Online Ranking: At each round, the learner produces an ordered list of items, then suffers loss or receives reward. *Example: search result ranking*



In this paper, loss is:

the number of items needed to achieve some coverage objective *Example:* The cost at each round is the number of pages the user needs to view to deduce the complete information they desire.

Repeated Active Learning is an interesting special case where the list consists of questions to ask or tests to perform. *Example: diagnosis*



Here a reasonable loss is the number of the tests we need to perform before we can make a accurate diagnosis.

For these applications we propose a new online learning problem we call **online submodular set cover**.

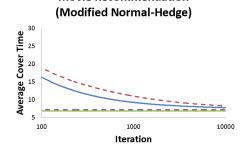
- At round t we pick a sequence $S^t = v_1, v_2, \dots v_n$.
- A monotone, submodular objective F^t is then revealed.
- We pay cost equal to the cover time of F^t : the minimum value $c \in \{1, 2, ... n\}$ such that $F^t(\bigcup_{i=1}^c \{v_i\}) \ge 1$.

Example: $F^t(S)$ is proportional to the number of candidate diseases eliminated by the set of tests S.

Related but not equivalent to online submodular maximization and online min-sum submodular set cover (Streeter and Golovin, 2008)

Our results:

- A low-regret algorithm for online submodular set cover, building on a recent offline algorithm of Azar and Gamzu.
- Extensions to handle multiple objectives, partial information, context.
- Experimental results on synthetic data and a movie recommendation repeated active learning problem.



Movie Recommendation

- Online Cumulative
- Offline Adaptive Residual
- Offline Cumulative