

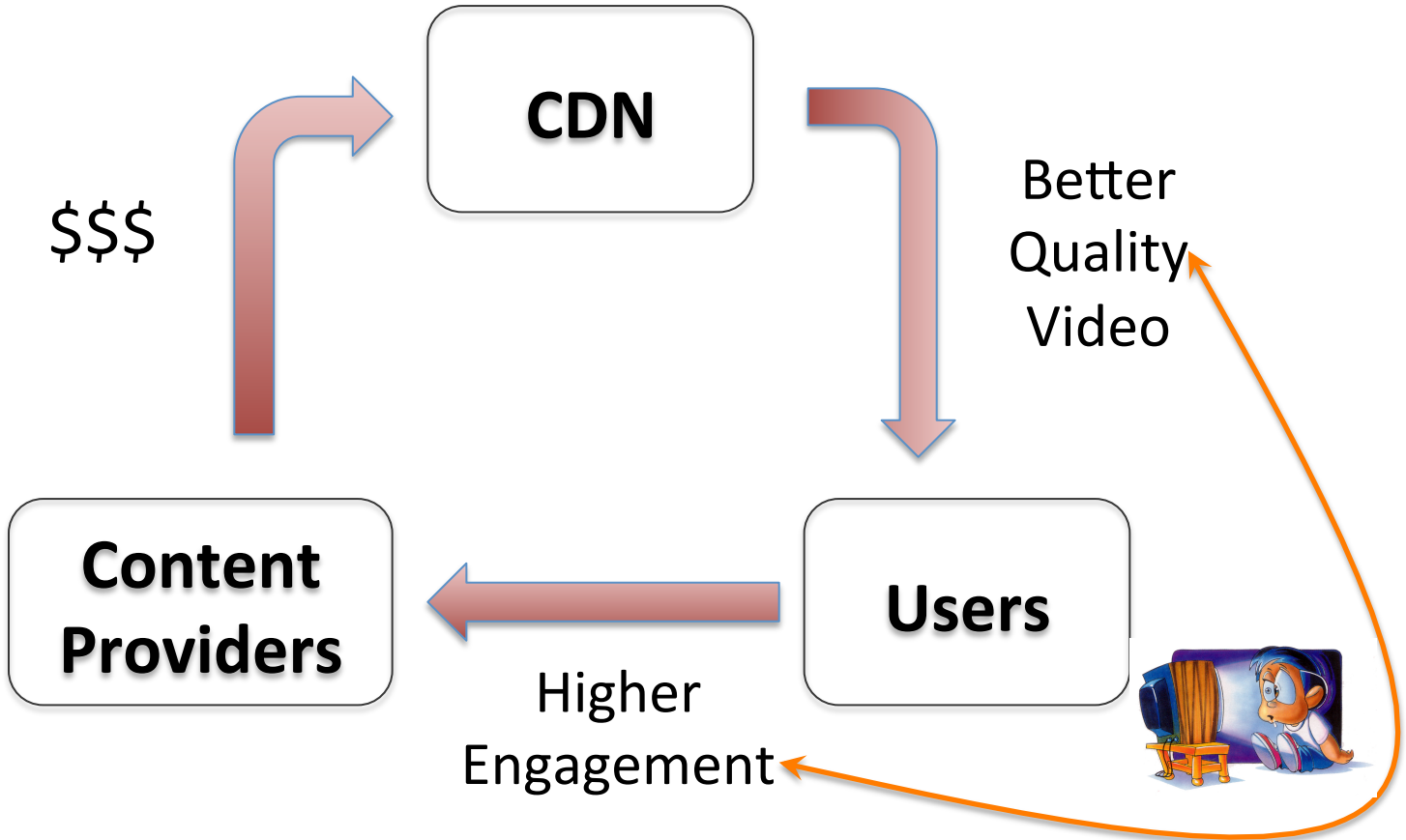
# Developing a Predictive Model for Internet Video Quality-of-Experience

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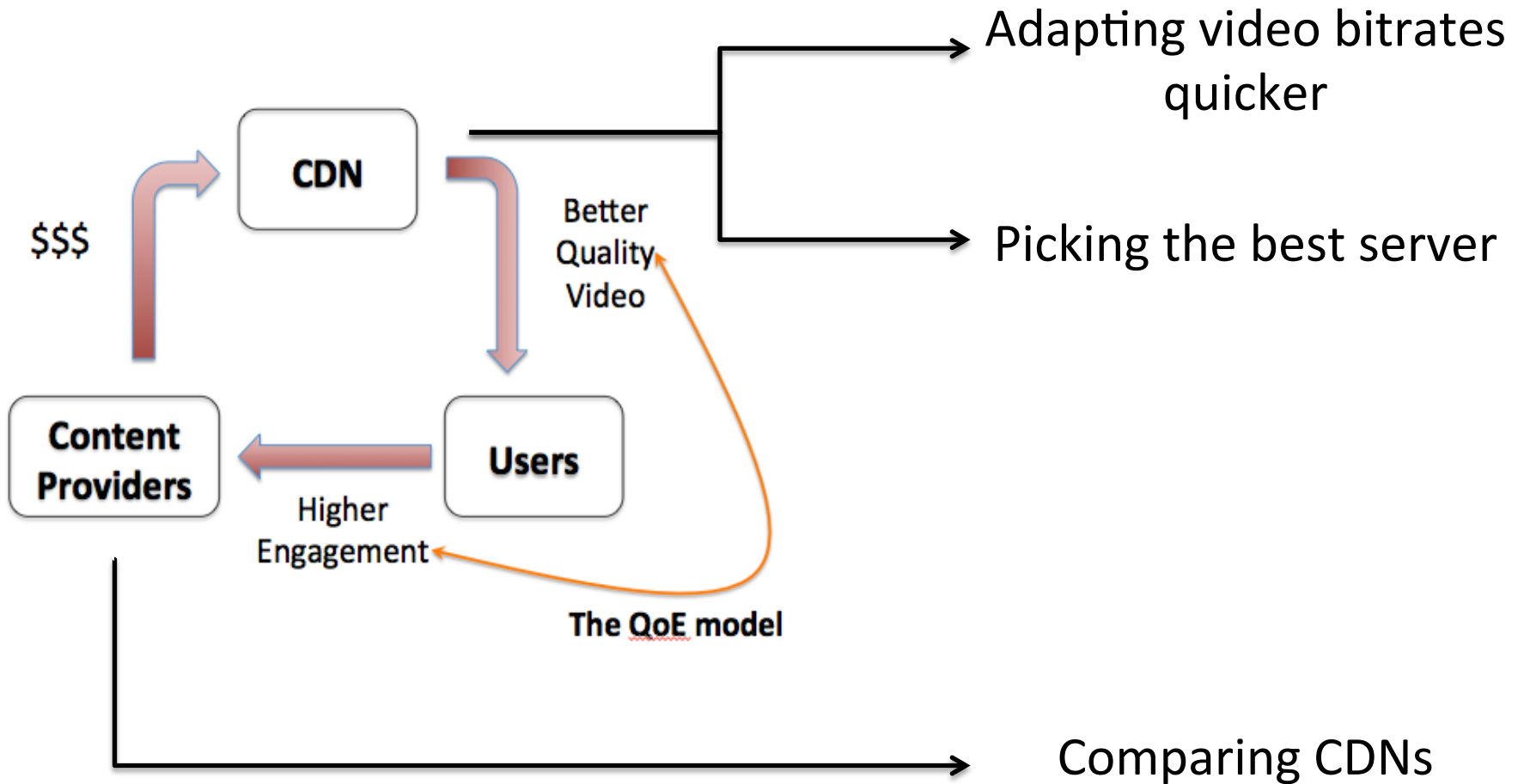
**CONVIVA®**

QoE → \$\$\$



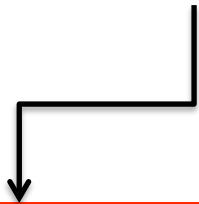
The QoE model

# Why do we need a QoE model?

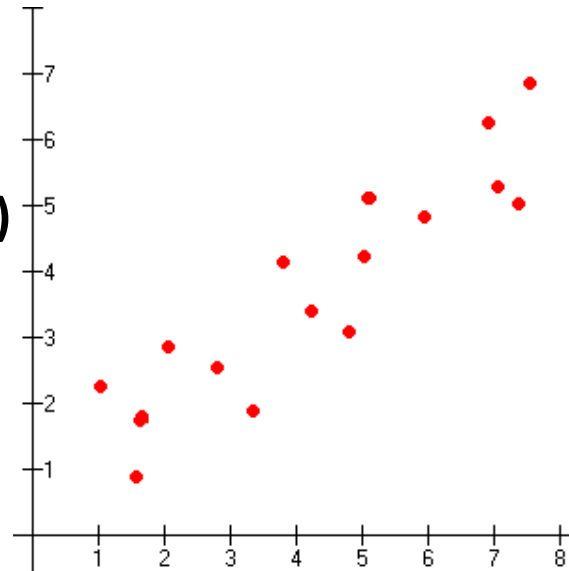


# Traditional Video Quality Metrics

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



User studies not representative  
of “in-the-wild” experience

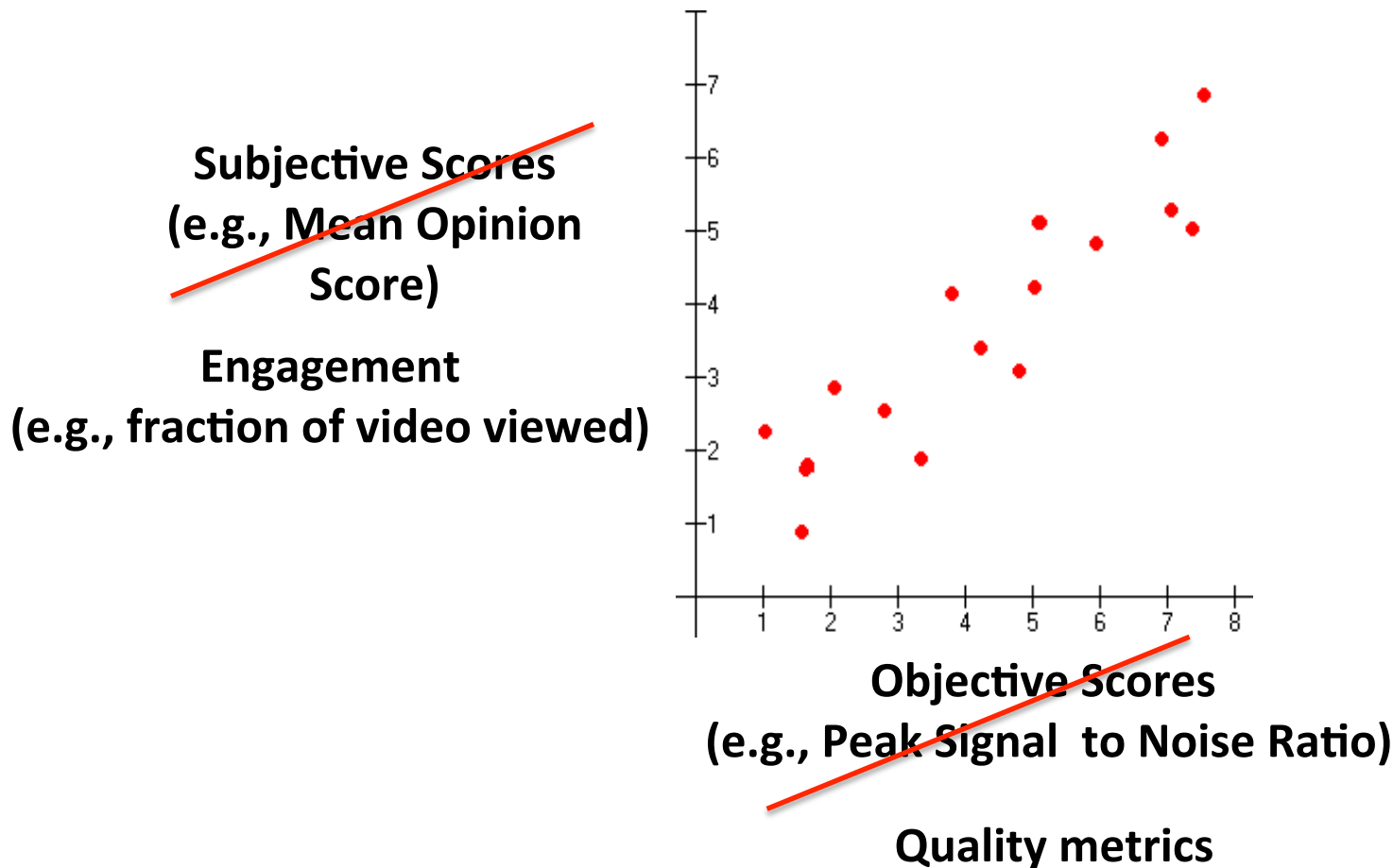


**Objective Scores**  
(e.g., Peak Signal to Noise Ratio)



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

# Internet Video is a new ball game



# Commonly used Quality Metrics

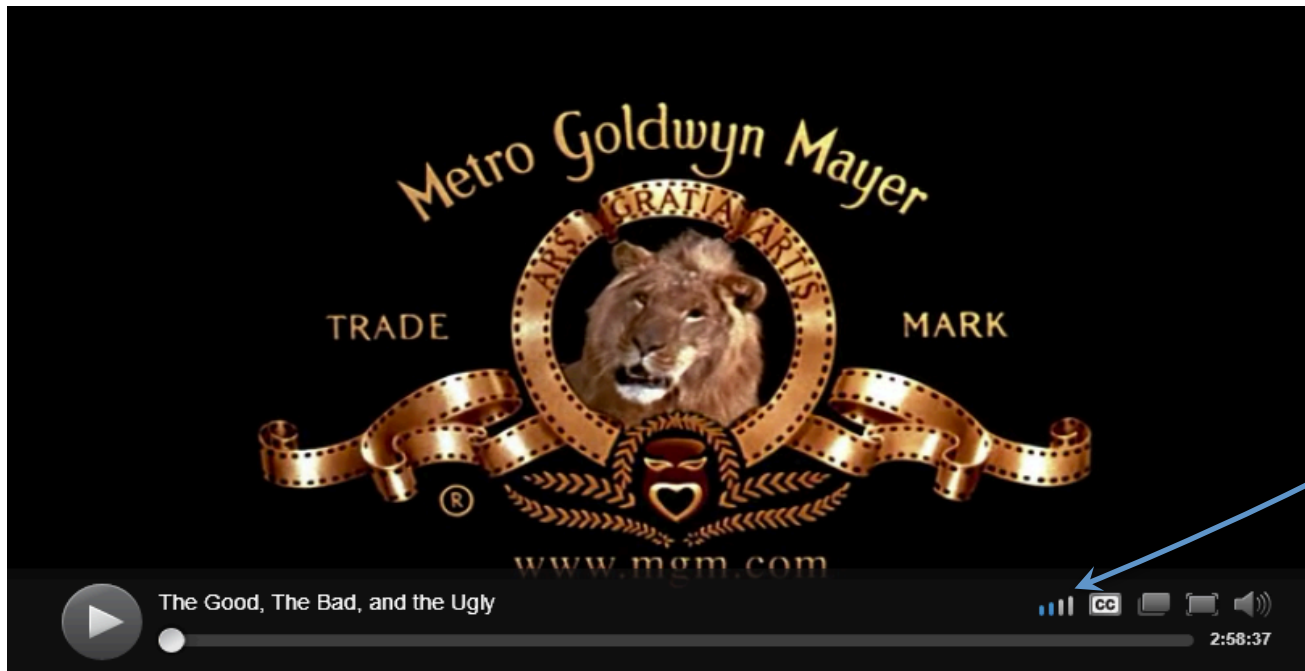
Join Time

Buffering ratio

Rate of switching

Rate of buffering

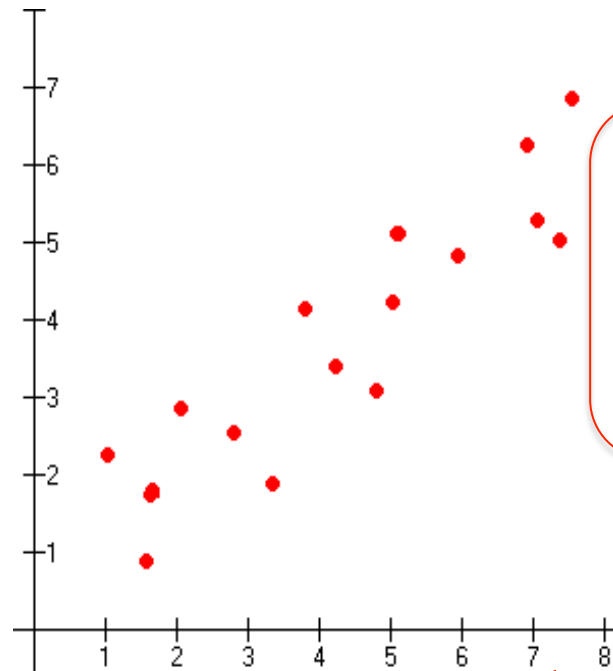
Average Bitrate



# Which metric should we use?

~~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

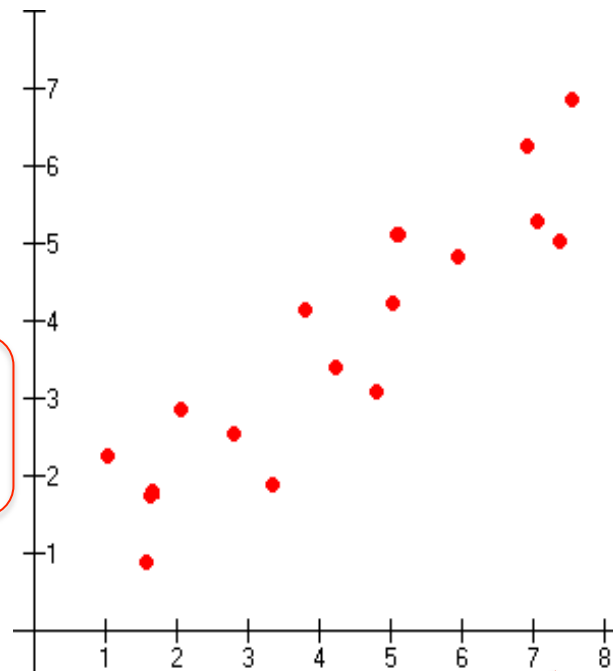
Buffering Ratio, Average bitrate?

Today:  
Qualitative  
Single-metric

# 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?

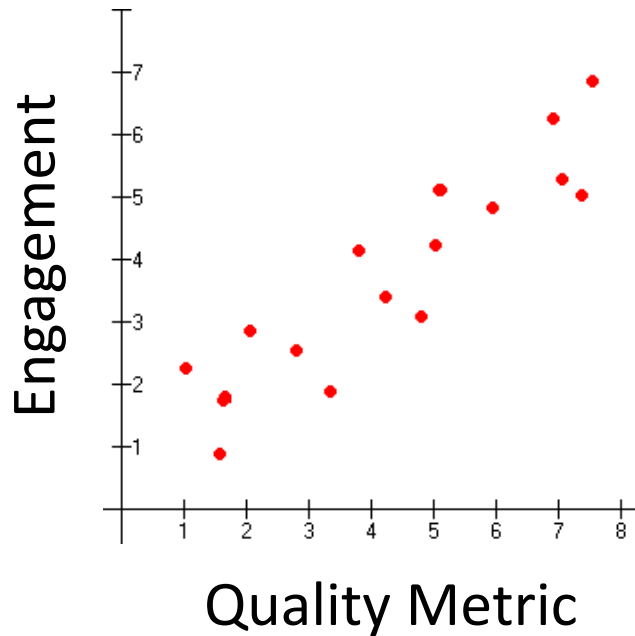
**$f$  (Buffering Ratio, Average bitrate,...)**



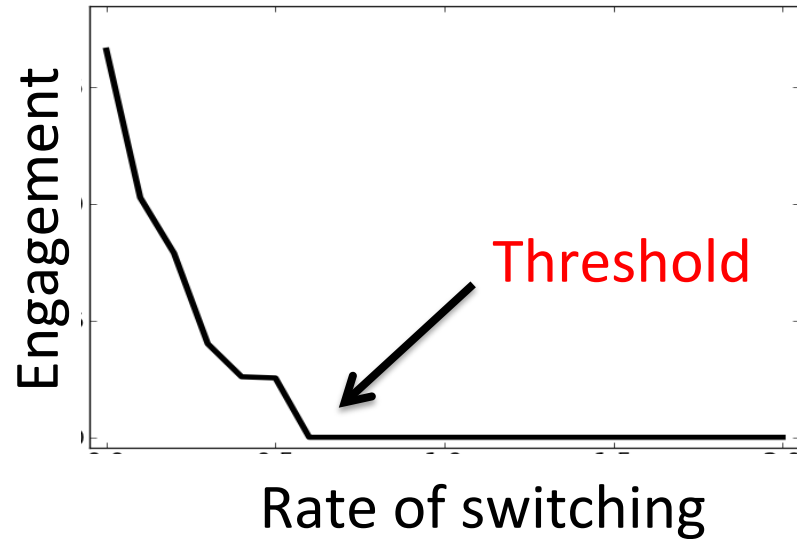
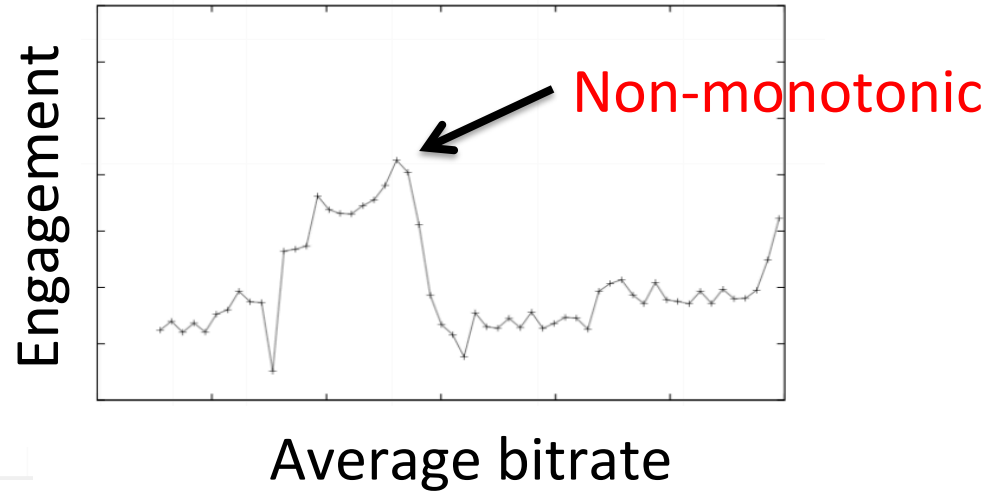
# Outline

- **What makes this hard?**
- **Our approach**
- Conclusion

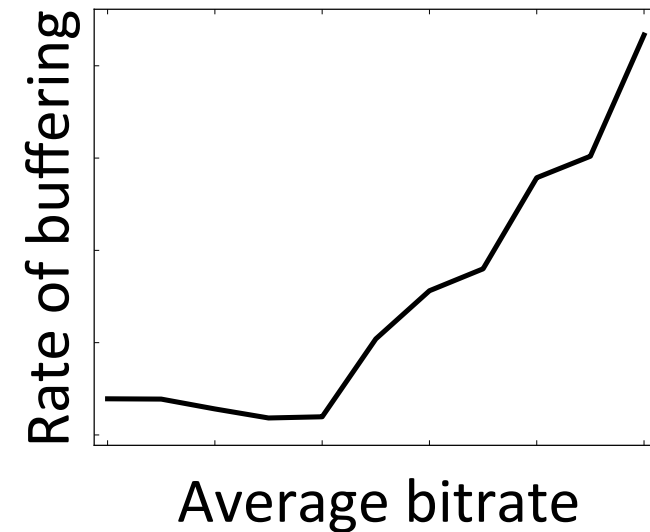
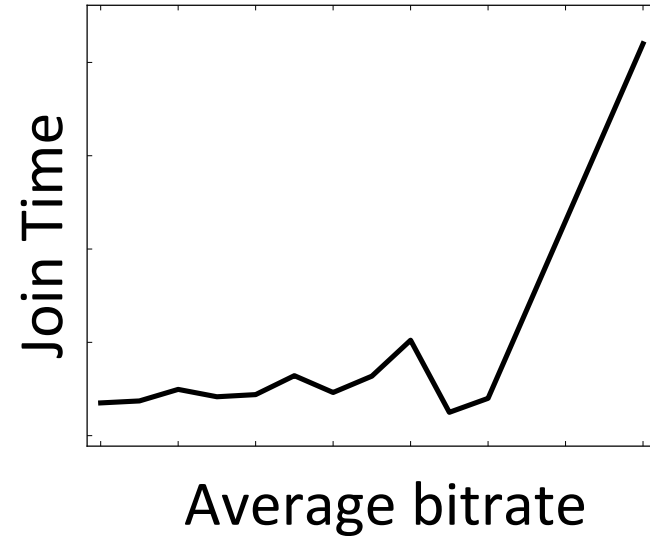
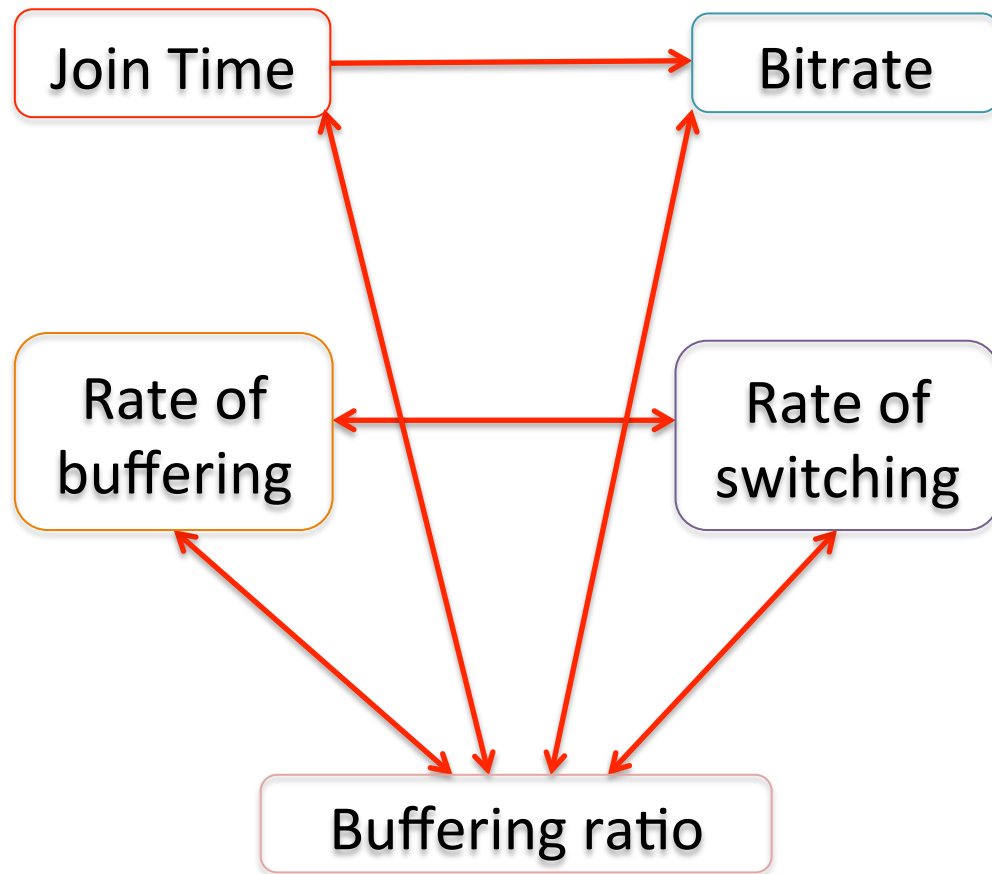
# Complex Engagement-to-metric Relationships



Ideal Scenario



# Complex Metric Interdependencies

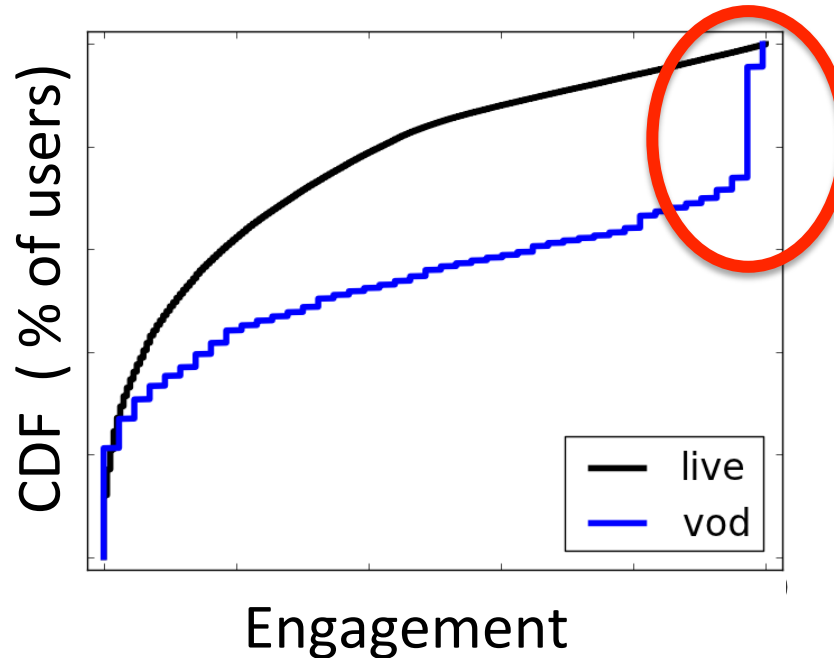


# Confounding Factors



Confounding Factors can affect:

1) Engagement



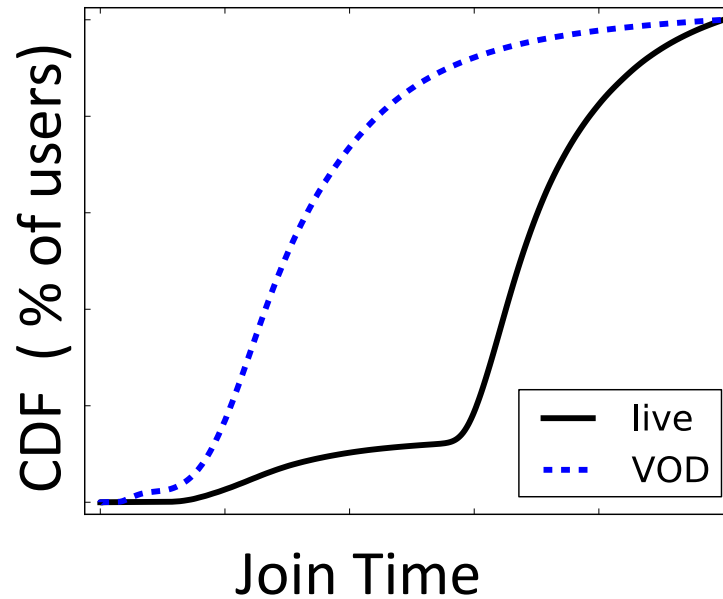
**Live and Video on Demand (VOD) sessions have different viewing patterns.**

# Confounding Factors



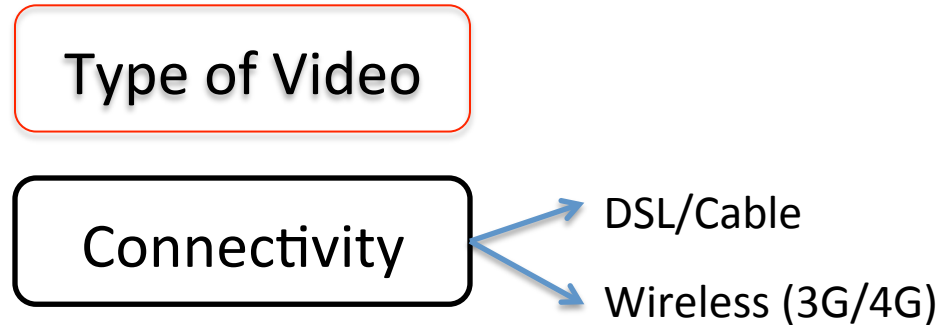
Confounding Factors can affect:

- 1) Engagement
- 2) Quality Metrics



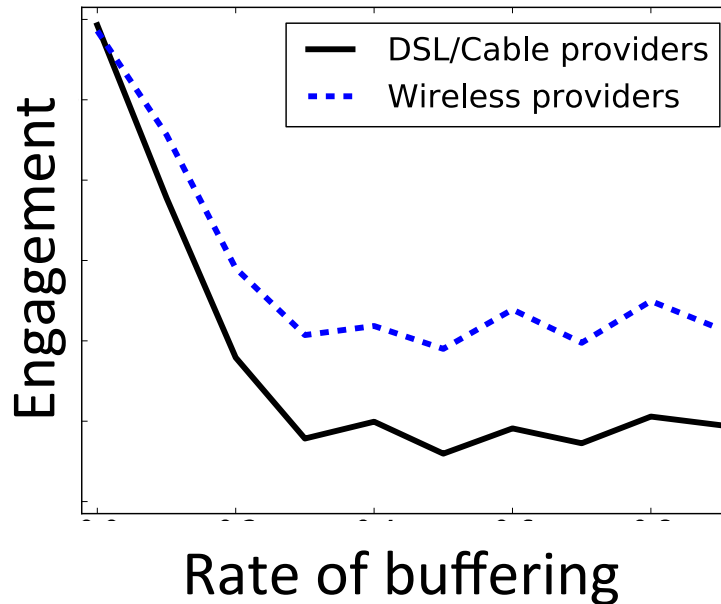
**Live and Video on Demand (VOD) sessions had different join time distribution.**

# Confounding Factors



Confounding Factors can affect:

- 1) Engagement
- 2) Quality Metrics
- 3) **Quality Metric → Engagement**



**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

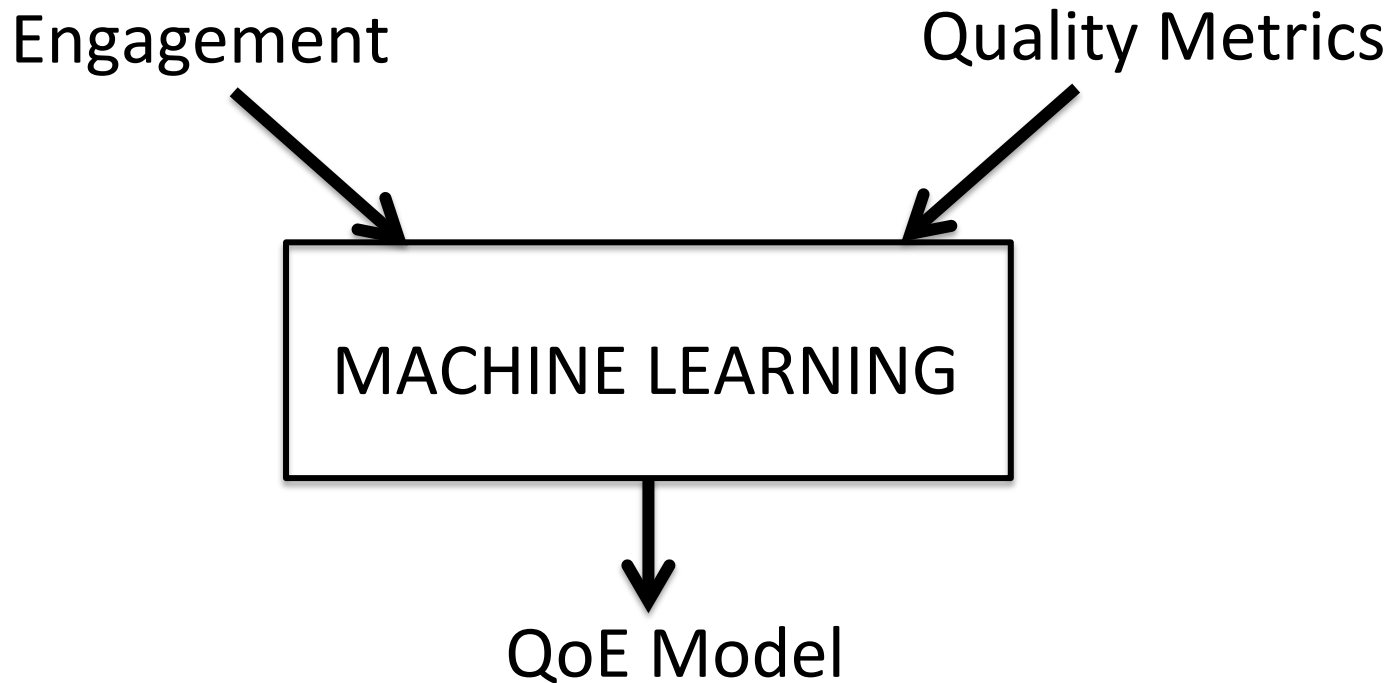


# Outline

- What makes this hard?
- **Our approach**
- Conclusion

**Challenge 1:** Capture complex relationships

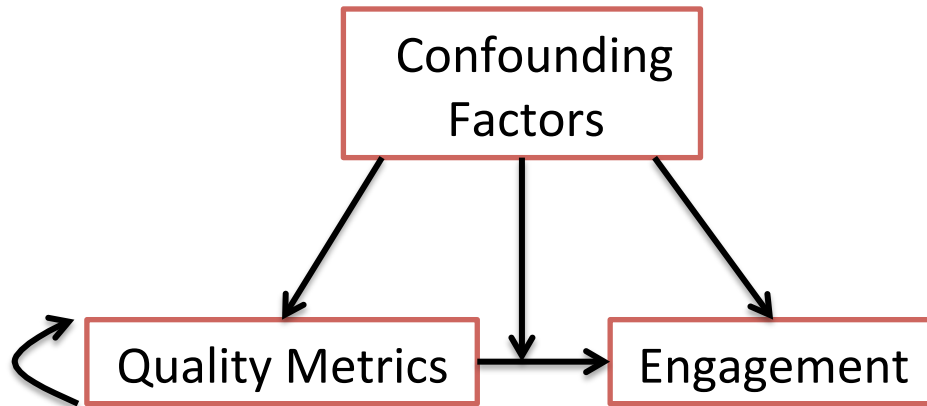
# Cast as a Learning Problem



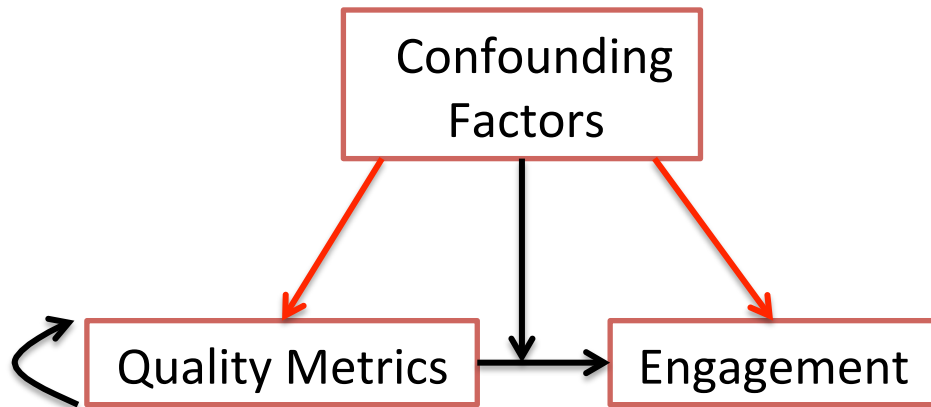
**Decision Trees performed the best.  
Accuracy of 40% for predicting within a 10% bucket.**

**Challenge 2:** Identify the confounding factors

# Test Potential Factors

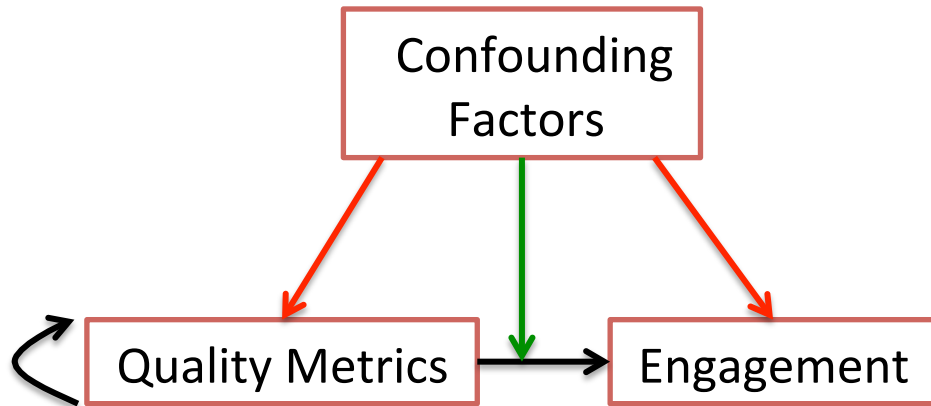


# Test Potential Factors



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	✗	✗	✗

VOD users on different devices have different levels of tolerance for rate of buffering and average bitrate



# Identifying Key Confounding Factors

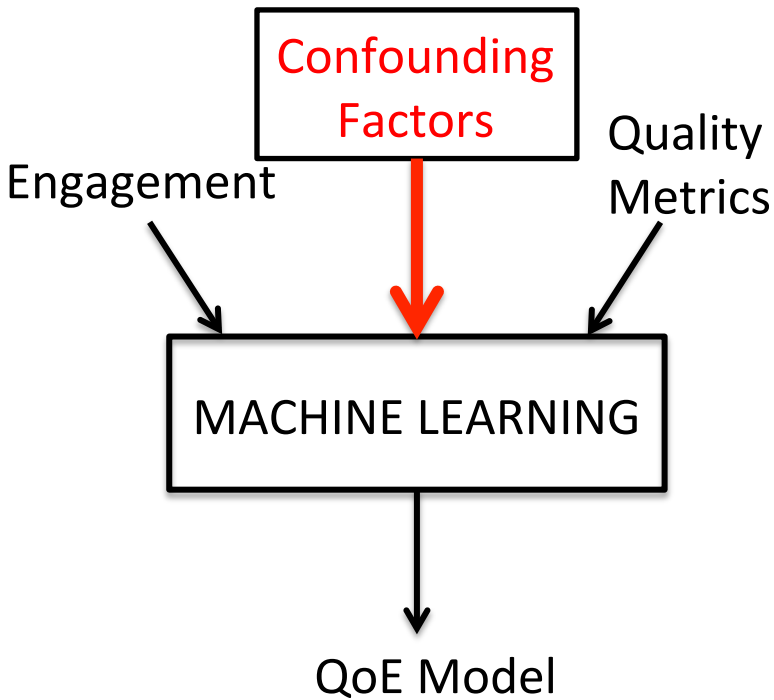
We are doing feature selection here:

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

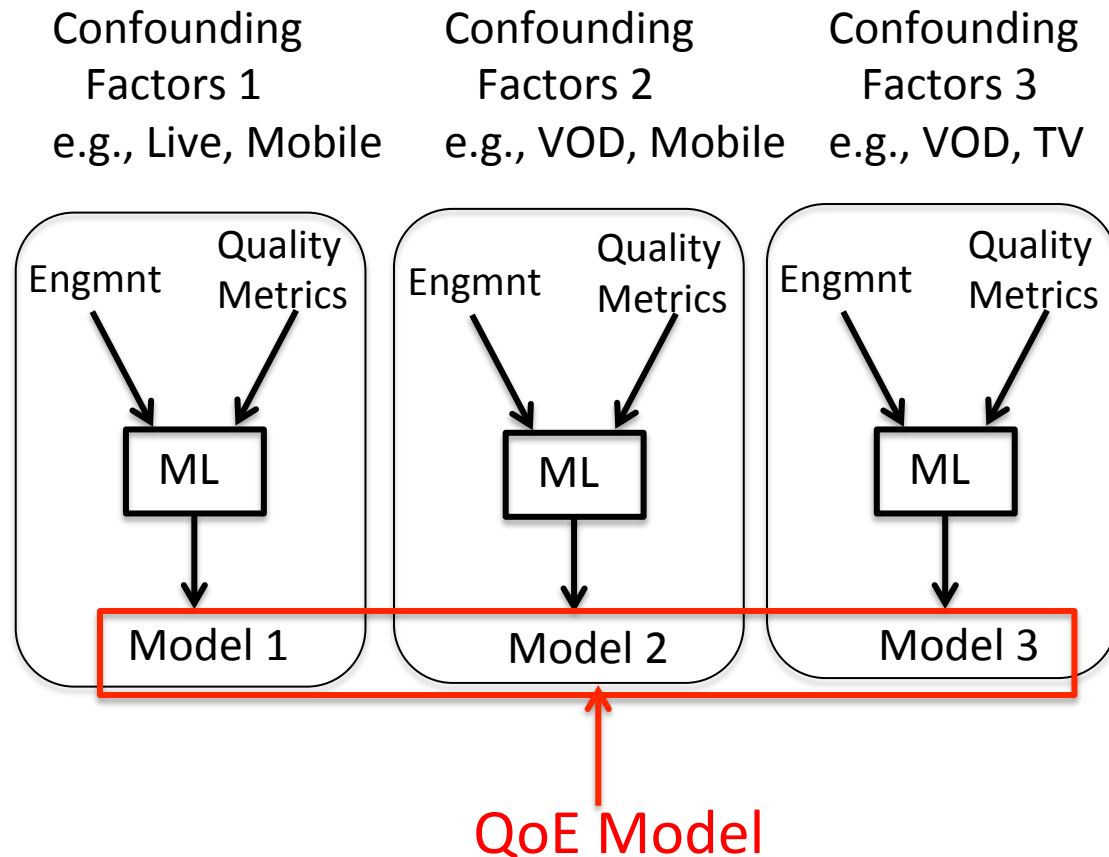
**Challenge 3:** Incorporate the confounding factors

# Refine the Model

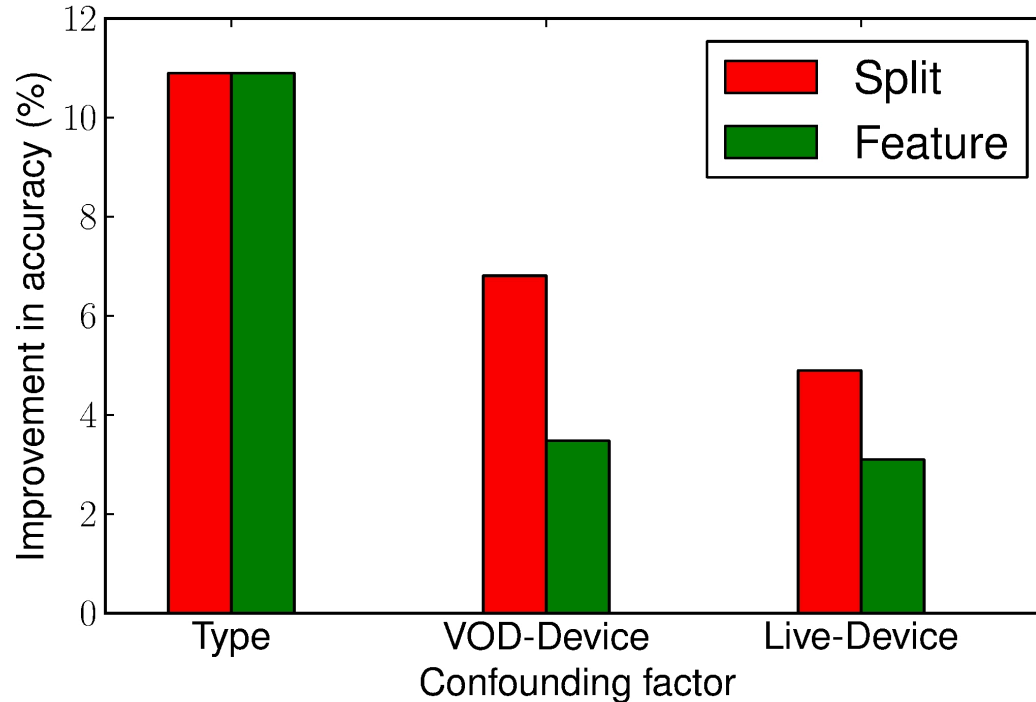
## Adding as a feature



## Splitting the data



# 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

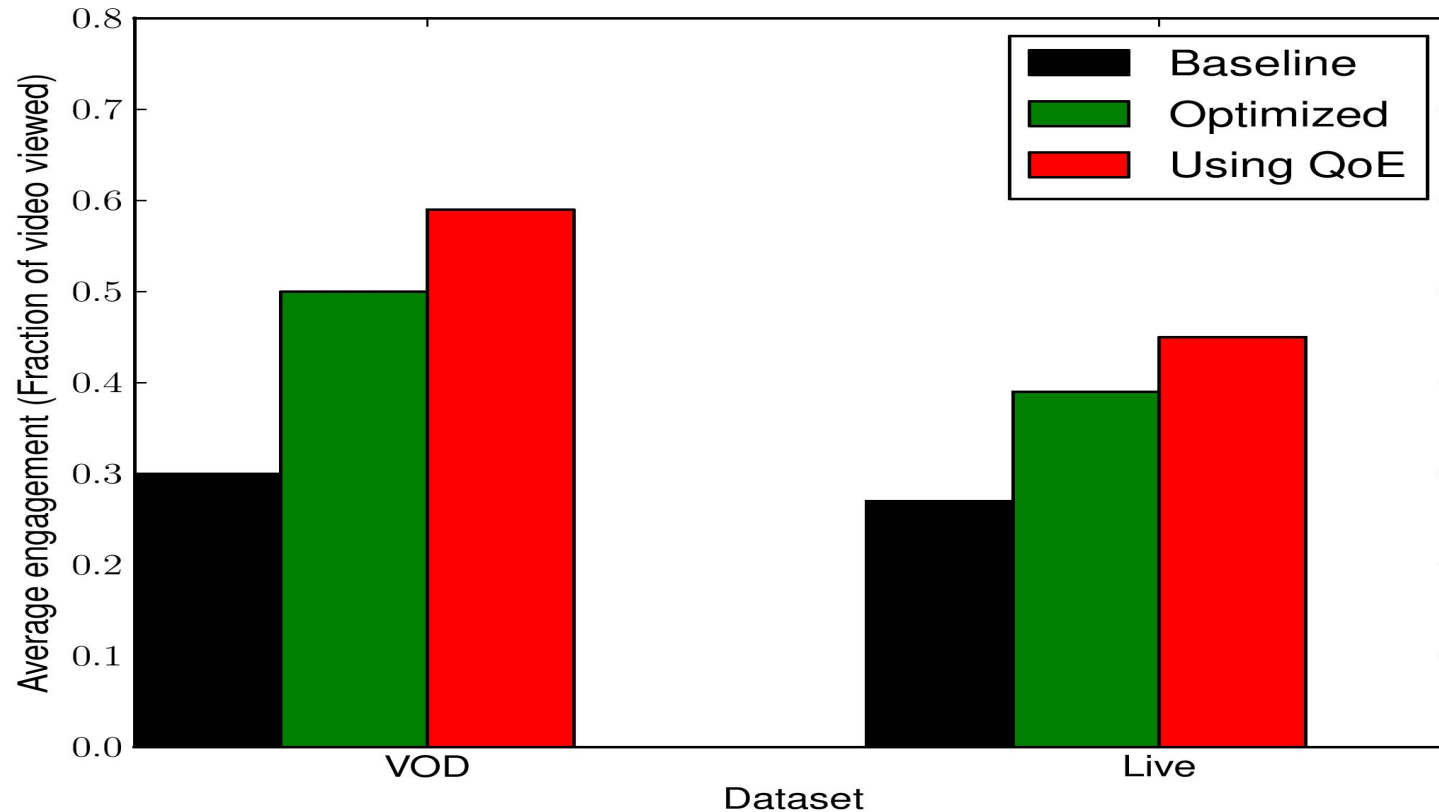
2. Identify confounding factors

→ 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