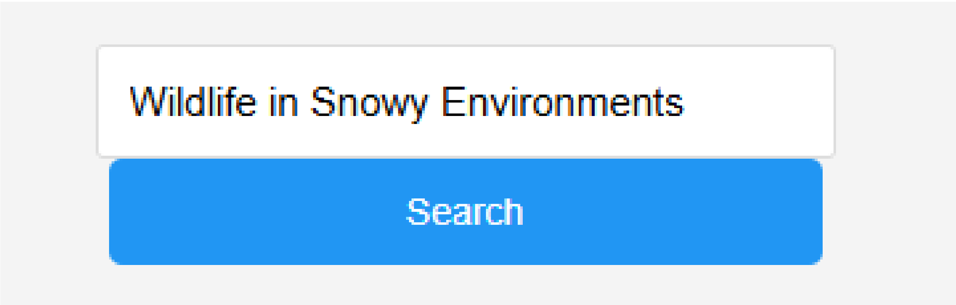
A Comparative Demonstration of Relevance Feedback Methods for Image Retrieval

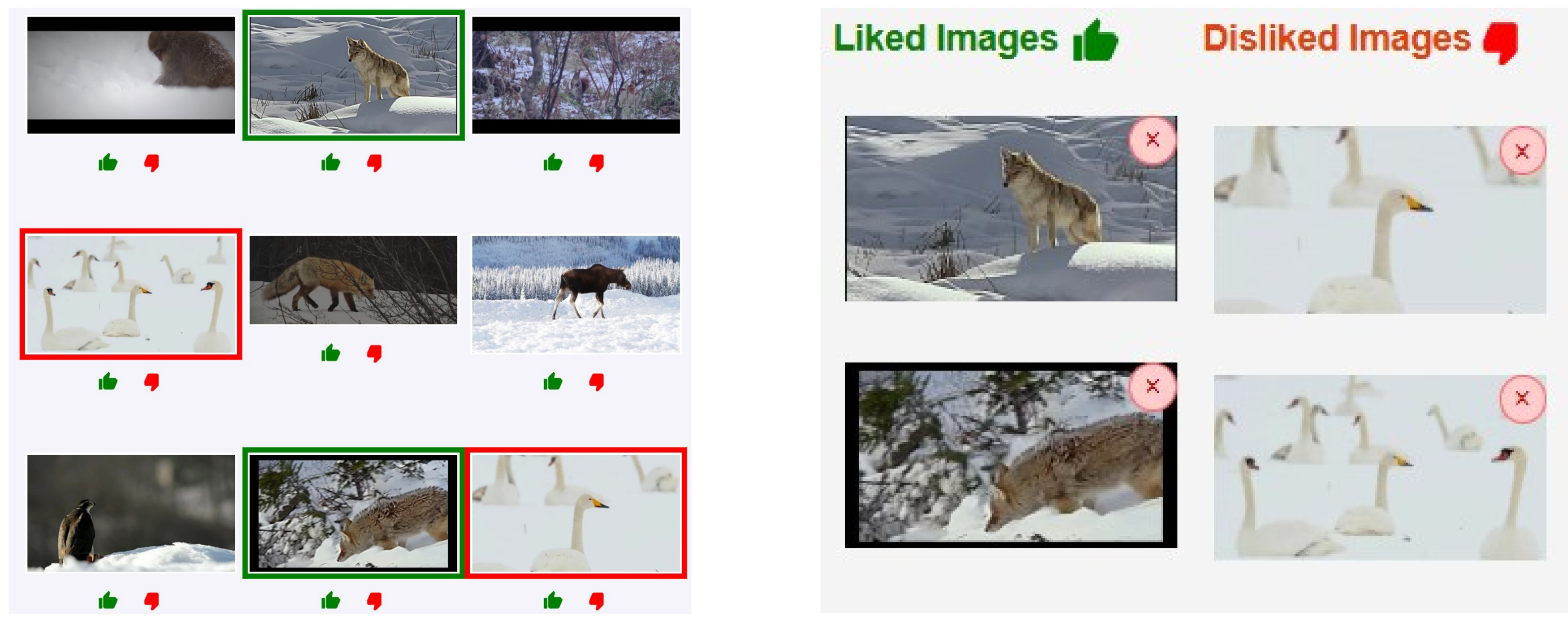
Francesca Scotti, Lucia Vadicamo, Giuseppe Amato and Fabio Carrara

Institute of Information Science and Technologies (ISTI), CNR, Italy

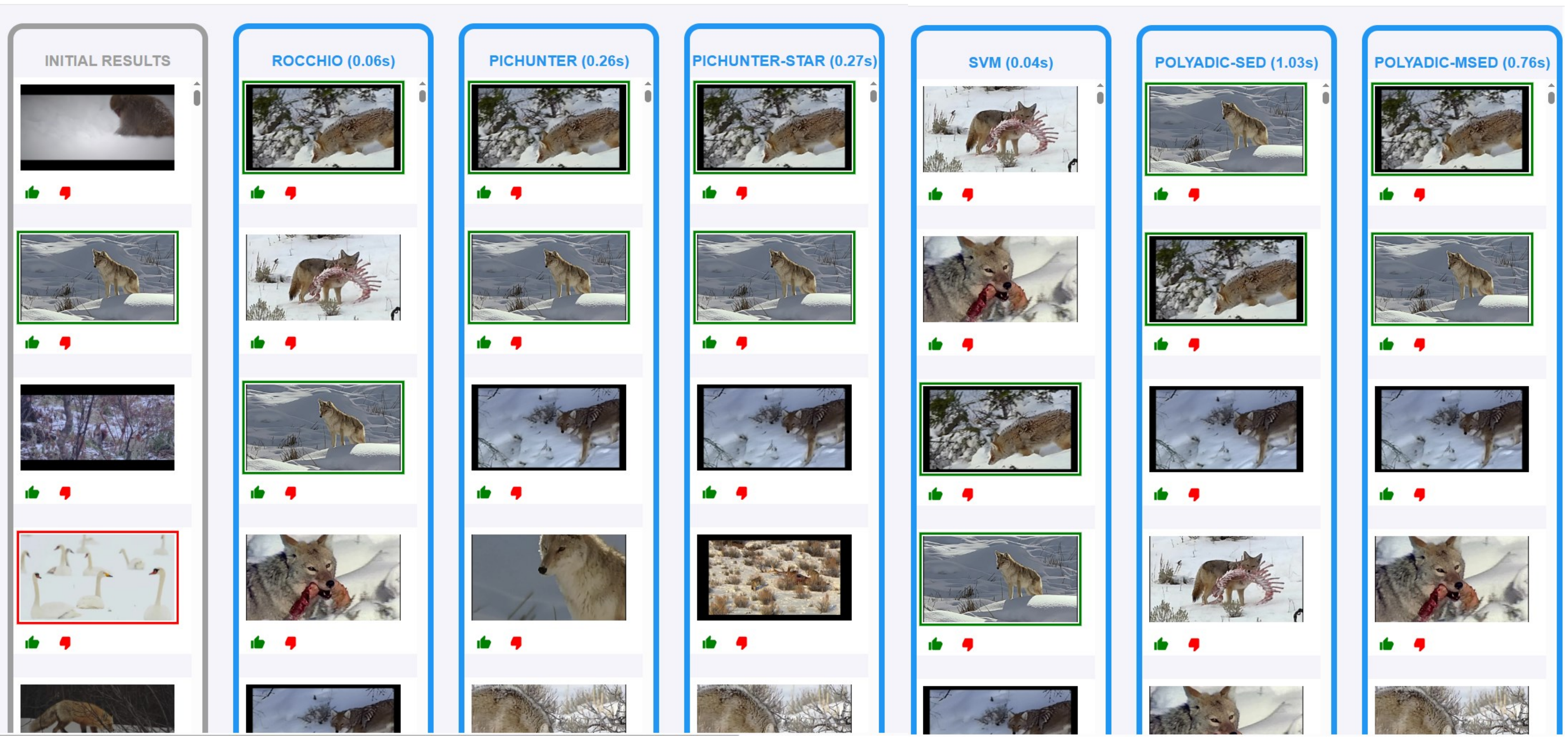
Enter initial query



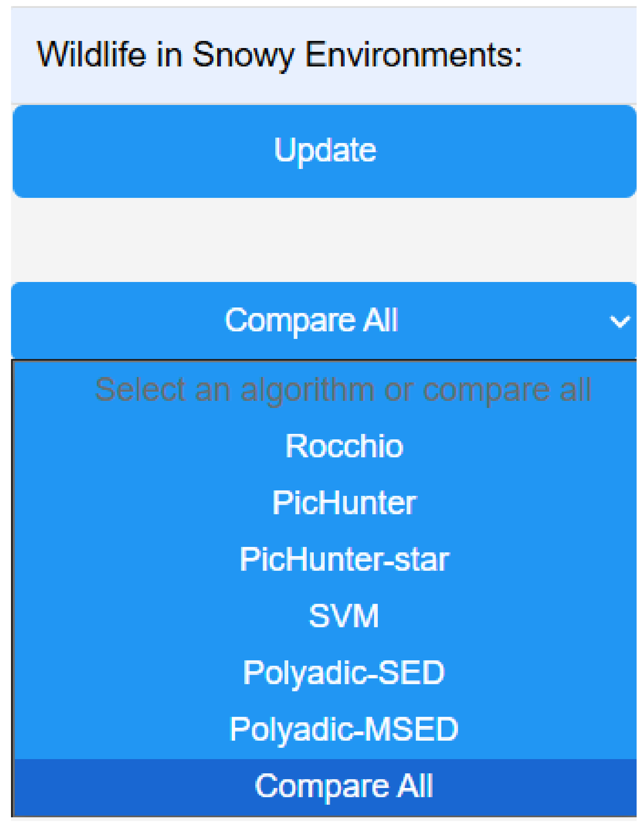
Select relevant and non-relevant images from the shown results



The process is iterative; the user can select more images or remove previous selection and update the results



Choose a specific relevance feedback algorithm, or «Compare All»



Rocchio

Adjust the query vector closer to relevant examples, farther from non-relevant ones.

$$q_{new} = \alpha q_t + \beta \frac{1}{|A^+_{\le t}|}\sum_{x^+\in A^+_{\le t}} x^+ \; - \gamma \frac{1}{|A^-_{\le t}|}\sum_{x^-\in A^-_{\le t}} x^-$$

A_t^+ =positive examples iter t

A_t^- =negative examples iter t

$A^\pm_{\le t} = \bigcup_{i\le t} A_i^\pm$

PicHunter

Updates posterior probability $\boldsymbol{P(T = o_i \mid H_t)}$ based on user feedback after displaying a set of images D_t, using the Bayes' Theorem.

$$\boldsymbol{P(T = o_i \mid H_t)} = \frac{\boldsymbol{P(A_t|T = o_i, H_{t-1}, D_t)}\, P(T = o_i|H_{t-1})}{\sum_{j=1}^{n} \boldsymbol{P(A_t|T = o_j, H_{t-1}, D_t)} P(T = o_j|H_{t-1})}$$

$$\boldsymbol{P(A_t|T = o_i, H_{t-1}, D_t)} = \prod_{o_j\in A_t^+} \boldsymbol{P_{softmin}}\left(A_t^+ = o_{j_a} \,\middle|\, T = o_i, D_t\right)$$

User Model

$\boldsymbol{H_t}$ = History of display and actions

$\boldsymbol{T}$ = Target image random variable

$$\boldsymbol{A_t} = \boldsymbol{A_t^+}$$

PicHunter★

$$P(\boldsymbol{A_t}|T = o_i, D_t) = \prod_{o_j\in A_t^+} P_{softmin}(A_t^+ = o_{j_a}|T = o_i, D_t) \prod_{o_j\in A_t^-} P_{softmax}(A_t^- = o_{j_a}|T = o_i, D_t)$$

User Model

$$\boldsymbol{A_t} = [A_t^+, A_t^-]$$

SVM

A_t^+ and A_t^- are used to train a linear SVM. The k most relevant images shown in the next iteration are the **farthest** (most confident) from the SVM hyperplane on the relevant side.

Polyadic

The k images with highest score ρ are shown in the next iteration. SED and MSED are information distance measures.

$$\rho_{t+1}(o_i) = \alpha\rho_0(o_i) + \beta s(\boldsymbol{A^+_{\le t}}, o_i) - \gamma s(\boldsymbol{A^-_{\le t}}, o_i)$$

$s = 1 - d$, where d is computed using SED or MSED

$$d_{MSED}(\mathrm{A}, o) = MSED(\{f(\mathrm{x}_1), f(x_2), \dots, f(x_m)\} \cup \{f(o)\})$$

$$d_{SED}(\mathrm{A}, o) = \mathrm{SED}\left(\sum_{x\in A} \frac{f(x)}{|A|}, f(o)\right)$$

$f = softmax$

$$MSED(V) = \frac{1}{m-1}\left(\frac{C\left(\frac{1}{m}\sum_{v_i\in V} v_i\right)}{\sqrt[m]{\prod_{v\in V} C(v_i)}} - 1\right)$$

$$SED(\boldsymbol{v}, \boldsymbol{w}) = \frac{C\left(\frac{\boldsymbol{v}+\boldsymbol{w}}{2}\right)}{\sqrt{C(\boldsymbol{v})C(\boldsymbol{w})}} - 1$$