CABaRet: Leveraging Recommendation Systems for Mobile Edge Caching

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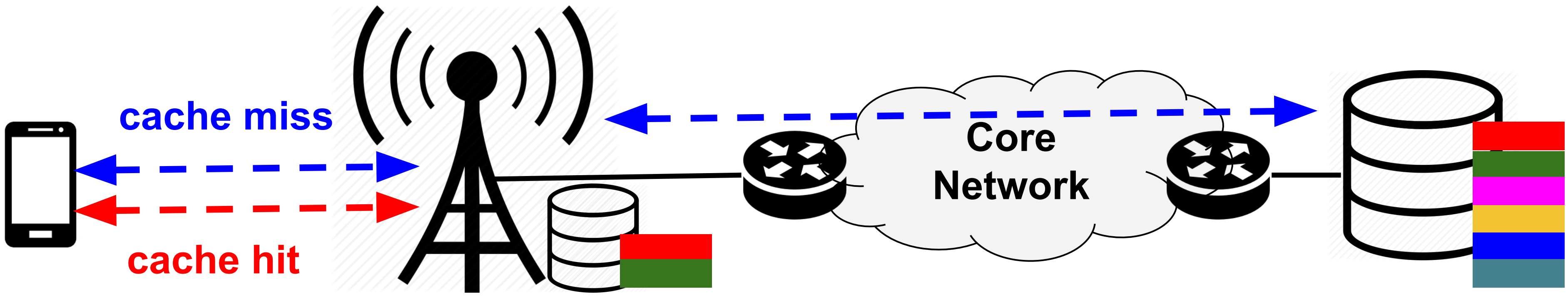
Mobile edge caching



✔ Win-Win (user & network): reduces access latency & network load

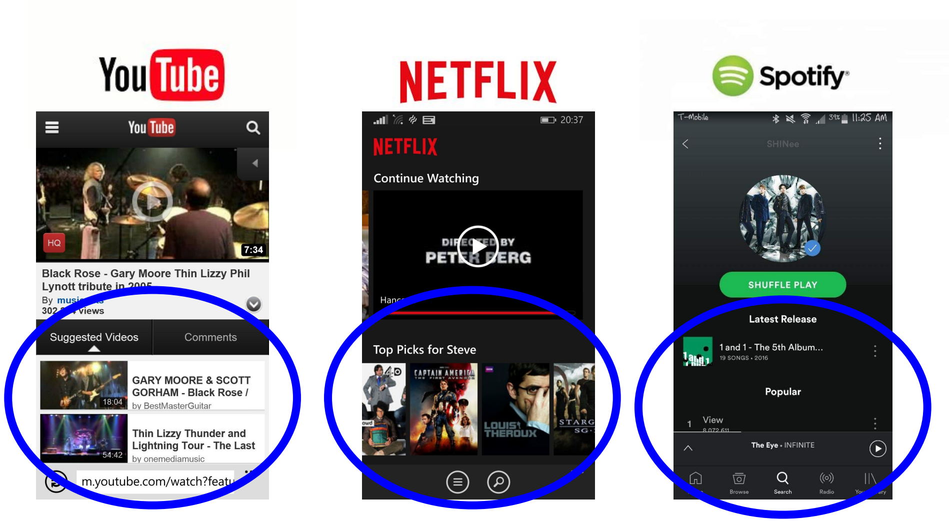
✘ Low cache hit ratio (CHR)

- **small caches** (size ~GB vs. catalog size ~PB)
- **caching algorithms limitations** (variable traffic, frequent changes of users)

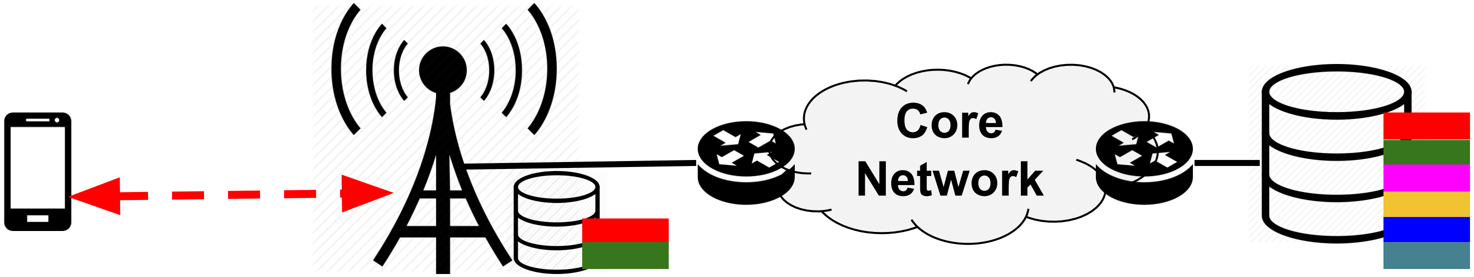
A solution: Leverage recommendation systems

- **Why recommendation systems (RS)?**
  - Integrated in *popular* services (YouTube, Netflix, Spotify, etc.)
  - Drive content consumption (~80% in Netflix, >50% in YouTube)

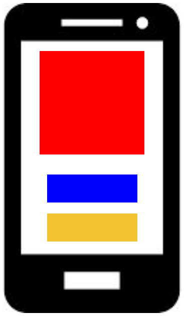
- **How to leverage RS?**
  - Recommend contents that are cached *e.g.,[**ToMM'15, WoWMoM'18**]*
  - Cache contents that can be recommended *e.g., [**Globecom'17, JSAC'18**]*
  - Jointly decide caching and recommendations *e.g., [**INFOCOM'16**]*



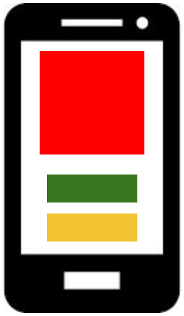
Caching & Recommendation: An example



Initial Recommendations:
- Blue content
- Yellow content



Biased Recommendations:
- Green content
- Yellow content



Caching & Recommendation: An example

Initial Recommendations

Biased Recommendations

Caching & Recommendation: An example

Initial Recommendations

Biased Recommendations

Limitations (or, challenges) & Contributions

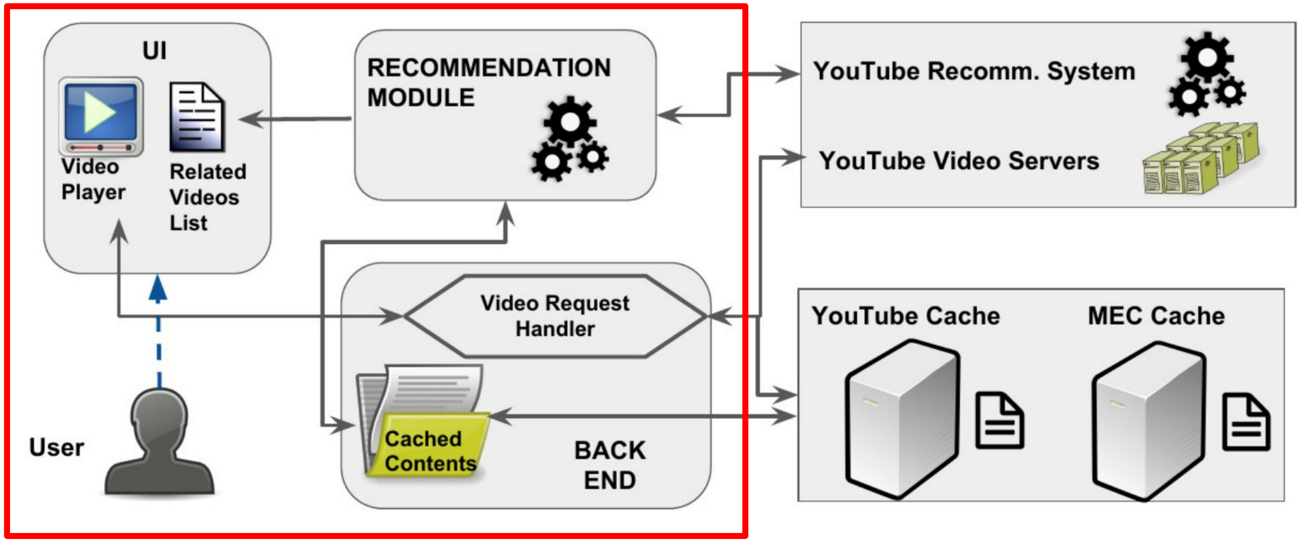
- Joint caching and recommendation, needs control / information about:
  - cached contents (i.e., caching)
  - content relations / user preferences (i.e., “good” recommendations)

- **Who controls recommendations?** → content provider
- **Who controls caching?**→ network operator *or* content provider *(e.g. MVNO)*
- **Who cares about network load?**→ network operator

→ Existing approaches for joint caching and recommendation, require collaboration between network operator & content provider

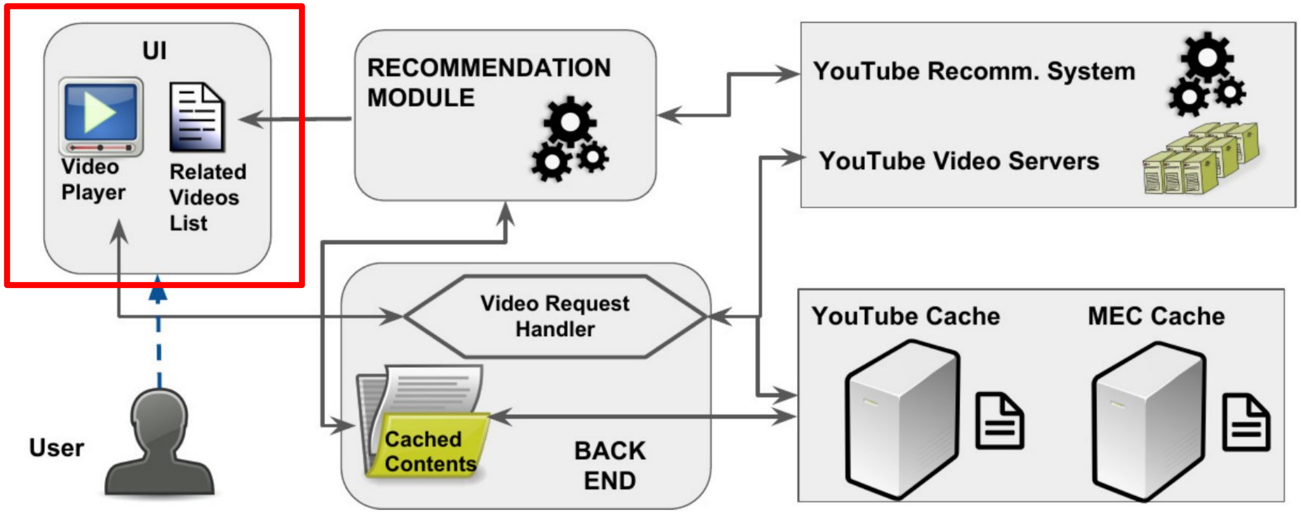
Our approach / contributions
- only network operator, without collaboration with content provider
- practical system & recommendations *(i.e., we did a prototype, it works!)*
- performance evaluation with experiments *(i.e., it works well!)*

System overview



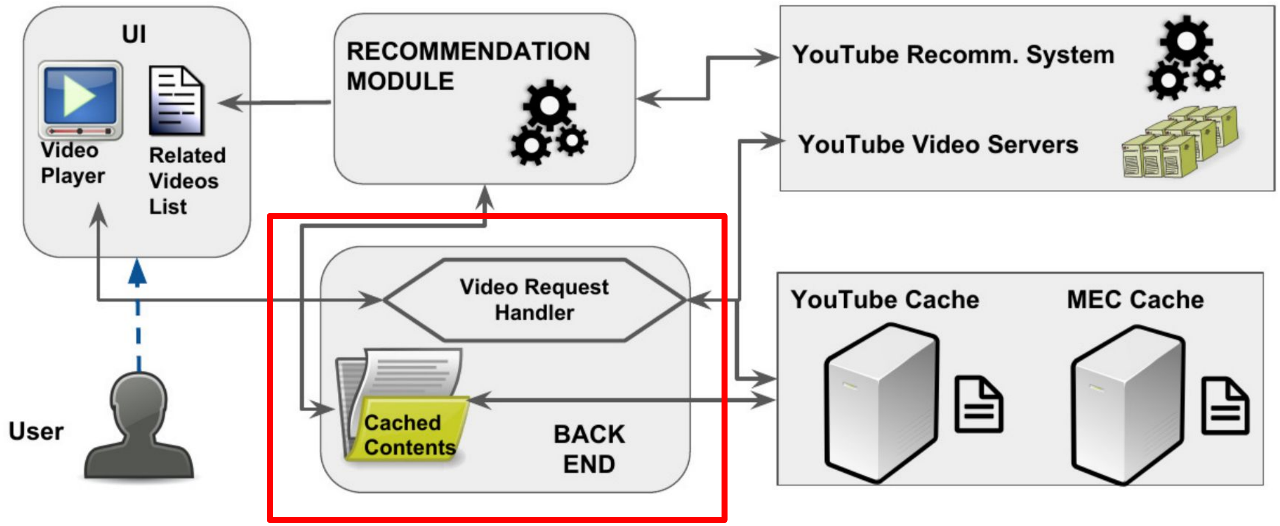
- Lightweight system (e.g., mobile app)
- Run only by the network operator (or, even the user)
- Here we focus on YouTube, but it can be generic (for Netflix, Spotify, etc.)

System overview: User-Interface



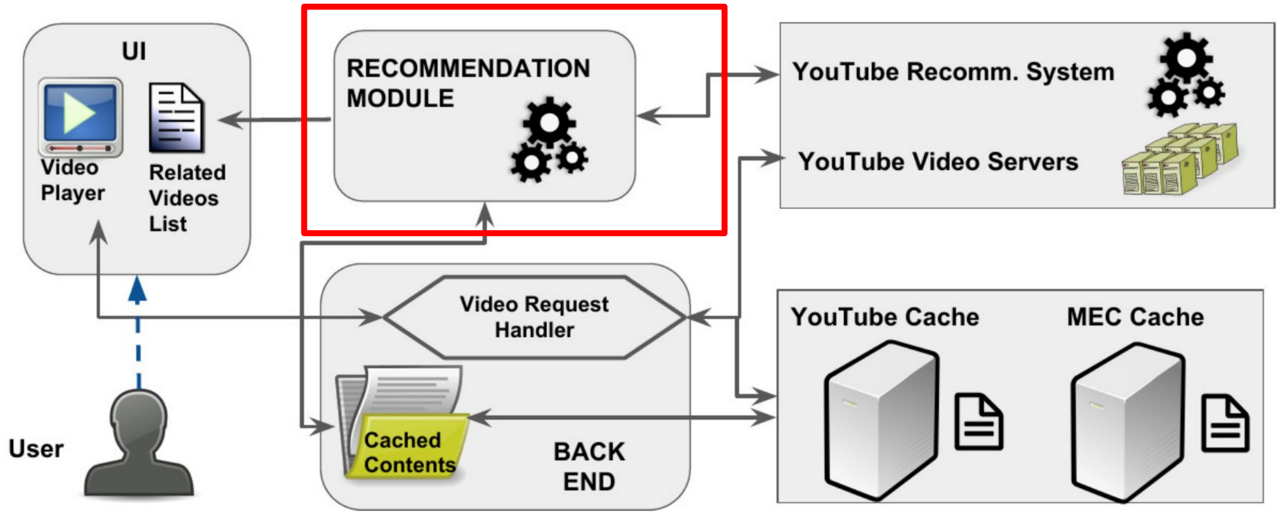
- **User-Interface (UI)**
  - search bar
  - video player
  - recommendations list
  - etc.

System overview: Back-end



- **Back-end**
  - retrieve list of cached video IDs
    (e.g., from network operator or content provider)
  - stream videos to UI

System overview: Recommendation module



- **Recommendation Module**
  - retrieve <u>publicly available information</u> → i.e., no collaboration (from the content provider's recommendation system, e.g. ,YouTube API)
  - retrieve the list of cached contents (from the back-end)
  - build a new recommendation list of ***related & cached contents***

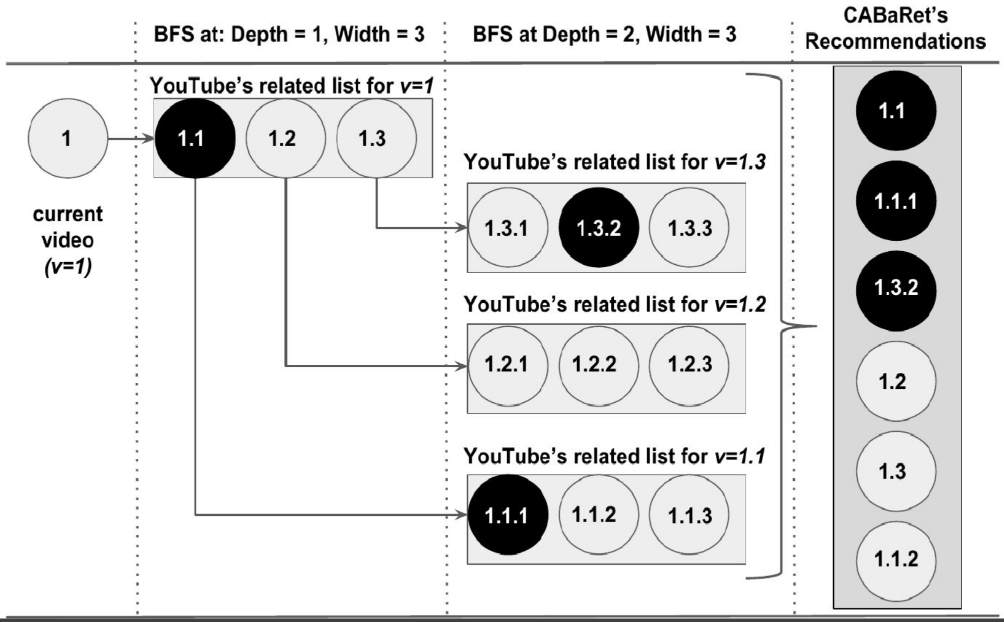
Recommendation module: CABaRet

The recommendation algorithm (CABaRet)

1. a user watches a video ***v***
2. retrieve from the YouTube API the list of videos related to ***v****; let this list be* ***L***
3. for each videos in ***L***, retrieve its related videos, and add them to ***L***
4. final list ***L***: contains many videos (directly or indirectly) related to ***v***
5. retrieve the list of cached videos ***C***
6. recommend ***N*** videos that are both in ***L*** (i.e., related) and ***C*** (i.e., cached)

breadth first search (BFS)

CABaRet: example
($D_{BFS}=2$, $W_{BFS}=3$, $N=6$)



CABaRet characteristics

- Input: video ***v***, BFS depth ***D*** *and* width ***W***, #recommendations ***N***
- Output: list of recommended videos ~ $L \cap C$

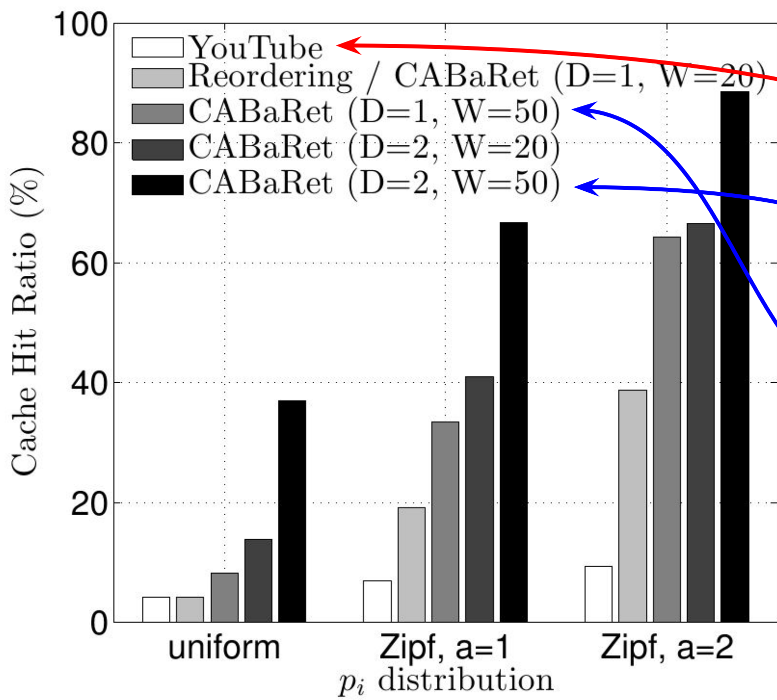
- **Tuning**
  - we want large ***L*** → more videos, more options for recommendations
    - $|L| = W + W^2 + \ldots + W^D$ *(e.g., W=50, D=2 → |L|=2550)*
    - larger ***W, D*** →larger ***L***
  - we want "good" recommendations
    - larger ***D*** → videos less related to ***v***

- **High-quality recommendations**
  - ***D=1***: <u>directly</u> related/recommended videos
  - ***D=2***: <u>indirectly</u> related videos ... e.g., if a→b and b→c, then a→c

W	10	20	50
Related videos overlap (at ***D=1*** and ***D=2***)	70%	85%	92%

Performance evaluation

- Experiments over YouTube service
  - **Caching**: top ***C*** most popular contents in a region
  - **Recommendations**: YouTube or CABaRet with ***W*** and ***D***
  - **User demand:** starts from a popular content, and follows one of the ***N*** recommendations; *uniformly* or preference to order of appearance (*Zipf*)



- CHR (YouTube) **5-10%**
- CHR (CABaRet, W=50, D=2) **35-90%**
  → up to **8-10 times higher** CHR than YouTube

- Even for ***D=1*** (high recommendation quality)
  - **2-6 times higher** CHR than YouTube
  - **~2 times higher** than Reordering [ToMM'15]

CABaRet + Caching optimization

- What if the network operator controls caching as well?
  - Further improvement in CHR
  - How? → optimize caching + then apply CABaRet recommendations

Optimization problem

- for a content ***v***: CABaRet calculates ***L(v)*** and recommends ***{L(v)}∩{C}***
- find ***C*** that maximizes CHR, i.e., ~ ***{L(v)}∩{C}*** *for all **v***

Optimization algorithm

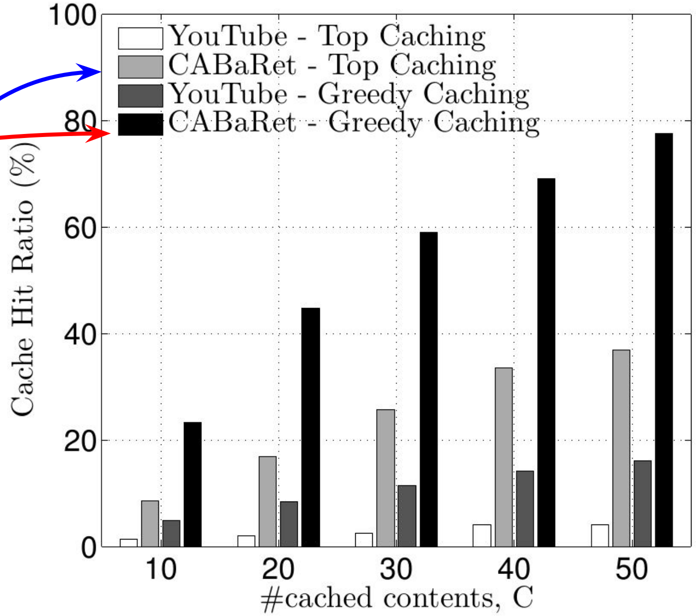
✘ NP-hard problem (max set cover)

✔ submodular + monotone

- greedy algorithm: (1-1/e) approximation

CABaRet + Caching optimization: Results

- Parameters: ***N=20, uniform, W_{BFS}=20 , D_{BFS}=2***
- CABaRet: Greedy caching vs. Most popular caching
  - more than **2 times higher** CHR



Total gains:

- CABaRet vs. YouTube: **8-10 times higher** CHR
- CABaRet + greedy vs. YouTube: **2*(8-10) times higher** CHR

Summarizing...

The problem

- Caching alone is not enough → leverage recommendation systems
- Existing approaches require collaboration of network operator & content provider

The contributions

- Our approach: enable caching & recommendation by the network operator
  - no collaboration with the content provider (only public information)
- Practical recommendation algorithm: CABaRet
- Significant gains in practice (experiments over YouTube)
  - **8-10 times** higher CHR due to recommendations
  - extra **2 times** higher CHR due to caching

Future work

- Experiments with real users:
  - **“Can you tell the difference between YouTube and CABaRet recommendations?... do you like them?”**
  - Test it here!!

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