II-20: Intelligent and pragmatic analytic categorization of image collections

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Abstract—In this paper, we introduce II-20 (Image Insight 2020), a multimedia analytics approach for analytic categorization of image collections. Advanced visualizations for image collections exist, but they need tight integration with a machine model to support the task of analytic categorization. Directly employing computer vision and interactive learning techniques gravitates towards search. Analytic categorization, however, is not machine classification (the difference between the two is called the pragmatic gap): a human adds/redefines/deletes categories of relevance on the fly to build insight, whereas the machine classifier is rigid and non-adaptive. Analytic categorization that truly brings the user to insight requires a flexible machine model that allows dynamic sliding on the exploration-search axis, as well as semantic interactions: a human thinks about image data mostly in semantic terms. II-20 brings three major contributions to multimedia analytics on image collections and towards closing the pragmatic gap. Firstly, a new machine model that closely follows the user’s interactions and dynamically models her categories of relevance. II-20’s machine model, in addition to matching and exceeding the state of the art’s ability to produce relevant suggestions, allows the user to dynamically slide on the exploration-search axis without any additional input from her side. Secondly, the dynamic, 1-image-at-a-time Tetris metaphor that synergizes with the model. It allows a well-trained model to analyze the collection by itself with minimal interaction from the user and complements the classic grid metaphor. Thirdly, the fast-forward interaction, allowing the user to harness the model to quickly expand (“fast-forward”) the categories of relevance, expands the multimedia analytics semantic interaction dictionary. Automated experiments show that II-20’s machine model outperforms the existing state of the art and also demonstrate the Tetris metaphor’s analytic quality. User studies further confirm that II-20 is an intuitive, efficient, and effective multimedia analytics tool.

Index Terms—Multimedia analytics, image data, analytic categorization, pragmatic gap

1 INTRODUCTION

The growing wealth and importance of multimedia data (images, text, videos, audio, and associated metadata) is evident. The ability to process them meaningfully and efficiently has become crucial for an increasing number of scientific and commercial domains, e.g., media and news, forensics, security, marketing, and health. The ubiquity and availability of cameras have made casual multimedia content more important than ever. Social networks are a multi-billion dollar industry and user-contributed content is a valuable resource. Visual data (images and videos) are at the core of the multimedia explosion and there is a great need for advanced analytics of visual data collections.

In recent years, our ability to automatically process large volumes of visual data has improved greatly. The chief reason is the dramatic increase of the semantic quality of machine feature representations, spearheaded by deep neural networks [23]. In many tasks, deep nets approach or even surpass a human’s ability to accurately label images, e.g., in object recognition (given equal noise levels during training and testing) [11]. Indeed, the semantic gap [34] has been closed for many
to multimedia analytics and is rapidly closing for others. The quality and accessibility of advanced classifiers and indexing techniques have entrenched the search engine as the golden standard for analyzing image collections. However, not all multimedia analytics tasks boil down to just search. In a general analytics task on multimedia data, the user dynamically oscillates between exploration and search on the exploration-task axis \( [44] \). Examples of tasks that are not purely search include:

- **Structuring the collection** — make sense of what is in a collection with unknown contents, and structuring it based on multiple categories of relevance.
- **Finding needles in the haystack** — in a collection with only a small portion of relevant items, find them based on complex, often domain- and expertise-dependent semantics.

For example, a forensics analyst trying to establish whether there is criminal content on a suspect’s seized computer.

- **Subjective/highly contextual content retrieval** — labeling of the content into categories which can only be defined by the user as they are subjective or contextually defined.

In this case as the notion of relevance cannot be defined beforehand or grounded objectively, the content-based indexes have trouble matching the user’s input to their dictionary. An example here is “show me art that I like” which does not match predefined content labels very well.

The need to support varied tasks can be addressed by employing the visual analytics approach, supporting knowledge/insight gain by tight integration of advanced visualizations with a machine model \([2][22][32]\). Image collection analytics belongs to multimedia analytics \([5]\), which has a number of specifics: among others, strong focus on semantics, high information bandwidth, and difficult summarization.

In general, multimedia analytics tasks can be modeled as analytic categorization, in which the user defines the categories of relevance herself on the fly, and the model adapts to them as the session progresses \([44]\). This is very different from the classic machine learning definition of classification, and the difference between the two is the pragmatic gap \([44]\). Analytic categorization requires support for multiple categories of relevance at once, creating/defining/deleting categories on the fly during the analytic session, and strong emphasis on interactivity: the user interactions drive the categorization and vice versa, and they complete in interactive time (low seconds at most). New visualizations and models built specifically around tight integration of the two and support of analytic categorization are needed.

There are approaches that incorporate interactive model building to cover a wider range of the exploration-search axis. To advance the analytic session, they usually make use of a rich set of filters on the data (e.g., \([1][19][20][38][39]\)), an interactive (multimodal) learning model (e.g., \([13][39]\)), or a combination of both. Whilst these techniques go beyond mere search, on the exploration-search axis, they tend to lean towards search anyway: they simply fetch what the users are looking for or what they found relevant previously. To date, multimedia analytics retains an hourglass interface-model structure: a wide array of visualizations on the one hand, a wide array of automatic multimedia analysis techniques on the other, and a narrow set of interactions between the two — filter, search, interactive learning (relevance feedback, active learning).

To enable meaningful interaction, semantic interactions are vital to multimedia analytics. Semantic interactions translate user interactions performed on high-level visual artifacts in the interface to low-level analytic model adjustments, coupling cognitive and computational processes \([9]\). The user does not train the model and adjust its parameters directly, but rather interacts within her domain of expertise, and the model uses those interactions to improve itself. Developing new ones and thus widening the hourglass would certainly improve multimedia analytics capabilities further.

To address the above challenges, we present II-20 (Image Insight 2020), a multimedia analytics approach for image collections that brings the following contributions:

- **A new analytic categorization model** that supports multiple categories of relevance at once and dynamically slides on the exploration-search axis without requiring any extra effort from the user. The model is fully interactive even on large (> 1M) datasets and metaphor-agnostic. To the best of our knowledge, II-20’s model is the first model to fully support analytic categorization of image collections.

- The Tetris metaphor based on the eponymous game that streams the images in one-by-one, with the user steering them to the correct categories of relevance. As the model learns, it starts playing the Tetris game by itself with the user only correcting the model’s mistakes. The metaphor is tightly integrated with the model with a clear benefit to the user: the number of interactions required from her is inversely proportional to the quality of the model whilst providing the same or better analytic outcome.

- The fast-forward interaction that allows the user to swiftly categorize a large number of images at once based on the current state of the model.

The rest of the paper is organized as follows. Sect. 2 overviews the related work. Sect. 3 describes II-20. Sect. 4 outlines the experimental setup, results are discussed in Sect. 5. Sect. 6 concludes the paper.

### 2 Related work

Analytic categorization of image collections is iterative, requiring tight and well-oiled integration between the visual metaphor and the machine model that suggests relevant images to the user. This is in line with the established general visual analytics theory \([21][22][29][32]\). As discussed in the introduction, to truly support analytic categorization as a task, we must enable semantic interactions (this challenge is shared with general visual analytics \([9]\)), allow dynamic sliding on the exploration-search axis, and close the pragmatic gap \([44]\). In this section, we review related work on the constituent parts of a multimedia analytics system (interface and model) and on means of integrating the two, bearing the specific challenges of visual and multimedia analytics in mind.

There is a great variety of visual metaphors for analytics of image collections. The classic, time-tested approach used by the vast majority of systems visualizing image collections is the grid. Grids score near-perfectly on efficiency of screen space utilization and are very intuitive. They can be enhanced so as to convey collection structure \([13][30][45]\). Beyond grids, there are many other visual metaphors for image collections, such as spreadsheet-based that integrate the image content tightly with metadata \([7][19][39]\), semantic-navigation-based that allow the user to pursue threads of interest, often semantic \([48]\), or even metadata-driven \([17][20]\). The rapid serial visual presentation (RSVP) approaches present images dynamically, flashing images or video clips in a fast-paced manner, with the user providing a simple, rapid response \([14][35][36]\). There are plenty of visual metaphors to choose from, with various niches.

Models supporting multimedia analytics can be split roughly into two groups (hybridization possible): index-based and interactive-learning-based. Index-based techniques involve precomputing a collection index which is used for filtering and/or search queries. The basic, yet still effective approach is the metadata-based index. Content-based indexing requires extraction of features and/or concept labels from raw image data, and the contemporary computer vision standard is to use deep convolutional neural networks \([23]\). The features (esp. semantically meaningful ones, such as concept labels) can be used as additional metadata (e.g., \([38]\)) or to build a content-based index to fuel search capabilities. Indexing approaches include clustering-based approaches such as product quantization \([17]\) or extended cluster pruning \([13]\), and hash-based approaches \([2]\), especially those based on locality-sensitive hashing \([6]\). The current state of the art in indexing offers a broad range of techniques that establish a semantic structure of the collection.
Relying on indexing alone in multimedia analytics, however, reduces analytics to just search. The model is rigid, does not adapt to the user, and hence does not address the pragmatic gap.

Interactive-learning-based approaches collect feedback from the user in the form of explicit “relevant” and “not relevant” labels, then train a new model based on those labels, rank the data according to the new model, and suggest more relevant items. The entire interaction round should happen in interactive time. Following visual analytics theory [15], this means operating in the real-time (<0.1 s latency) or direct manipulation (0.1 – 2.3 s) regime. There are two dominant approaches. Firstly, relevance feedback [47], which suggests images that are most relevant according to the model. Secondly, active learning [13], which suggests the model is least sure about w. r. t. relevance. This maximizes the model’s learning gain and minimizes the number of user interactions. Algorithmically, most of the techniques come from the 2000s (the aforementioned surveys provide a good overview). In the 2010s, interactive learning struggled with the rapid increase in data scale. Recently, interactive learning has been improved to work on modern large-scale collections by introducing efficient compression [41] and clustering [18]. Interactive learning is adaptive and flexible: it learns solely, explicitly, and dynamically from the user, making it a good fit for closing the pragmatic gap. On its own, however, interactive learning still gravitates towards search, and is limited by latency: there is only so much that can be computed in interactive time.

In the 2000s and 2010s, there have been a number of successful systems that integrate advanced visualizations with machine learning-based models in both visual analytics [10] and multimedia analytics [44]. Moreover, visual analytics has been employed to explain machine learning models. A recent notable instance of this is the effort to explain deep neural networks [16]. Most of the visual analytics systems revolve around direct manipulation of the machine learning model by the user, which is useful for the data scientist, but might be difficult for an analyst who is not a machine learning expert or statistician. The multimedia analytics, where semantic navigation is of paramount importance, usually operate with a narrow semantic interaction dictionary: “filter”, “search” (by example, by text query...), and “perform interactive learning”. Additional semantic interactions would definitely be a big boon for both visual and multimedia analytics [9,44].

As discussed in the introduction, II-20 brings three main contributions. II-20’s machine model combines the advantages of index-based and interactive-learning-based approaches. By flexibly supporting dynamic sliding on the exploration-search axis, it is to the best of our knowledge the first model closing the pragmatic gap [44]. The Tetris metaphor, beyond expanding the family of metaphors for image collections, has a tighter integration with the model than others, decreasing the number of interactions as the model improves. Finally, the fast-forward interaction expands the semantic interaction dictionary, answering a clear visual and multimedia analytics research challenge [7,44].

3 II-20

II-20 is tailored for full support of analytic categorization, defined as the task of assigning images 1, ..., n from the collection I into analytic categories, which we henceforth call buckets consistently with the terminology introduced in related work [7,39]. The machine model requires the images to be represented with a machine-readable representation that preserves semantics.
discards the non-relevant ones, the model learns from those interactions and provides relevant image suggestions. In addition, II-20 provides a small number of exploration candidates not tied to any particular bucket to increase coverage of the exploration-search axis.

The grid image view (Fig. 3) is the static, batch mode showing multiple images at once. Due to the familiarity of the grid metaphor, it is II-20’s default image view mode. The grid view is integrated into the model rather loosely: it waits for the user’s explicit feedback (the user selects the bucket to be labelled and the images to be assigned there) and explicit instructions to recompose the grid and show more images. Image suggestions for a bucket appear with a dashed border in the bucket’s color with brightness proportional to bucket confidence (the brighter, the more confident the model). The grid is resizable, so the user can choose to see more images or more detail. The user can also preview individual images by right-clicking them in the grid.

3.1.2 Tetris metaphor
In addition to the classic grid, the image view offers the new Tetris metaphor (shown in Fig. 1). Tetris complements the grid: it is a dynamic, 1-image-at-a-time metaphor with very tight integration to the model: in fact, a good model is able to steer the analytics autonomously in a way that is easily monitored by the user. The Tetris metaphor, inspired by the famous game, operates as follows: images flow from the top one at a time, and descend to one of the buckets in the bucket banner. When an image reaches the bucket, it gets assigned to it, the model processes the assignment, and the next image starts flowing from the top. The user can steer the images between buckets by pressing the left and right arrow keys, pause the flow by hitting spacebar and increase/decrease the descent speed by hitting the down and up arrow, respectively. Speed and pause/play can also be controlled by the respective buttons in the control panel.

The model will mostly suggest images for the buckets that are active. These flow in already positioned above their suggested bucket, connected to the bucket by a line in the bucket’s colour. Exploration suggestions appear over the discard pile without a connecting line to any bucket: they tend to be from previously unseen areas of the collection, so whilst providing exploration directions, they are likely incorrect.

Tetris has the following key strengths:

- **Decreases the number of required interactions as the model quality increases** — a well-trained model simply feeds images into the correct bucket on its own and the user interacts only once in a while to correct wrong suggestions. To the best of our knowledge, II-20’s Tetris is the first image analytics metaphor with this degree of integration with the model, which results in a clear benefit for the user.

- **Lower number of processed images in total** — since in the Tetris mode, the model learns incrementally and the image view only shows the top relevant image, the user needs to process a lower number of images in total to get the same number of relevant images. In other words, the Tetris metaphor reaches the same or higher precision and recall growth compared to the classic grid (we evaluate this claim in the experiments).

- **Complements the grid** — a grid shows a lot of images at once statically, Tetris is a dynamic mode focusing on 1 image at a time. Therefore, one has the potential to cover the weaknesses of the other, as well as being a possibly well-compromised choice of pace (working with one metaphor for too long might be perceived as tedious).

Each bucket has an entry in the bucket control panel (the top part of the control panel). Bucket deactivation is useful whenever the user wants to focus on something else for the moment and return to the bucket in the future. A bucket can be deactivated by clicking its name or icon. This will remove the bucket from the bucket banner, gray it out in the control panel, and the model will not provide suggestions for that bucket. However, the bucket will be preserved and the user can reactivate it by clicking the icon/name again at any time.

The eye button next to the bucket name in the control panel opens up the bucket view, showing all bucket images in a grid. The grid can be switched between 3 (default) and 1 images per row, toggling between more images on the screen and more details per image, respectively. The brightness of an image border is proportional to bucket confidence (the brighter, the more confident the model is). The bucket view allows sorting by bucket confidence and by the time the image was added to the bucket (newest/oldest first). Finally, the bucket view allows transfer of images between buckets - images can be selected by clicking on them, and then moved or copied to another bucket.

In addition to the role it plays for the image view metaphors, the bucket banner serves as a quick overview of the state of the buckets. It shows the number of images in the bucket, as well as the bucket confidence and bucket total size. Images can be sorted by bucket confidence and by the time the image was added to the bucket. The user can thus quickly gauge if the model understands well what she means by her bucket definition.

3.2 Machine model
II-20’s model’s pipeline for suggesting relevant images is depicted in Fig. 3. The core (employing just the black-coloured steps) is simply the interactive learning pipeline. II-20’s model enhances this pipeline significantly, producing exploration and search suggestions dynamically by monitoring its own performance, all without the user having to specify whether she wants to explore or search.

3.2.1 Data structures
To extract image features, we use the ImageNet Shuffle deep neural network [25] with 4437 concepts (classification labels representing visual presence of nouns in the image) providing rich semantic descriptiveness. We extract two feature representations: the concept representation with the 4437 concepts, i.e., recording the output of the output layer, and the abstract representation with the output of the second fully-connected layer containing 1024 denser, but abstract features that encode the same semantic information (meaningless to the user, but suitable for indexing). The features are used to construct two key data structures.

Firstly, the **collection index**, which establishes an efficient and fully interactive semantic similarity structure on the collection. To compute the index, we employ product quantization [17] on the abstract representation, splitting the 1024 features into 32 submatrices of 32 features each (setting \(m = 32\)) and setting \(k = \min(1024, \sqrt{n})\), where \(n\) is the number of images in the collection.

Secondly, the **interactive learning representation** built using Blackthorn [11]. We use the 4437 concepts feature representation, compressed using the Blackthorn compression method set to preserve the top 25 concepts by value per image. This number is deliberately larger than the recommendation of 6 [41] due to our chosen concept dictionary size \(\sim 4\times\) the size of theirs. The resulting sparse representation preserves most of the image semantics and reduces the size by more than 99 percent. II-20’s prototype uses the scikit-learn module [25] that supports sparse matrices, resulting in high computational efficiency with no further implementational requirements.

3.2.2 Model components
To cover the entirety of the exploration-search axis, II-20’s model has three components capable of suggesting images (as outlined in Fig. 2): the interactive classifier, nearest-neighbour search, and the randomized explorer. The position of each component on the exploration-search axis is shown in Fig. 4.

The **interactive classifier** maintains a linear SVM model \(\sigma_{i}\) for each non-empty bucket \(b \in B\). This classifier choice is consistent with the state of the art in interactive multimodal learning [18,41], linear SVM exhibits good performance in interactive time on even very large datasets. The interactive classifier’s suggestions are the top images \(i \in I\) by classifier score \((\text{score}(\sigma_{i}, i))\).

Since each interactive classifier is explicitly tied to a bucket, it is the component used to compute bucket confidence, the belief that an image \(i \in I\) belongs to bucket \(b \in B\) is given by:
As described in Sect. 3.1, bucket confidence is used throughout II-20’s interface to provide the user with additional information about the model’s reasoning. Easy translation to bucket colour brightness is the reason bucket confidence is confined to the [0, 1] range. If $\sigma_b = \emptyset$, bucket confidence is undefined (but in that case, the model is not suggesting for $b$ anyway).

Nearest neighbour search utilizes the collection index to search for the images with the lowest distance to the given bucket. This component has two modes: k-NN (k nearest neighbours) and aNN (approximate nearest neighbours). As shown in Fig. 4, they occupy slightly different positions on the exploration-search axis, and also on the “exactness vs. computational efficiency” tradeoff: the k-NN mode is more exact, but requires a full k-NN matrix of the dataset (especially difficult for datasets of >1M images), whereas the aNN mode is more randomized, but utilizes no precomputed structures. We experimentally evaluate both modes to determine which is better for analytic support.

The k-NN mode relies on a precomputed k-NN matrix that records the 10 nearest neighbours by product-quantization distance for each image in the collection. To produce $s^b_{nn}$ suggestions for bucket $b \in B$, the k-NN mode uniformly samples $s^b_{nn}$ images from the set of all recorded neighbours of the images in $b$ (for computational efficiency reasons, if $|b| > 50$, the neighbours of a uniform random sample of size 50 drawn from $b$ is used instead).

The aNN mode produces $s^b_{an}$ suggestions as follows. First, it uniformly samples 50000 candidates ($C_{an}$) from $I \setminus P$. Secondly, it computes their distance to up to 25 images in $b$ (sampling uniformly if $|b| > 25$). The distance of each $c \in C_{an}$ to the bucket is the minimal distance between $c$ and any image in the bucket (sample). Finally, it returns the top $s^b_{an}$ candidates sorted by the distance to bucket $b$ in ascending order. The aNN sample caps of 50000 and 25, respectively, were chosen to preserve interactive response time.

Finally, II-20 has a randomized explorer component to support the exploration side of the axis. The randomized explorer suggests random images that are as far away from what the user has already processed as possible. This allows quick semantic traversal to the unseen parts of the collection. To produce $s_{rand}$ suggestions, the randomized explorer suggests first randomly samples $C_{rand}$ candidate suggestions from $I \setminus P$. Then, it sorts $C_{rand}$ by maximum distance to $P$: the distance of each candidate $c \in C_{rand}$ to $P$ is equal to $\min_{p \in P} \text{dist}(c, i)$. The top $s_{rand}$ images in the sorted $C_{rand}$ set are the randomized explorer suggestions. $|C_{rand}|$ is a performance-boundary parameter: the larger we can afford without violating the interactive response time, the better. In the II-20 prototype, $|C_{rand}| = 100 \cdot s_{rand}$.

3.2.3 Bucket model

To model buckets, in addition to $B$ and $D$, II-20 maintains three extra sets of images per bucket. Firstly, bucket suggestions ($S_b$), i.e., all images suggested for bucket $b \in B$ throughout the analytics session. Secondly, correct bucket suggestions ($C_b$), a set of all images which were at any point in the analytics suggested for bucket $b \in B$ and subsequently added to it by the user. Thirdly, wrong bucket suggestions ($W_b$), a set of all images which were at any point in the analytics suggested for bucket $b \in B$, but were then discarded or added to a different bucket by the user. Further, $S_{b, last}$ and $S_{b, mn}$ denote the suggestions produced by the interactive classifier and nearest neighbour search, respectively (similarly for $C_b$ and $W_b$). Let $[\cdot]_w$ denote the sliding window operator, which selects exactly those images added in the last $w$ interaction rounds to the image set. For instance, $[S_b]_1$ selects the outstanding suggestions for $b$ (active in the UD) produced last interaction round.

3.2.4 Suggesting relevant images

The relevant images suggestion procedure takes two inputs: Firstly, $F$, the user feedback. $F$ is a set of key-value pairs with any image as the key and its assigned bucket $b_a, b_b \in B \cup d$. Secondly, $s_{tr}$, the number of suggestions for each bucket requested by the metaphor. The suggestion procedure (see Fig. 5) for bucket $b \in B$ operates as follows.

**Feedback processing** — Establish $F_b = \{i \in F | value(i) = b\}$, the set of all images added to bucket $b$ by the user. Further let $F_{-b} = F \setminus F_b$. Then, split the feedback into positive, neutral, and negative; process each separately. Add the positive feedback, $F_{+b} = F_b \cap [S_b]_1$, and the neutral feedback, $F_{\pm b} = \{i \in F_b | i \notin [S_b]_1\}$, to the bucket: $b = b + F_{+b} \cup F_{\pm b}$. Add the negative feedback images, $F_{-b} = F_{-b} \cap [S_b]_1$, to the set of wrong suggestions: $W_b = W_b \cup F_{-b}$.

**Train images pruning** — By default, $\sigma_b$ uses all images in $b$ as positive training examples. For increased classifier quality, it may be worthwhile to prune the set of train images. Generally, the more data, the better, but reinforcing the importance of the archetypal images or clarifying the decision boundary might lead to improved performance. To that end, we propose three strategies to construct the positive training set for $\sigma_b$ (note that if $\sigma_b = \emptyset$, II-20 falls back to the default of taking all images from $b$):

- **Relevance feedback** — The $n_r$ images from $b$ with the highest score according to the current $\sigma_b$, emphasizes the archetypes.
- **Active learning** — The $n_r$ images from $b$ with the lowest score according to the current $\sigma_b$, focuses on the decision boundary between the bucket and the remainder of images.
- **Hybrid** — A relevance feedback images and $\frac{2}{n_r}$ active learning images are obtained, the result is the union of the two sets. Trims images that are neither archetypal nor near the decision boundary.

We experimentally compare all four strategies with various $n_r$ to each other and to the default setting (simply taking all images from $b$).

**Classifier training** — If $b \neq \emptyset$, train the classifier. The set of positives ($T^+$) is taken from the previous step, the set of negative training examples ($T^-$) is initialized to $T^- = W_b$. For classifier robustness, we want to have at least twice as many negatives as positives. If $|T^-| < 2 \cdot |T^+|$, $T^-$ is supplemented with (a random sample of) the images in the discard pile, and if that still is not enough, $T^-$ is filled to the desired size by a random sample from all images in the collection.

**Null classifier case** — If $\sigma_b = \emptyset$, return $S_b$ randomized explorer suggestions.

**Oracle queries** — As mentioned in Sect. 2, employing active learning often leads to improved classifier quality whilst reducing the required number of user interactions. II-20 must chiefly employ relevance feedback, as relevant images is what the user is looking for, but it might help to ask the user (= the oracle) for judgment on a certain number of difficult images. Posing an oracle query means that instead of the image with the highest $\sigma_b$ score, II-20 shows an image with the score closest to 0 (= nearest to the decision boundary) and marks it with a question mark. Let $\sigma$ denote the proportion of oracle queries within all suggestions ($\sigma = 0$: pure relevance feedback, $\sigma = 1$: pure active learning). II-20 produces oracle queries $O_b$ by replacing each suggestion with an oracle query with probability $\sigma$. Then, $O_b$ is reduced by the number of oracle queries such that the correct requested number of images is maintained: $s_{tr} := s_{tr} - |O_b|$. In the experiments, we vary $\sigma$ to gauge the benefits of employing active learning.

**Exploration-search split** — The model decides the proportion between classifier, nearest neighbour, and randomized explorer suggestions based on the precision achieved by the classifier ($p^{\text{class}}$) and nearest neighbour search ($p^{\text{mn}}$) in the last $w$ interaction rounds ($w$ is a parameter subject to experimentation):

$$p^{\text{class}} = \frac{|C_b|}{|S_{b, last}| \cdot \|w\}$$

$$p^{\text{mn}} = \frac{|S_{b, mn}|}{|S_{b, mn}| \cdot \|w\}$$

$$p = \frac{p^{\text{class}} + p^{\text{mn}}}{2}$$
Fig. 5. The procedure for suggesting relevant images: feedback is collected from the interface, processed, a new interactive classifier is trained, and then suggestions covering the entire exploration-search axis are produced. The components innovated by II-20 are coloured orange.

\[p_m = \frac{[c_m]}{[c_m]_w}\]

If \([c_m] = \emptyset\), \(p_m = 1\) (similarly to \(p_m\)). For each suggestion to be produced, roulette selection is performed. A uniform random number \(r \in [0, 1]\) determines the suggestion source:

- \(0 \leq r < p_{\text{class}}\): interactive classifier
- \(p_{\text{class}} \leq r < p_{\text{class}} + (1 - p_{\text{class}}) \cdot p_{\text{nn}}\): nearest neighbour search
- \(p_{\text{class}} + (1 - p_{\text{class}}) \cdot p_{\text{nn}} \leq r < 1\): randomized explorer

In other words, the percentage of interactive classifier suggestions is equal to its current precision. Should the interactive classifier start faltering, the nearest neighbour search comes in, shifting the position on the exploration-search axis. If neither provides suggestions meaningful to the user, it is time for exploration: as both \(p_{\text{class}}\) and \(p_{\text{nn}}\) fall to zero, most of the suggestions will be produced by the randomized explorer, which is by design traversing to yet unseen parts of the collection. Over a couple of exploration rounds, new bucket images (or even buckets) will hopefully manifest, the sliding window will “forget” the bad streak and when the time is right, the analytics will shift toward search again.

**Final suggestions** — Based on the exploration-search split, image suggestions are produced by each of the model components, concatenated with \(O_b\), and returned to the user.

### 3.3 Fast-forward

The fast-forward interaction quickly expands a bucket using the current model. Fast-forward takes two inputs from the user: the bucket to be expanded \((B_f \in \text{Bucket}, B_f \neq \emptyset\) and the number of images to be added to \(b_{ff}\) (denoted \(n_{ff}\)). As the shorthand notation, we propose “fast-forwarding \(b_{ff}\) by \(n_{ff}\)”.

After receiving the input, the model directly adds the top \(n_{ff}\) images according to interactive classifier score to \(b_{ff}\). Immediately afterwards, the user is taken to the bucket view with the fast-forwarded images shown at the top of the grid, marked with the fast-forward symbol (double right-pointing triangle) in the top left corner. The user can review the fast-forwarded images as she would any other bucket images, e.g., transferring the incorrectly-added ones to the discard pile. Note that the fast-forwarded images have already been added to the bucket — not interacting with them will keep them in the bucket, i.e., fast-forward does not merely provide \(n_{ff}\) regular suggestions. Closing the bucket view commits the fast-forward, and the fast-forwarded images will subsequently appear as regular bucket images.

Fast-forwarding brings the following advantages:

- **Good model = sped up analytic session** — Fast-forward provides a “gear shift” for the analytic session: fast-forwarding a bucket is much faster than producing the same number of regular suggestions, regardless of the image view mode (grid, Tetris).

- **Responsive** — The model processing part of a fast-forward always completes in interactive time, regardless of \(n_{ff}\), due to the model scoring all images in the collection whenever producing suggestions (Sect. 3.2.4). The final list of fast-forwards is produced by simply trimming the list to \(n_{ff}\), which is computationally trivial.

- **Easy discarding** — The user can fast-forward not only the buckets, but also the discard pile. This allows quick disposal of large chunks of non-relevant data. Model judgments on which images are not relevant tend to be more reliable than on the relevant ones. Therefore, the user can fast-forward the discard pile by a large number of images. This will be much quicker than discarding the same number of images through regular model suggestions.

- **Semantic** — “Fast-forwarding a bucket” is a comprehensively, clearly defined interaction universally usable across domains of expertise which directly translates to a model adjustment. As such, it answers the call for more semantic interactions [9][44].

### 4 Experimental setup

We evaluate II-20 twofold: firstly, we verify the analytic quality of the model with automated experiments, secondly, we perform an open-ended user study gauging II-20’s usability and ability to provide insight.

#### 4.1 Datasets

For the experiments, we have selected three datasets that cover different analytic niches: VOPE-8hr, a needles-in-the-haystack dataset with a clear associated analytic task (used for both the user study and the automated experiments), and two datasets widely used for evaluation in computer vision that we use for the automated experiments: CelebA, a face images dataset with high binary annotation coverage, and Places205, a large-scale scene recognition dataset with scene categories of varied granularity.

**VOPE-8hr** is a custom dataset on the topic of violent online political extremism (VOPE). The dataset comprises 8 hours of video. 8% is
VOPE content from 3 categories: neo-Nazi, Islamic terrorism, and Scottish ultra-nationalism. 28% of the content is “red herring” content, which exhibits some visual similarity to the VOPE content, but is safe (e.g., comedy skits featuring Nazi paraphernalia in a mocking manner). The rest, 64% of the content, is fluff, ranging from gaming streams through feature-length films to fashion and football documentaries. We have extracted 1 frame per 3 seconds of video, resulting in a dataset of 9618 images. VOPE-8hr is a challenging dataset: only a small part of the content is relevant (VOPE), and it is obfuscated by three times as much red herring content. This makes the dataset very suitable for insight-based evaluation.

CelebA contains 202K face images annotated with 40 binary attributes such as “eyeglasses” or “wearing hat”. There can be more attributes per image, and in fact, there often are, resulting in a large overlap of image sets per attribute. CelebA is the representative of narrow-domain datasets in our experiments. Places205 comprises 2.5M scene images, each from one of 205 scene categories. Places205 brings the challenge of scale (it is not trivial to process 2.5M images interactively), as well as variation in the scope of individual categories: some are quite general (e.g., “ocean” or “office”), some more nuanced (e.g., “herb garden” or “shoe shop”).

4.2 Automated experiments

The automated experiments were conducted in order to answer the following research questions:

Q1) Does II-20’s model yield better performance (precision, recall) than classic interactive learning?

Q2) How does the Tetris metaphor perform in comparison to the grid?

Q3) What parameter configuration of II-20 performs the best?

The baseline for our experiments is the state of the art in interactive learning, namely Blackthorn [4]. In two oracle strategy variants. The first one, further labelled baseline-ref, employs pure relevance feedback (a = 0), the second one, labelled baseline-al_0.2, is an active-learning modification with a = 0.2. The original Blackthorn is a pure relevance feedback approach, the active learning variant is an adaptation that allows us to evaluate mixing in active learning.

The baselines are pitted against various configurations of II-20, varying the parameters defined in Sect. 3.2 independently. Firstly, the nearest neighbour mode: ann on all three datasets, knn on VOPE-8hr and CelebA due to Places205 being prohibitively large for k-NN matrix computation. Secondly, w ∈ {5, 10}, the number of last interaction rounds considered for the exploration-search split. Thirdly, a ∈ {0, 0.2} (rf, al_0.2), the proportion of oracle queries within the suggested images. Forthly, the pruning strategies for training positives: all (no pruning), rf (relevance feedback), al (active learning), hybrid. Finally, m_s ∈ {100, 500, 1000}, the number of bucket images to be kept when using the pruning. Henceforth, ii20-<nn_mode>-w<oracle>-<pruning>-m_s identifier is used for II-20 configurations.

For the automated experiments, we employ an enhanced version of the analytic quality evaluation protocol [42]: artificial actors interact with II-20 in place of a user, putting relevant images in buckets and discarding the non-relevant ones, and we report their achieved precision and recall over time. The artificial actors base their judgment on ground truth annotations that come with each dataset: the VOPE categories in VOPE-8hr, the facial attribute annotations in CelebA, and the scene categories in Places205. Note that for evaluation purposes, the ground truth is known only to the actors and withheld from II-20
in all analytics sessions; II-20 only sees unannotated image data. Each actor for the given dataset considers images from a subset of ground truth annotations as relevant and discards all others. Each annotation is treated as a separate bucket. For the VOPE-8hr dataset, we run the experiment on all combinations, i.e., 7 notions of relevance in total. For both CelebA and Places205, we randomly sample 5 notions of relevance for each bucket cardinality from 1 to 7 (matching the number of buckets limit between 1 and 7 as described in Sect. 3), resulting in 35 notions of relevance total for each dataset.

In addition to a notion of relevance, each actor has an inherent error rate $err_r \in \{0, \ldots, 2\}$: users can make mistakes in their interactions and it is important to test the robustness of the model. Introducing actor errors not only acknowledges the fact that human users are fallible, but also tests resilience against fast-forward errors overlooked by the user. For each label to be produced by the actor, we sample a uniform random number $r \in \{0, 1\}$. If $r < err_r$, the actor makes one of the following mistakes (with uniform probability): ignores the image (provides no feedback at all), flips relevance (a non-relevant image will be assigned to a random bucket, a relevant image will be discarded), or confuses buckets if applicable (adds the image to a different bucket than it belongs to). The actors vary $err_r$ and the notions of relevance independently, resulting in 14 actors total for VOPE-8hr and 70 actors for CelebA and Places205 each.

### 4.3 User study

The user study aims to answer the following research questions:

**Q4)** What are the main strengths and weaknesses of II-20?
**Q5)** How does the Tetris metaphor fare in the eyes of the participants?
**Q6)** How efficient/useful is the fast-forward interaction?

We employ an open-ended insight-based evaluation protocol, in which the users think aloud, recording their insights as they progress with their evaluated tasks [26][27]. The evaluated system’s analytic efficiency is then gauged by analyzing these insights. The II-20 user studies are designed to be remote, so the “thinking aloud” is replaced by the users hitting the “Record insight” button and recording whatever is on their mind at any point in their session.

The user study scenario has four steps:

1. **Introduction** — The user is greeted by a brief description of II-20, analytic categorization as a task, and an outline of the user study. Further, the user is linked to a tutorial video on YouTube and informed that they can refer back to the video whenever they want.

2. **Warm-up** — The user tries II-20 out on a toy dataset (same as in the tutorial video). Her objective is to familiarize herself with II-20 controls. The user is not being recorded in this step.

3. **User study task** — After the warm-up, the user performs the evaluated task proper (described in detail below).

4. **Final questionnaire** — The user answers three open-ended questions: main strengths of II-20, main weaknesses, and any other comments.

The user study task is inspired by digital forensics. The user investigates extremists that create or post propaganda on the Internet. She has just received image data from a suspect’s computer and is asked to establish whether they contain extremist content or not, and if so, what kind. Apart from this main question, the user is asked to record general insights about any content encountered in order to profile the suspect.

The user study task runs on the VOPE-8hr dataset, i.e., the user should investigate extremists that create or post propaganda on the Internet. She has just received image data from a suspect’s computer and is asked to establish whether they contain extremist content or not, and if so, what kind. Apart from this main question, the user is asked to record general insights about any content encountered in order to profile the suspect. The user is instructed to take as much time as needed and can stop the analytic session at any time. In addition to explicit insight, we record user actions and all II-20’s image suggestions.

11 users participated in the user study: 9 computer scientists and 2 robotics experts. 9 participants have a master’s degree or higher, 2 participants are master students. None of the participants are domain experts on the task topic (violent online political extremism); the role of a digital forensics investigator was a role-playing task for all of them.

### 5 Results and discussion

Fig. 6 reports the precision and recall of the evaluated algorithms, split by dataset and metaphor simulated by the actors. Each curve is the average across all the actors running on the dataset. In each plot, for each metaphor, we report the results of the baselines and the best-performing II-20 variants. The $x$ axis is the number of images processed by the user, which has a direct mapping to time (e.g., considering a hypothetical fast user that processes 1 image per second, the $x$ axis is time in seconds).

The experiments show that II-20 outperforms the baselines on all datasets with respect to both precision and recall, except for the later stages of analytics on CelebA, where the baselines pull ahead slightly (even then, II-20’s performance remains quite acceptable). This makes sense: CelebA is a dataset with high coverage of the annotations used to construct the actors. Therefore, there are plenty of positive examples, which increases the reliability of the vanilla interactive learning approach. VOPE-8hr and Places205, however, have more of a needles-in-the-haystack nature: positives for a particular category are a rare asset. II-20 is strictly dominant on these datasets, often by quite a large margin. Therefore, we answer Q1 positively, in favour of II-20.

Comparing the metaphor usage simulations reveals that Tetris indeed shows analytic promise. Interestingly enough, from Fig. 6 it appears that Tetris’s performance is strongly tied to whether II-20’s model was used: Tetris in combination with II-20 tends to be the dominant approach (esp. in early stages), whereas the baselines are usually better off with the grid. Also, there tends to be a breakpoint where switching from Tetris to the grid increases precision and recall. We explain this by the difference in availability of positive training examples in various stages of the session. At first, positives are rare, and fine-grained feedback after each image (Tetris) is very beneficial to the model. Later
on, there are usually enough positives to flesh the model out, but the remaining ones are trickier to find (the clear-cut cases have already been seen before), so it’s beneficial to be “fishing” for more by showing a larger portion of the ranking in the grid. Whenever this stage of nuanced, difficult positives is encountered, it might be worthwhile for the user to switch to the grid. We answer Q2 by remarking that Tetris certainly has strong analytic potential, complementing the grid well and even outperforming it at times.

To answer Q3, we have performed parameter tuning and report the results in Fig. 7 normalized precision at 900 processed images (15 minutes at 1 image/s) and normalized recall at 1800 processed images (30 minutes at 1 image/s), i.e., early precision, late recall. Each bar reports the average normalized precision/recall across all experiments, metaphors, and datasets. Each normalized value is obtained by dividing the absolute value by the maximum achieved on that dataset. This is done to remove differences in absolute performance between datasets.

Overall, the differences are not statistically significant, i.e., none of the parameters seem to drastically influence the performance (at least within the evaluated values). However, certain observations can be made. First and foremost, the parameter tuning confirms what Fig. 6 shows as well: the aNN nearest neighbour mode edges ahead of the k-NN. This is fortunate: aNN is easier to compute, as it does not require a k-NN matrix. The shorter exploration-search window came ahead, which hints at confirming the importance of the exploration-search sliding being dynamic. Employing oracle queries seems to improve the model, and pruning should not be done too aggressively (if at all).

Fig. 8 shows the insights recorded by the user study participants over time. The insights are split into five categories. The first are insights related to II-20’s functionality, the second are insights related to general task progress (an example of such obtained user insight: “user plays a lot of video games”), and the remaining three correspond to the three categories of actual VOPE content — neo-Nazi, ISIS, Scottish ultranationalism — where the users have explicitly referred to the content being extremist in the correct category (e.g., as one user wrote, “At the moment I can tell that the suspect does have extremist content from islamic terrorism”). The triangular markers mark the time when the first image from a VOPE category appeared for the user.

We believe II-20 was able to sufficiently support the task. All participants were suggested VOPE content, 9 out of 11 participants explicitly noted extremism in their insights: all 9 have found out about Islamic terrorism content, 5 have found evidence of neo-Nazi content, and 1 has found out about Scottish ultranationalism (note: this is a difficult category with highly contextual content incl. Gaelic slogans, and none of our test users were Scottish). None of the users have ended their session prematurely due to being confused or finding the system unusable.

Regarding main strengths and weaknesses, the received feedback is diverse. The main strengths as reported in the final questionnaire were: intuitive interface and user-friendliness (6 users), having full control of the buckets (4 users), and good performance in finding similar images (4 users). The main reported weakness, by far, was receiving very similar, non-diverse images from the system (7 users). To an extent, this is an artifact of the dataset (frames extracted from videos, often monotonical), but that of course does not invalidate the feedback. Another weaknesses include missing progress bar (“how much of the collection has been already seen”) mentioned by 2 users, and diverse feedback by 1 user each, such as the dark design of the interface or unintuitiveness of certain tools (e.g., grid bucket selection and the meaning of discard). Regarding Q5, we conclude that II-20 has succeeded as a tool, as it is intuitive and provides good performance, but additional diversification capabilities and UI improvements are needed.

The Tetris metaphor has received a mixed response. Overall, it is fair to say that the vast majority of the users’ time was spent in the grid interface. In fact, only 5 of the 11 users have swapped to Tetris at any point in the session. That makes sense: the grid is a familiar, useful, and also the default metaphor. Moreover, we have deliberately not drawn any attention to Tetris specifically so as to obtain fair, unbiased feedback. One user has strongly liked Tetris, one has found it not useful, and one stated that it would be much better if it had a static variant with immediate accept/reject functionality. The honest answer to Q5 is that Tetris has not yet gained significant traction and probably requires extended functionality and clearer outline of its niche: after all, it has shown very promising results in the automated experiments.

Fast-forward, compared to Tetris, has been seen quite some more action: 8 users have used the functionality at least once. The fast-forwards were by 10–25 images, all fast-forwards concerned user buckets (no user fast-forwarded the discard pile). One user has lauded fast-forward as one of the main strengths of II-20, there has been no negative feedback or suggestions for improvement. Therefore, to answer Q6, we conclude that fast-forward has been shown as a useful, intuitive interaction to those users that have chosen to use it.

6 Conclusion

In this paper, we have presented II-20, an approach for multimedia analytics on image collections that addresses open challenges in visual and multimedia analytics and closing the pragmatic gap. II-20’s new machine model is the first model to fully support dynamic sliding on the exploration-search axis without explicit input from the user, and in the automated experiments, it has proven superior to state-of-the-art interactive learning. The Tetris metaphor is a dynamic metaphor with high synergy with the model: an accurate model can “play the game” fully autonomously. Out of the three contributions, Tetris needs the most work, namely increased clarity to the users and enhanced functionality, but its analytic performance numbers are already promising. The fast-forward interaction expands the family of semantic interactions, so needed for multimedia analytics. It provides an intuitive, fully controllable way to speed up the analytics process.

We especially value that II-20’s contributions, in addition to passing the experimental evaluation, have overall turned out to be considered intuitive by the users. User agency is one of the key design paradigms of II-20: the basis is a familiar interface backed by a powerful model, and it’s completely up to the user when she wants to engage with the new interactions and interface elements. The II-20 prototype is a complete multimedia analytics system, which will be made open-source and available to the research community and applied domains alike. We hope that II-20 has contributed to kicking off truly intelligent and pragmatic multimedia analytics fit for the new decade.

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