Introduction

- We combine different image retrieval interactions to allow faster image search.
- We use a reinforcement learning approach which dynamically decides how to combine: drawing a sketch, providing free-form attribute feedback, or answering attribute-based questions. Our system optimizes informativeness and exploration capabilities for fast and accurate image retrieval.
- Our approach outperforms three different baselines on three datasets.
- We discover the RL agent prioritizes human-initiated feedback and complements it with machine-initiated feedback later in the search cycle.

Motivation

- In prior work, the way to guide the image retrieval is with feedback initiated by either the user (Kovashka et al., CVPR 2012) or system (Ferecatu and Geman, TPAMI 2009; Kovashka and Grauman, ICCV 2013), but not both.
- Lack of prior work to jointly explore textual and visual feedback.
- Is there an intelligent way to combine user and system interactions with multimodal feedback?

Approach

Reinforcement learning agent

- We formulate reinforcement learning as a Markov decision process (MDP).
- Actions: attribute-based and sketch-based feedback
- State: history of positive and negative proxies of the target image, current top images and actions. Image is represented using features from AlexNet.
- Rewards:
  - Distance to positive proxies should decrease.
  - Distance to negative proxies should increase.
  - Assign a negative rewards if sketch action is queried more than once.

Learning:

- We use Q-learning, which receives a state and predicts the best action.
- We employ a neural network with convolutions, because they capture information about image features and ordering.
- We follow a replay-memory mechanism to collect many instances as the agent is running. It is also useful to remove short-term correlation and makes our algorithm more robust and stable.
- We generate random actions with probability decreasing from 1 to 0.1 as training progresses. Random actions are useful at initial stages to explore the problem. Later on, this information is exploited by the agent.

Evaluation

- We first conduct simulated experiments, where we compare our reinforcement learning method with three different baselines using percentile rank (higher is better):
  - Whittle Search (WS): In each iteration, users select a (reference image, attribute) and compare target and reference for the chosen attribute ("more / less / equally").
  - Pivot round-robin (PRR): In each iteration, PRR provides a (reference image, attribute) pair and users select a more / less / equally response.
  - Sketch retrieval + Pivot round robin (SK_PRR): In the first iteration, we ask for a sketch. In later iterations, the system follows the pivot round-robin strategy.

- We also conduct live experiments, where we recruit university and Amazon Mechanical Turk participants to conduct 100 searches total via a web interface.
  - Our RL agent queries the next action using a REST API.
  - We only run experiments for Shoes because there were no appropriate sketch annotations for Pubfig and Scenes.
  - We verify the benefit of our adaptive feedback strategy in this realistic scenario.

Evaluation

- In order to understand the success of our approach, we visualize some generated sketch-to-image conversions, show the predicted actions on our test split, and finally we present some sketches provided by live users.

Summary and contributions

- We explored choosing interactions in a mixed-initiative image retrieval system. Our approach selects the most appropriate interaction per iteration using RL.
  - Our model prefers human-initiated feedback in early iterations, and complements it with machine-based feedback requests (i.e. questions) in later iterations.
  - We outperform standard image retrieval methods with simulated and real users.