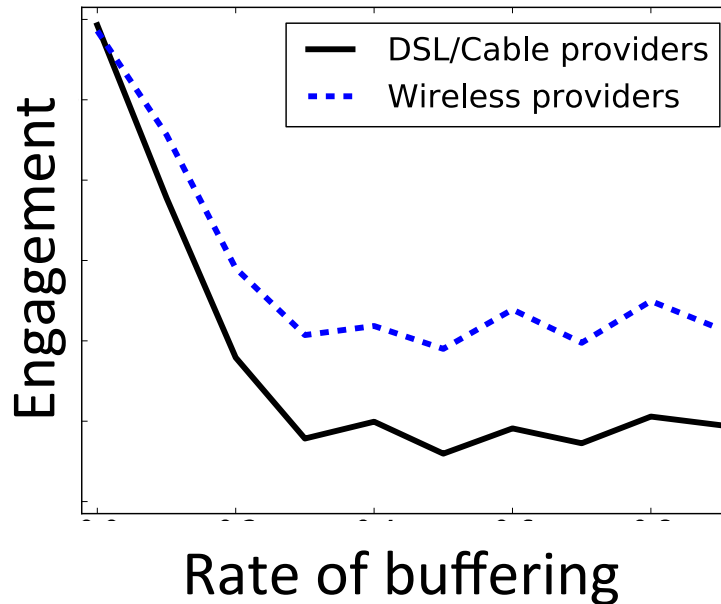
Users on wireless connectivity were more tolerant to rate of buffering.

Confounding Factors

Device

Type of Video

Popularity

Location

Connectivity

Time of day

Day of week

Need systematic approach to
identify and incorporate confounding factors

Summary of Challenges

1. Capture complex engagement-to-metric relationships and metric-to-metric dependencies.

2. Identify confounding factors

3. Incorporate confounding factors

Outline

- What makes this hard?

- **Our approach**

- Conclusion

Challenge 1: Capture complex relationships

Cast as a Learning Problem

Engagement   Quality Metrics

MACHINE LEARNING

QoE Model
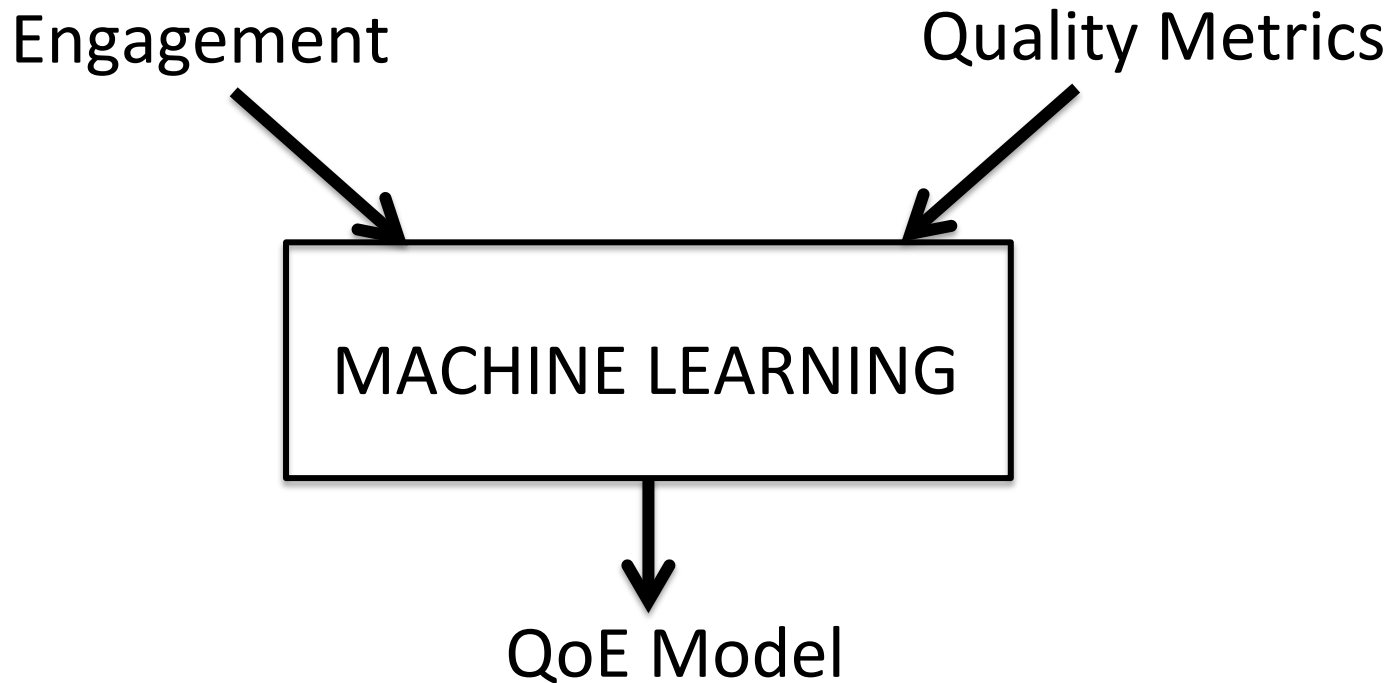
Decision Trees performed the best.
Accuracy of 40% for predicting within a 10% bucket.

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Challenge 2: Identify the confounding factors
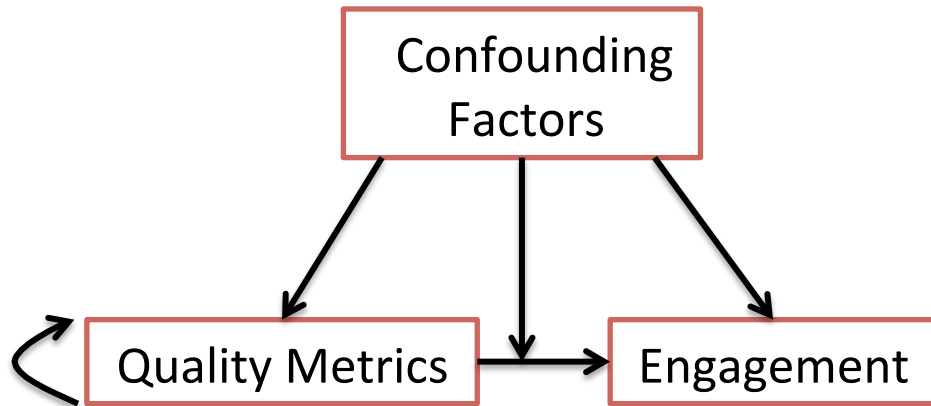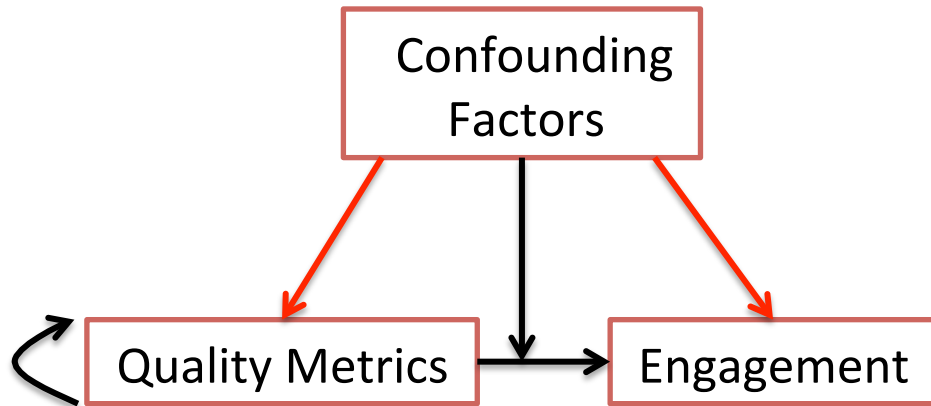
Test Potential Factors

Test Potential Factors

Test 1: Relative Information Gain

Test Potential Factors
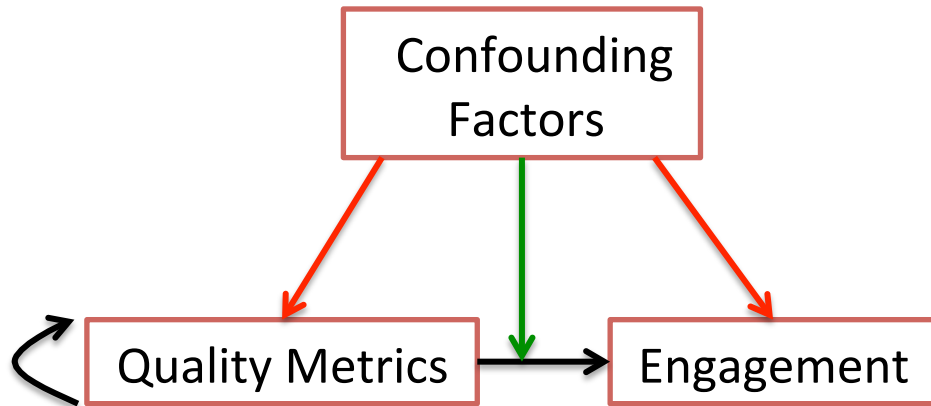
Test 1: Relative Information Gain
Test 2: Decision Tree Structure
Test 3: Tolerance Level

Identifying Key Confounding Factors

Factor	Relative Information Gain	Decision Tree Structure	Tolerance Level
Type of video	✓	✓	✓
Popularity	✗	✗	✗
Location	✗	✗	✗
Device	✗	✓	✓
Connectivity	✗	✗	✓
Time of day	✗	✗	✓
Day of week	✗	✗	✗

Identifying Key Confounding Factors

Factor	Relative Information Gain	Decision Tree Structure	Tolerance Level
Type of video	✓	✓	✓
Popularity	✗	✗	✗
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Device	✗	✓	✓
Connectivity	✗	✗	✓
Time of day	✗	✗	✓
Day of week	✗	✗	✗

Challenge 3: Incorporate the confounding factors

Refine the Model

Adding as a feature

Confounding Factors

Engagement

Quality Metrics

MACHINE LEARNING

QoE Model

Splitting the data

Confounding Factors 1
e.g., Live, Mobile

Confounding Factors 2
e.g., VOD, Mobile

Confounding Factors 3
e.g., VOD, TV

Engmnt   Quality Metrics

ML

Model 1

Engmnt   Quality Metrics

ML

Model 2

Engmnt   Quality Metrics

ML

Model 3

QoE Model
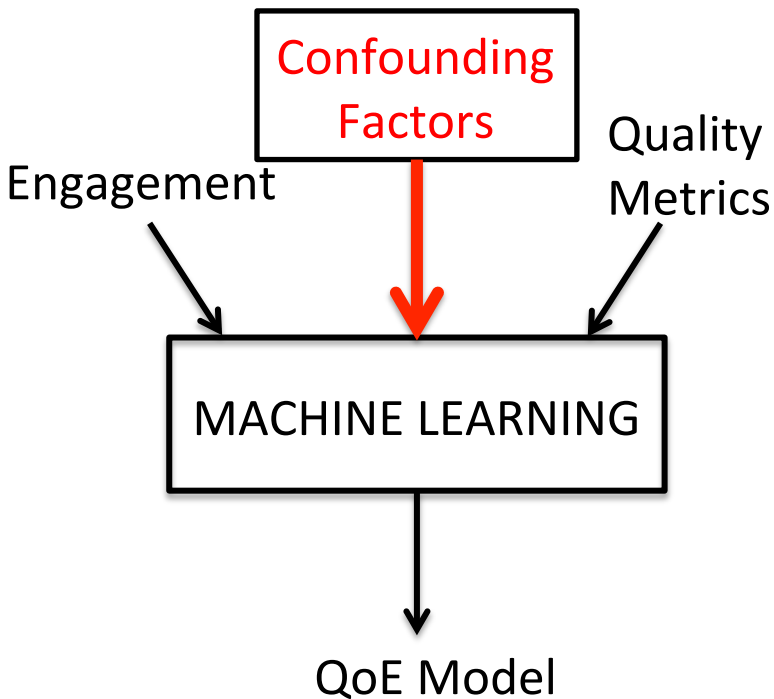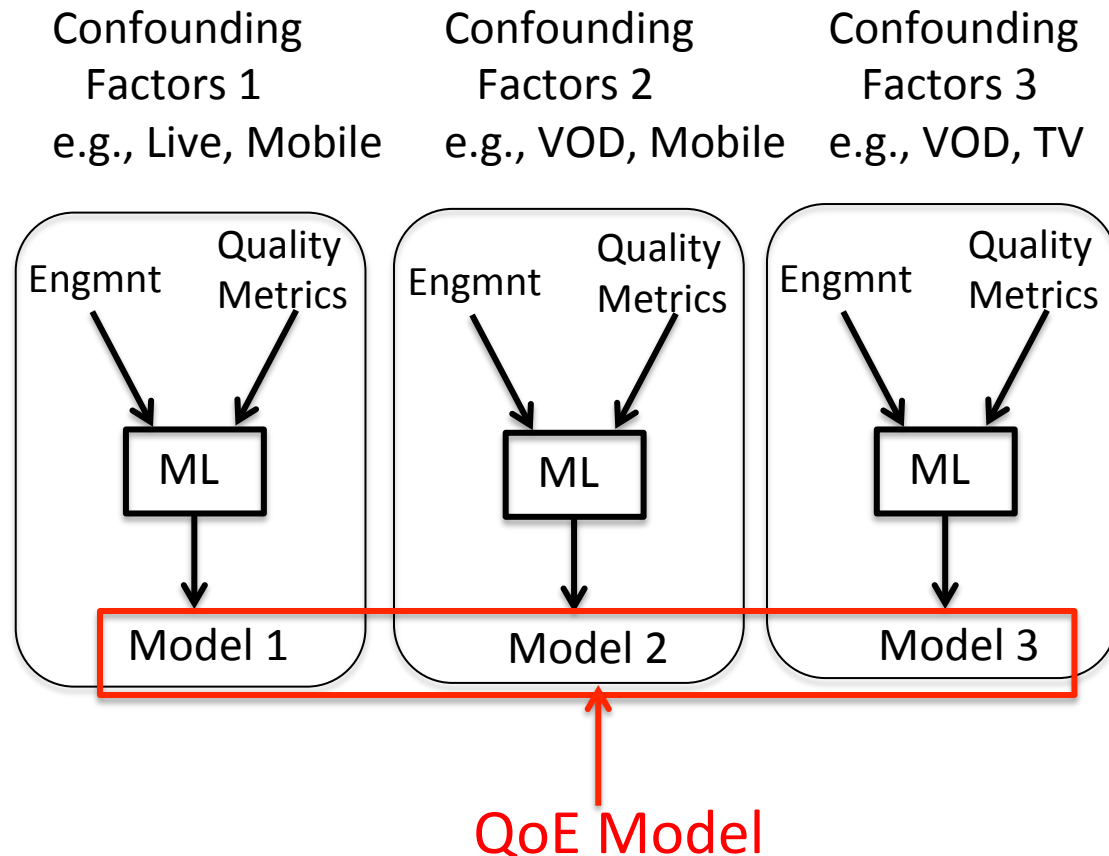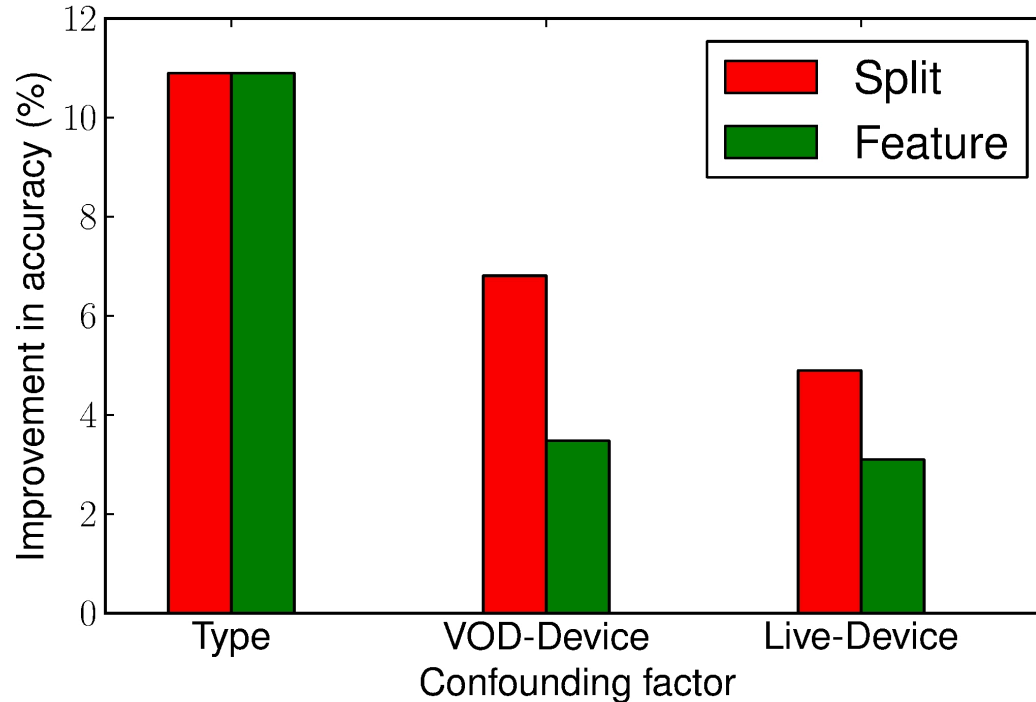
Comparing Candidate Solutions

Final Model: Collection of decision trees
Final Accuracy- 70% (*c.f.* 40%) for 10% buckets

Summary of Our Approach

1. Capture complex engagement-to-metric relationships and metric-to-metric dependencies

   → Use Machine Learning

2. Identify confounding factors

   → Tests

3. Incorporate confounding factors

   → Split

Evaluation: Benefit of the QoE Model
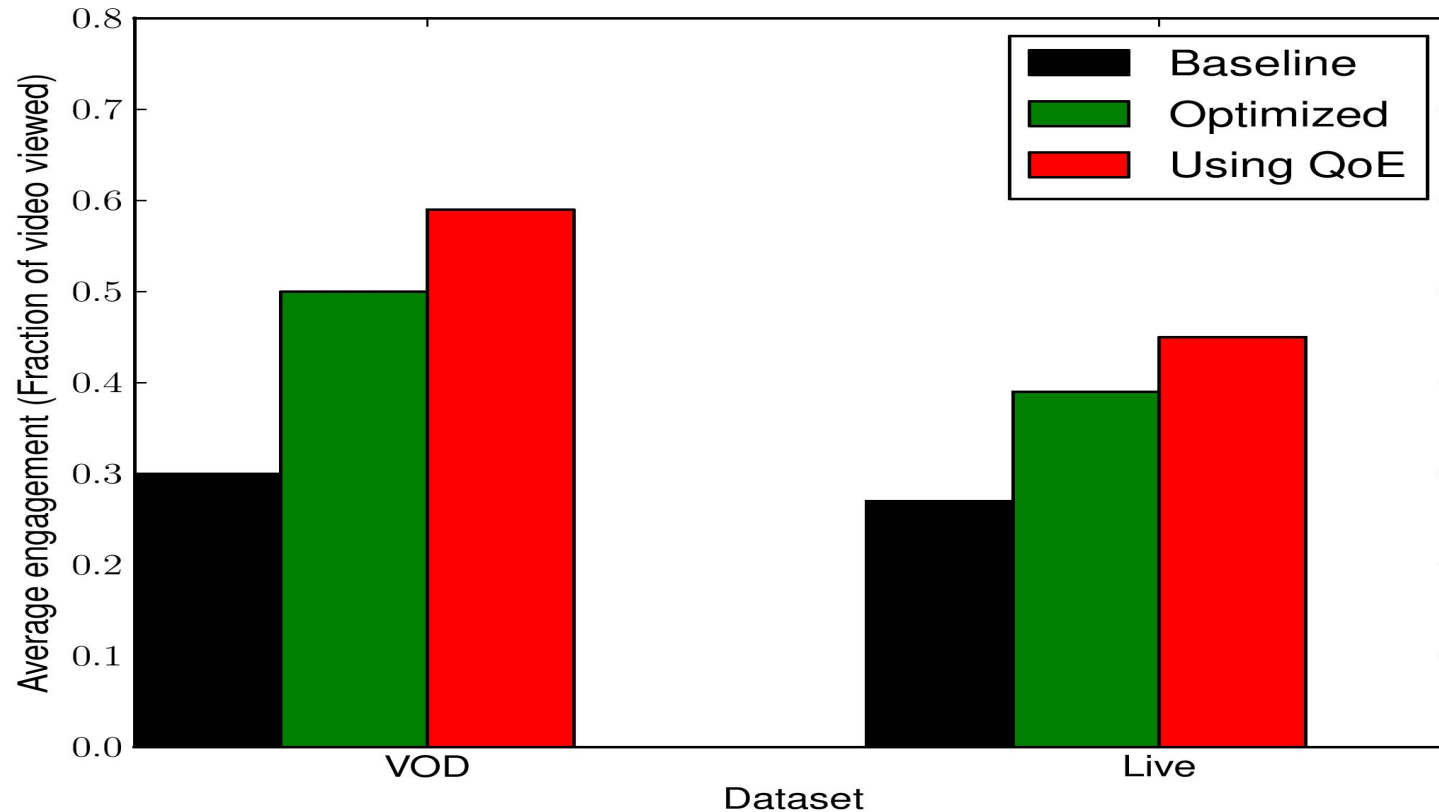
Preliminary results show that using QoE model to select bitrate leads to 20% improvement in engagement

Conclusions

- Internet Video needs a unified and quantitative QoE model

- What makes this hard?
    - Complex relationships
    - Confounding factors (e.g., type of video, device)

- Developing a model
    - ML + refinements => Collection of decision trees

- Preliminary evaluation shows that using the QoE model can lead to 20% improvement in engagement

- What's missing?
    - Coverage over confounding factors
    - Evolution of the metric with time